CESifo WORKING PAPERS

8827
2021

January 2021

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 8827*

Public Health Insurance and Medical Spending: Evidence from the ACA Medicaid Expansion

Abstract

This paper investigates the short-run impact of public insurance expansion under the Affordable Care Act on out-of-pocket medical spending (OOP) and risk exposure among low-income, eligible households as well as the incidence of the cost of providing insurance. Using data from the Medical Expenditures Panel Survey (MEPS), I exploit exogenous variation in Medicaid eligibility rules across states, income groups and time. I find that public insurance eligibility reduced mean OOP by 18.2% among targeted households, but it did not causally increase total expenditures among beneficiaries. Rather, Medicaid expansion shifted the burden of payment from eligible households and private insurance (17% reduction) to taxpayers in the form of public insurance (45.7% increase). The efficiency of these public funds can be summarized by a Marginal Value of Public Funds ranging from 0.06 to 0.59 that is highest for households with at least one pre-existing condition.

JEL-Codes: D040, D610, H440, I130.

Keywords: public health insurance, risk protection, MVPF, Medicaid, out-of-pocket expenditures, Affordable Care Act.

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December 30, 2020
Consumer Financial Protection Bureau, Office of Research, 1700 G Street NW, Washington, DC 20552. The views expressed are those of the author and do not necessarily reflect those of the Consumer Financial Protection Bureau or the United States. I am grateful to Khalid Elfayoumi, Nathan Hendren, Claus Thustrup Kreiner, Søren Leth-Petersen, David Neumark, Mark Pauly, Carsten Schröder, Hannes Ullrich, Amelie Wuppermann, Georg Weizsäcker and participants at the 2020 EEA Annual Conference, 2020 Econometric Society World Conference, CEBI research seminar, 2019 ASHEcon Annual Conference, the CFPB Research Seminar, IIPF 2019 Annual Conference, US Census Bureau Research Seminar, DIW Public Economics Cluster Seminar, the University of Potsdam Research Seminar, the EUHEA Digital Seminar and CESIfo Area Conference on Public Economics for helpful comments. All remaining errors are my own. I also thank the Federal Agency for Healthcare Research and Quality (AHRQ) for granting access to the restricted Medical Expenditure Panel Survey data and in particular Ray Kuntz for his assistance at the Data Center and in running code remotely.

1 Introduction

In the United States, Medicaid public insurance comprises the third largest domestic spending item in the federal budget, amounting to just under $604 billion in 2019 (Kaiser Family Foundation, 2020). Against the background of rising health care spending from both private out-of-pocket and public sources, recent policy proposals for health care reform range from significantly cutting Medicaid entitlements to expanding them to universal coverage (Glied and Lambrew, 2018; Holahan and McMorrow, 2019). These debates highlight the importance of understanding the impact of public insurance on the affordability of care and risk protection among eligible households as well as the cost to taxpayers of providing it. This paper exploits the unique quasi-experiment of the Affordable Care Act (ACA) Medicaid expansions in order to examine these causal relationships.

The incidence of the cost burden associated with expanding public health insurance to low-income adults remains underexplored in the literature. This paper will first identify the impact of ACA Medicaid eligibility on out-of-pocket (OOP) medical spending and risk protection among beneficiary households. In a second step, it quantifies the cost shifting of medical expenditures paid on behalf of beneficiary households to public and private sources and examines the corresponding efficiency, or marginal value of public funds (MVPF), of these expenditures. To my knowledge, this paper presents the first assessment of this cost shifting in the context of Medicaid expansion and the first analysis of the impact of the ACA expansion on risk protection. It furthermore adds to a small body of literature that has examined the effect of public insurance expansion on OOP medical spending among low-income adults.

The present analysis extends previous research on the role of Medicaid in improving measures of financial well-being for extreme outcomes of realized risk such as medical debt and bankruptcies for low-income households. Gross and Notowidigdo (2011) investigated earlier Medicaid expansions between 1990-2004 targeted toward protected groups such as children and pregnant women and found they led to decreased personal bankruptcies among eligible households. Within the context of the Oregon Experiment, Finkelstein et al. (2012) showed that adults who won the Medicaid lottery in 2008 had less medical debt one year after they received public insurance, compared to those who did not win the lottery. With respect to the large, nation-wide eligibility expansions of the ACA, Hu et al. (2018), Brevoort et al. (2019), Caswell and Waidmann (2019) and Allen et al. (2017) have found reductions in medical bills sent to collections, improved credit scores and reduced pay-day borrowing in expansion states (counties) in comparison to non-expansion states (counties). These findings suggest that effects from health insurance may spill over into these other areas of consumer finance and have lasting positive impacts on financial health and consumption among liquidity-constrained, low-income households.[1] These potential long-run impacts on consumption and financial health provide a case for the existence of a positive fiscal externality from health insurance. This paper quantifies the risk exposure reduction attributable to the ACA expansion and incorporates it into the MVPF framework (Hendren and Sprung-Keyser, 2020), allowing for a direct comparison of its impact on social welfare with that of other policies.

Regarding the impact of the ACA Medicaid expansions on mean out-of-pocket spending, Abramowitz (2018), Buchmueller et al. (2019) and Blavin et al. (2018) compare outcomes in expansion and non-expansion states and hone in on sections of the population that experienced the largest increase in eligibility by restricting their sample to single households below 138% of FPL, or to those between 100-138% of FPL. Results range from a zero effect to substantial reductions in OOP.[2] I add to this earlier work by showing that individual identification of eligibility leads to smaller estimates of OOP spending reductions due in part to spillover effects from previously eligible households.

In order to establish a causal relationship between OOP medical expenditures and exposure to Medicaid, I exploit variation in eligibility rules across regions, income groups and time. Rather than differencing average outcomes in expansion and non-expansion states in a traditional difference-in-differences approach, identification in this paper additionally uses higher income households as a within-state comparison group that helps to net out possible omitted differences between expansion and non-expansion states that affect out-of-pocket medical spending. I identify an intention to treat (ITT), which is the effect of offering public insurance eligibility, rather than the effect of having it. In order to address possible endogeneity of Medicaid eligibility, I instrument observed eligibility with a simulated eligibility measure in the spirit of Cutler and Gruber (1996) and Currie and Gruber (1996) that isolates the exogenous variation in policy generosity from individual-level endogeneity.

I find that the ACA Medicaid expansion reduced mean household out-of-pocket expenditures for medical services and products by 18.2% among households with positive OOP costs and increased the probability of having zero OOP expenditures by 6.2%. Intensive margin OOP reductions are strongest for prescription drugs and hospital visits (both emergency and non-emergency room) and among households with at least one pre-existing

[1]Himmelstein et al. (2009) attribute as much as 62.1% of consumer bankruptcies prior to the onset of the Great Recession in 2007 to medical bills. Gross and Notowidigdo (2011) estimate this share to be much lower, around 26%. Even based on the lower bound, however, this figure remains economically relevant.

[2]Blavin et al. (2018) find the largest reductions in OOP on account of the ACA expansion, in the order of $344 in average spending and a 7.7 percentage point decrease in the probability of having any OOP; Abramowitz (2018) does not find any impact on positive spending, but a lower probability of having any OOP spending; Buchmueller et al. (2019) find an average reduction of $240 annually.

condition. Results from the instrumental variable analysis do not differ significantly from those that treat eligibility as exogenous.

In line with findings from the Oregon Medicaid Experiment, quantile regressions reveal that reductions in both the mean and variance of medical spending are highest for large payments in the upper percentiles of the OOP distribution (Finkelstein et al., 2012). However, estimates of the private willingness to pay (WTP) for these expected reductions in the mean and variance of costs are lower than in the Oregon Medicaid Experiment (see Finkelstein et al. (2019a)), as the latter setting reflects a LATE estimate for previously uninsured compliers who sign up for an insurance lottery and then choose to enroll if selected. The current paper adds to this discussion by providing estimates based on an ITT, or the impact of insurance eligibility on the average low-income childless household. ITT estimates may be of particular interest to current non-expansion states that wish to anticipate the expansion costs and WTP among all eligible households, who are likely healthier, have a lower average heath care demand and may be switching from either private insurance or no insurance. Additionally, the welfare analysis outlines a distribution of heterogeneous WTP estimates that increase with (assumed) risk aversion and poorer health.

Despite inducing reductions in OOP expenditures among beneficiary households, the expansion did not causally increase total expenditures paid on their behalf. Rather, it shifted the burden of payment from eligible households and private insurance to non-eligible tax payers. Reductions in the share of total medical expenditures paid by private insurance (17.0%) and OOP (25.3%) were compensated by a 47.1% increase in the share paid by the taxpayer through public insurance. The welfare analysis offers a ballpark figure for the MVPF, which ranges from 0.05 to 0.59, with the highest value among households with at least one pre-existing condition.

The paper is structured as follows. Section 2 discusses the policy background and main cornerstones of the ACA Medicaid expansion. Section 3 describes the empirical approach, including the data, sample selection and econometric specification. Section 4 presents results of the causal analysis for mean medical spending, risk exposure to high medical payments and the short-run welfare analysis. Section 5 concludes.

2 Policy Background

Although Medicaid has existed in the United States since 1965, coverage prior to the ACA had been restricted to protected groups such as pregnant women, the disabled, children and parents of eligible children with very low incomes. Eligibility depended on having household income below the threshold for the individual's respective category. Medicaid was and continues to be a federal-state cooperation, with some variation in programs and coverage across states. The ACA introduced an additional category for childless adults and granted eligibility to those with marginal adjusted gross income below 138% of the federal poverty line.[3] Following the 2012 Supreme Court ruling in the case *National Federation of Independent Business v. Sebelius*, only 26 states, roughly half, implemented this expansion in eligibility in 2014 and 5 more by 2016. The state-level expansion decision offers quasi-exogenous variation from the perspective of the individual household and is the most exploited identifying variation in the literature examining various outcomes of the ACA Medicaid reform (Sommers et al., 2015; Wherry and Miller, 2016; Mas and Leung, 2018; Duggan et al., 2019; Simon et al., 2017; Buchmueller et al., 2019; Wherry and Miller, 2019). Following Frean et al. (2017), the present paper additionally utilizes within-state income variation to identify eligibility at the individual level.

All household income in the Medicaid household unit (MHU) counts toward each individual's category-specific income threshold for the purpose of determining eligibility at the individual level. Who belongs to the same MHU depends on the tax filing status and tax dependent status. Medicaid households are smaller than or equal to the size of a health insurance unit (HIU) or a dwelling unit and thus, separating multiple MHUs within the same household in the following analysis will be essential in order not to underestimate eligibility.[4] As an example of such a distinction, an unmarried 20 year old living with her parents would be in the HIU of the parents, but only in the same MHU if she is also claimed by her parents as a tax dependent. Otherwise, she forms her own MHU and only her own income counts toward the Medicaid income threshold for eligibility.

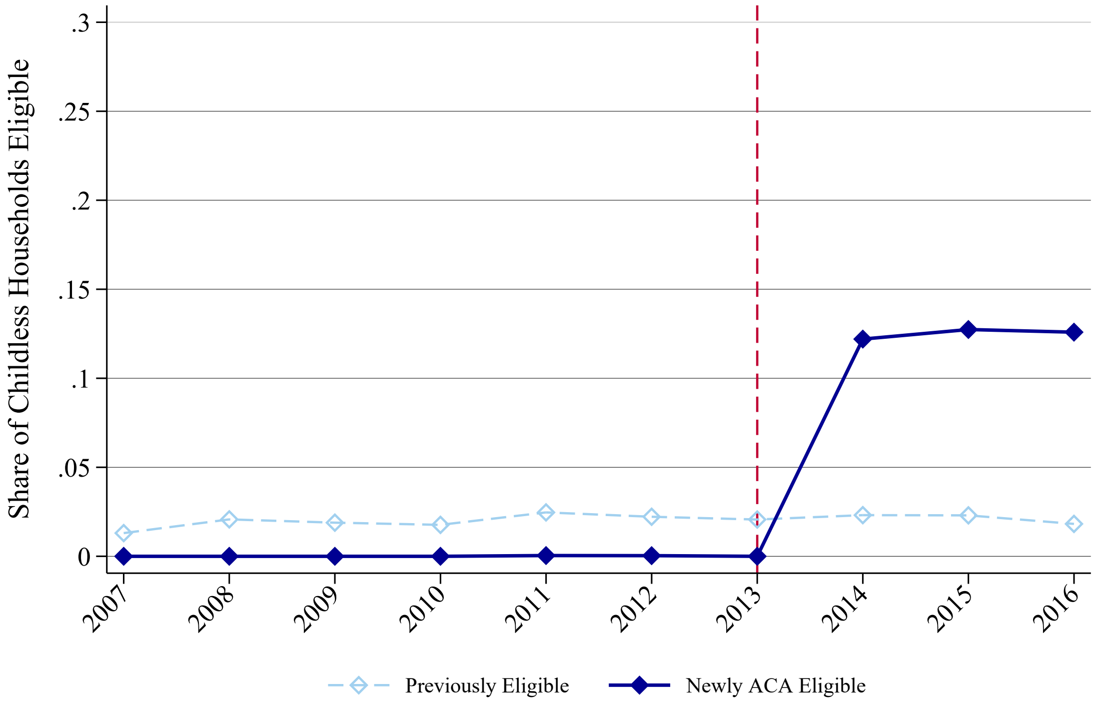
Figure 1 displays the ACA changes to Medicaid eligibility over time as well as actual insurance coverage for childless adult households in the sample. Only 1-2% of childless adult households are eligible for Medicaid according to the pre-ACA rules, whereas 13-14% become newly eligible beginning in 2014. In order to highlight the changes in eligibility exclusively from the ACA expansion, individuals already eligible for Medicaid according to pre-ACA rules are coded as not eligible, as they are not newly eligible. This strategy will also be employed in the causal analysis. Households who were already eligible according to pre-ACA rules are dropped from the sample in order to avoid using them as a control group, as previous work has found evidence of spillover effects of the ACA expansion on

[3] In 2016, the last year included in this analysis, the federal poverty line is $11,880 in annual taxable income for a single household and roughly double for a couple household. Some states expanded eligibility to childless adults above the 138% threshold.

[4] See for example the reference guide for Medicaid household rules from the Center on Budget and Policy Priorities, available at `http://www.healthreformbeyondthebasics.org/key-facts-determining-household-size-for-medicaid-and-chip/`.

this group (Frean et al., 2017).[5]

Figure 1: Changes to Medicaid Eligibility According to ACA Expansion Rules



Source: MEPS 2007-2016. Weighted shares using MEPS household weights. Figure does not include early expansion states and counties.

3 Empirical Approach

3.1 Data and Sample

The main data source used in the analysis is a pooled cross-section of the Household Component of the Medical Expenditures Panel Survey (MEPS).[6] This high-quality survey matches households to their medical providers and pharmacies, using a follow-up survey to validate and improve the expenditure information provided by households. It is the most detailed source of nationally representative data for the United States regarding medical conditions, health care utilization, insurance coverage, and expenditures by source of payment. Furthermore, it contains demographic and income information for each individual. In combination with the restricted geocodes available at the AHRQ Data

[5]Robustness results for retaining this group can be found in Appendix Section B.

[6]The MEPS data set is a two-year rotating panel. However, longitudinal and cross-sectional files are provided separately, each with its specific sample weights such that pooling years together in the cross section remains nationally representative.

Center in Rockville, Maryland, it allows for identification of Medicaid eligibility status at the individual level.

The sample consists of all childless adult households below the age of 65 in all states except Delaware, Massachusetts, New York, Vermont and Washington, which had ACA-like Medicaid programs prior to the reform.[7] Further, in order to ease interpretation of the ITT estimate in the event study specification, the sample excludes late expansion states in the main analysis, but robustness results with late expanders are provided in Appendix Section B.[8] Beyond these state and county exclusions, individuals without an identifiable Medicaid household unit (0.8% of the remaining non-elderly sample) were dropped.[9] The final cross-sectional sample encompasses approximately 52,000 households from 2007-2016.

In order to separate dwelling units into Medicaid household units (MHUs), I use the spouse, mother and father identifiers as well as the relationship to the head of household to determine the relationship status in larger households. I further rely on 1040 tax filing thresholds and dependent income thresholds to establish tax filing status and tax dependency according to the assumption of optimal filing behavior, irrespective of whether the household actually plans to or did file a tax return.[10] Following identification of Medicaid households, I calculate MHU gross income as the sum of the following individual income components: gross wages and salaries from employment, business and farm income, taxable interest income, rent income, trust fund income, alimony received less alimony paid, annuities, dividends, taxable pensions, and unemployment benefits.[11] To arrive at adjusted gross income (AGI), I apply NBER's TAXSIM program, version 27, to account for above-the-line deductions based on household gross income, expenses and composition. Calculating Modified Adjusted Gross Income (MAGI) would require adding untaxed foreign income, non-taxable Social Security benefits and tax-exempt in-

[7]These first four states follow exclusions made in Wherry and Miller (2016). I also exclude Washington state because the state-run Basic Health Plan covered a very similar group of people prior to 2011 when it began using federal funds for early expansion. Other states with less generous programs remain in the sample because a significant amount of the population experienced an increase in eligibility through the ACA.

[8]See Goodman-Bacon (2018) for a thorough discussion of interpreting difference-in-differences estimates in the presence of variation in treatment timing. Late expanders include Pennsylvania, Indiana, Alaska, Montana and Louisiana.

[9]Such cases arise when the relationship status to the head of household is unclear, for instance due to missing information about relationship status or if an individual states his marital status as married, but the spouse, and thus household income, is not observed.

[10]Due to a fundamental redesign of the MEPS in 2017, which omitted tax dependency status from the survey going forward, tax units are no longer as precisely identifiable after 2016.

[11]Dividends are treated as other property income in the TAXSIM model because the MEPS does not contain information about whether dividends are qualified. Capital gains are set to zero due to lack of information in MEPS. According to convention in the United States, I treat married couples as filing jointly for the purpose of calculating AGI.

terest to the AGI. Due to a lack of information on these last components, I use AGI rather MAGI. The importance of this restriction, however, is limited because AGI and MAGI are equivalent in the vast majority of households and in particular for the low-income groups targeted by the ACA Medicaid expansion.

Medicaid/CHIP eligibility thresholds by state, year, age and status stem from the Kaiser Family Foundation.[12] I apply these thresholds to households in the MEPS and determine individual eligibility according to their demographic, geographic and income characteristics. Because all childless adults belong to the same Medicaid category, either all or no members of a MHU will become eligible. Therefore, the treatment variable is equal to one if the household becomes newly eligible for Medicaid through the ACA expansion and zero otherwise. The regression analysis controls for the size of the household.

In order to take a closer look at household medical spending patterns before and after the reform in treatment and control groups, Table 1 displays weighted means for four groups: column (1) presents the average value for households that would have been eligible according to the ACA rules, had the reform been implemented between 2007-2013; column (2) presents the average value for the treatment$\times$post group that actually became eligible for Medicaid through the ACA expansion; columns (3) and (4) show weighted means for households that would not have met eligibility criteria for the ACA Medicaid expansion in any year, either because their income was too high or because they meet the income requirements, but do not reside in an expansion state. As such, column (2) shows the average expenditures and shares with any expenditures for the treatment group, while columns (1), (3) and (4) all serve as control groups. Appendix Table A.1 describes sample characteristics for these treatment and control groups, which enter into all regressions as control variables.

Table 1 presents the share of households with any positive non-premium OOP medical expenditures in row one, including those for medical services, care and products. Row two displays the average annual amount spent out-of-pocket conditional on having positive OOP expenditures. Households meeting the ACA eligibility requirements are 9 percentage points (69% compared to 78%) less likely to spend any money out of pocket on medical services, care or products compared to ineligible households. Conditional on having any non-premium OOP expenditure, 'would be' Medicaid eligible households (column (1)) with positive OOP medical spending spent roughly 30% less than their non-eligible counterparts prior to ACA expansion. Mean OOP spending decreased in the post-reform period for both groups, but did so more starkly for Medicaid-eligible households, in line with public insurance covering a large portion of their medical expenses.

[12]These can be found on the website of the Kaiser Family Foundation, under `https://www.kff.org/state-category/medicaid-chip/medicaidchip-eligibility-limits/` (accessed June 10, 2018).

Table 1: Non-Premium OOP Medical Expenditures of Treatment and Control Households, 2007-2016

	According to the ACA Medicaid Rules from 2014-2016:			
	Medicaid Eligible 2007-2013	Medicaid Eligible 2014-2016	Not Eligible 2007-2013	Not Eligible 2014-2016
	(1)	(2)	(3)	(4)
- Share with positive non-premium OOP	0.69	0.68	0.78	0.76
- Household non-premium OOP (if > \$0)	956.59	678.17	1366.57	1131.95
	(1778.01)	(1548.38)	(2100.18)	(1938.90)
Observations	5,017	2,402	30,560	13,612

Notes: Weighted means using household sample weights in the MEPS cross-sectional data 2007-2016. 'Medicaid Eligible' refers to would-be eligibility according to the ACA rules, had they been implemented in any year. Column (1) presents the average value for households that would have been eligible according to the ACA rules, had the reform been implemented between 2007-2013. Column (2) presents the average value for the treatment×post group that actually became eligible for Medicaid through the ACA expansion. Columns (3) and (4) show weighted means for households that would not have met eligibility criteria for the ACA Medicaid expansion in any year. Standard deviations in parentheses. Values have been adjusted to the CPI-med and are presented in constant 2017 dollars. Observations refer to the number of households in the sample.

3.2 Econometric Specification

To establish a causal relationship between public insurance expansion and medical spending, I rely on the exogenous variation in Medicaid eligibility rules across income, state and time. Rather than considering all households residing in an expansion state as treated, this strategy uses additional variation at the individual level in order to estimate an ITT parameter that focuses on the targeted group of low-income individuals without limiting the sample to those below 138% of FPL.[13] It also allows me to control for time-varying trends across states. This treatment effects analysis is illustrated in Equation 1:

$$\begin{aligned} Y_h = \alpha + \beta ELIG^{ACA}_{hst} + \theta(ELIG^{ACA}_{hst} \times Post_t) + \beta_{st} \\ + \xi X_{hst} + \varepsilon_h \end{aligned} \tag{1}$$

In the household spending analysis, the dependent variable, Y_h, represents the amount of non-premium out-of-pocket medical expenditures paid by the household in the year of observation. It does not include any subsidies received or payments made by third parties,

[13]The rationale for estimating an ITT rather than a LATE is twofold. First, the comparison of interest for cost shifting across the health care system is between eligible and non-eligible households. Second, as noted in Gallagher et al. (2020), the distinction between enrollment and eligibility is not particularly sharp, as eligible households are implicitly insured due to the rule that they can retroactively enroll for up to three months from the point of application.

insurance or otherwise. For the cost-shifting analysis, the dependent variable is the share of total expenditures paid out of pocket, by private insurance and by public sources on behalf of the household, respectively.

Treatment, $ELIG_{hst}^{ACA}$, is defined in both pre- and post-reform years as a indicator variable taking the value of one if the household income, state and composition in the given year would render it newly eligible for Medicaid according to the ACA rules from 2014 (and zero otherwise).[14] Following Frean et al. (2017), this measure uses as controls: 1) those households that would have been eligible for ACA Medicaid expansion in the years prior to the reform, had the reform been implemented earlier and 2) those households in expansion states that do not meet the means-tested income threshold. This latter group additionally helps control for within-state trends unrelated to Medicaid that influence medical spending.

Eligibility is inflation adjusted by using the year-specific federal poverty lines, which are increased for inflation each year. β_{st} denotes a full set of state-year fixed effects, including state and year fixed effects as well as interaction terms, that absorb differential trends in household spending across states over time as well as persistent differences between states with respect to income, health, availability of charity care and other public services that may affect OOP spending. The coefficient θ on the interaction of the post-reform years and treatment intensity yields the impact of Medicaid eligibility on the outcome of interest.

The matrix X_{hst} contains characteristics of the household such as household size as well as the age, sex, race and an indicator for Hispanic origin of the head of the household, an indicator for the respective income quintile of the household in each year, and an indicator variable for the following 12 income bands: below 50% FPL, [50-100% FPL), [100-138% FPL), [138-200% FPL), [200-250% FPL), [250-300% FPL), [300-350% FPL), [350-400% FPL), [400-500% FPL), [500-600% FPL), [600-800% FPL), [≥800% FPL).[15] Income bands flexibly absorb the positive correlation between levels of OOP and income that stem from the nature of health care as a normal good. As the triple interaction between state, time and income *group* determine Medicaid eligibility, controlling for the direct effect of the household's income group, state of residence and year allows for identifying variation to stem only from the interaction of these three factors.

In addition to the main specification, which measures the overall short-run effect

[14]For the robustness specification that includes late expansion states, the measure uses the average eligibility status from 2014-2016. For example, if an individual only becomes eligible in 2016, average eligibility of the individual in the post-reform period would be $0.\overline{3}$.

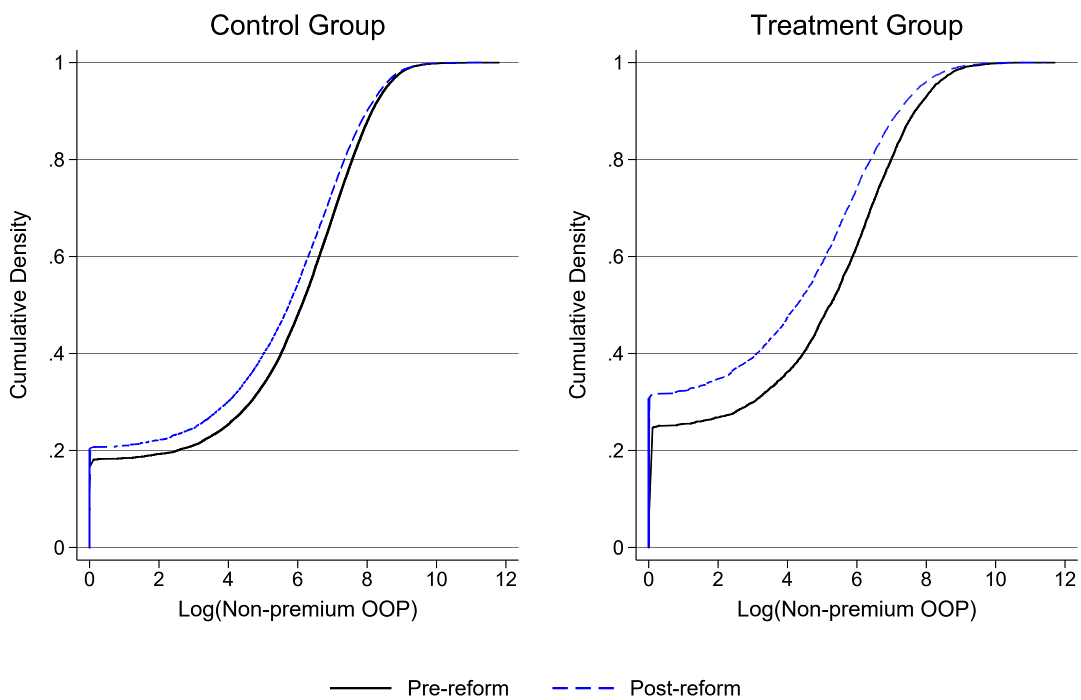
[15]These income bands straddle eligibility thresholds for Medicaid as well as private insurance subsidies, discussed in Appendix Section D. Regression results are robust to slightly different income bands, for example 100-150% FPL rather than 100-138%.

from the ACA Medicaid expansion, an event study version of Equation 1 serves the purpose of providing evidence against a violation of the common trend assumption, which is a stricter assumption than that required in this setting, as explained below. In the following equation:

$$Y_h = \alpha + \beta ELIG_{hst}^{ACA} + ELIG_{hst}^{ACA} \times \sum_{\substack{t=-3 \\ t\neq 0}}^{3} \theta_t 1(y - y_h* = t) + \beta_{st} + \xi X_{hst} + \varepsilon_h \quad (2)$$

$1(y - y_h* = t)$ is a set of indicator variables that measure the number of years relative to the year before the reform, which is 2013 in the main sample.[16] The indicator variable takes the value of zero in the pre-reform period and for all observations in every year that fail to meet the eligibility criteria according to the ACA Medicaid rules. All other variables are defined as in Equation 1. The event study design yields an annual ITT and shows whether the impact of the reform changes over time, for example due to pent up health care demand from the pre-reform period.

Figure 2: Cumulative Density of Medical OOP by Treatment Status



Source: MEPS 2007-2016. Households are classified as treated if they become newly eligible according to the 2014 ACA Medicaid expansion rules. Zero expenditures are transformed to one for exposition purposes in this figure only.

As is often the case with health expenditure data, OOP medical expenditures in the

[16] The main sample does not include late expansion states. The robustness results that include late expansion states use the pre-reform year 2014 (for 2015) or 2015 (for 2016).

MEPS data are highly skewed with a large mass of substantively relevant values at zero (see Figure A.4). In order to retain the zero values and obtain a consistent estimator, I estimate Equations 1 and 2 using a two-part Generalized Linear Model (GLM) estimated by Pseudo Maximum Likelihood with a log link function and gamma distribution. Appendix Section E details the choice of the log-link function and gamma distribution, although this estimator only requires correct specification of the conditional mean for consistency (Silva and Tenreyro, 2006; Manning and Mullahy, 2001; Limwattananon et al., 2015).[17]

Estimation of the GLM using Pseudo Maximum Likelihood has two main advantages compared to OLS estimation of out-of-pocket spending. First, it more accurately models the specific type of heteroskedasticity involved in expenditure data, which include both endogenous censoring and extreme values, by explicitly estimating the participation decision in a first step and then the positive expenditures among households with any OOP spending in the second. Secondly, because this estimator uses the log of the conditional expectation, stated below in Equation 3, it avoids problematic log, inverse hyperbolic sine or other transformations of zero values of OOP spending that would be necessary in an OLS estimation of total marginal effects that include zero values.[18] For comparison purposes, however, OLS estimates are also provided for the main results.

In the GLM framework with a log link, the expected value of out-of-pocket expenditures, conditional on treatment and other covariates can be expressed as the exponentiated linear index function of Equation 1 (Deb and Norton, 2018):

$$\begin{aligned} E[Y_h|ELIG_{hst}, Post_t, S_s, X_{hst}] = exp(&\beta ELIG_{hst} + \theta(ELIG_{hst} \times Post_t) \\ &+ \beta_{st} + \xi X_{hst}) \end{aligned} \tag{3}$$

Marginal effects of the ACA Medicaid expansion on OOP depend not only on the eligibility status of the household and time relative to the reform, but also on all of the other coefficients and covariates of the treated population. The ITT becomes:

$$\widehat{ITT} = \frac{1}{N_T} \sum_{h \in S_T} [exp(\hat{\theta}) - 1] \times E[Y_h|ELIG_{hst}, Post_t, S_s, X_{hst}] \tag{4}$$

where coefficients are estimated on the full sample and marginal effects averaged over

[17]For a thorough discussion of optimal modelling of health expenditure data with a two-part model, see Deb and Norton (2018).

[18]For more on the inverse hyperbolic sine transformation of extreme values, see Burbidge et al. (1988). Silva and Tenreyro (2006) show that OLS leads to biased parameters in log-linearized models with heteroskedastic errors and arbitrary transformations of zeros. Recent papers have applied the inverse hyperbolic sine in order to approximate the logarithmic function while retaining the zeros. However, Bellemare and Wichman (2019) demonstrate that this transformation is not innocuous, in particular when the data have a large mass at zero.

the subset of treated households, $h \in S_T$. Households belong to the treated set if they become newly eligible in the post-reform period ($ELIG_{hst} \times Post_t = 1$). Standard errors are calculated using the delta method. The identifying assumption in this model is that the relative change in the log of the conditional expectation of OOP medical expenditures between treatment and control groups would have been the same absent the reform. Although this assumption cannot be tested directly, Figures 3, A.2 and C.5 provide evidence that an even stricter condition is not violated, namely common trends in the level of OOP, source of payment, and actual Medicaid coverage, respectively.

3.3 Simulated Instrument

By identifying eligibility at the individual level, endogeneity concerns may arise with respect to the relationship between OOP and program eligibility. First, households may adjust their income in response to the ACA Medicaid expansion in order to qualify for benefits. Second, different income distributions across regions may qualify a larger share of the population in poorer states for Medicaid or otherwise influence demand for and thus prices of health care. Third, measurement error in the assignment to treatment may arise from imprecise survey responses regarding household income. In order to address these concerns, I instrument observed household eligibility with simulated eligibility.[19]

To construct the instrument, I take the entire national sample of observations from the MEPS and calculate average eligibility in each group and year defined by household size, age, gender, race and educational attainment level, according to the ACA eligibility rules of each state. Following the approach used in Gallagher et al. (2020), I utilize the national income distribution within each group to define the average probability of treatment for each group in the given state. Specifically, the instrument is defined as: $Prob(Elig)_{hst} = \frac{\sum 1(y_{hj} < \bar{y}_{st})}{N_{jt}}$ where y_{hj} is the income of household h in group j in the national sample, $\bar{y}_{st}$ denotes the Medicaid eligibility threshold in each state and year and N_{jt} is the number of households in each group and year. I then assign each observed household the average eligibility share, or the 'simulated eligibility', from its corresponding group and year from the national sample according to the eligibility rules in its state of residence. Table 2 shows that the means of the observed and simulated eligibility values for the years 2007-2016 are very similar.

The simulated instrument addresses the first endogeneity concern of individual-level selection into eligibility by using pre-determined predictors of income such that exogeneity

[19]Since the seminal papers of Cutler and Gruber (1996) and Currie and Gruber (1996), many papers have employed simulated instruments to isolate variation in policy generosity from possible confounders. Some recent examples include Lo Sasso and Buchmueller (2004), Schmidt et al. (2016), Frean et al. (2017), Dillender (2017) and Gallagher et al. (2020).

should hold at the group level. The use of average eligibility within the group cell from the national sample further mitigates the third concern with respect to measurement error, as it allows for less-precise measurement of income. Finally, by using the national sample of all households, the instrument solves the second potential endogeneity issue because results do not rely on each state's specific demographic characteristics, family structures or income distribution, but rather isolates the exogenous variation stemming from ACA changes to Medicaid rules in each state.

Following the construction of the simulated eligibility measure, I use it to instrument for actual eligibility at the household level, estimating regression Equation 1 with a control function approach.[20] In a first step, the endogenous variable, $ELIG_{hst}^{ACA}$, is regressed using OLS on all exogenous variables including the simulated instrument. In a second step, the estimated residuals from the regression are added to Equation 1 and estimation proceeds as in the case where the treatment variable is considered exogenous. The p-value on the residual coefficient offers a direct test of endogeneity of eligibility. Rather than bootstrapping the standard errors to account for the generated regressor in the two-step control function estimation, I cluster at the state level, as this procedure yields more conservative estimates than bootstrapping.

Table 2 displays the share of childless adult households that would be entitled to ACA Medicaid according to the rules from 2014-2016. Applying the ACA rules to households observed before the reform results in a similar average share of households eligible, which provides support of these household as good controls for those households that actually become eligible after 2014. A formal first stage F-test is shown in Table 3 and rejects that the simulated measure is a weak instrument.

[20] I estimate the regression with the control function method rather than 2SLS because of the non-linearity of the GLM. Wooldridge (2015) shows that the control function approach yields identical estimates to the 2SLS, but is more flexible in its application to non-linear models and has the added advantage of allowing for a direct test of endogeneity.

Table 2: Observed and Simulated ACA Medicaid Eligibility

	Household Composition from:	
	2007-2013	2014-2016
Medicaid Eligibility:		
(1) Observed	0.131	0.142
(2) Simulated	0.129	0.139
Observations	35,577	16,014

Notes: MEPS 2007-2016, main sample of childless adults using household sample weights. Row (1) treats eligibility as exogenous and calculates the share of childless adult households eligible for Medicaid under the ACA expansion according to their household composition and income as observed in each year. 2007-2013 refers to applying the post-reform rules to the household composition and income in the pre-reform years (CPI-adjusted) and 2014-2016 applies the post-reform rules to actual post-reform years. Row (2) calculates the average probability of becoming eligible based on the simulated eligibility measure. Shares are averaged over all pre- (2007-2013) and post-reform (2014-2016) years, respectively.

4 Results

4.1 Mean Out-of-Pocket Medical Spending

Pooled ITT Effect Table 3 displays marginal effects of Medicaid eligibility on non-premium OOP medical spending from the policy interaction term of interest, $(ELIG_{hst} \times Post_t)$, in Equation 1. For both Panels A and B, columns refer to 5 separately estimated regression equations: one to capture the overall effect using the GLM two-part model (column 5) and two each to disentangle the total effect into an extensive margin, or probability of having any OOP expenditures (columns 1-2), and an intensive margin response among households with positive OOP expenditures (columns 3-4). The recovered ITT parameters in columns (3)-(5) can be interpreted as a dollar effect.

Results in Panel A treat Medicaid eligibility as exogenous. Panel B shows results from the same equation, but treats eligibility as endogenous based on estimating each of the 5 models with the simulated instrument. The first-stage F-statistic of 1239.47 shows that simulated eligibility is a strong instrument for observed eligibility. Comparing the two panels, equality of effects between the OLS and IV specifications cannot be rejected at any of the margins, but the test of instrument exogeneity is rejected at the intensive margin, indicating the presence of some endogeneity of eligibility that is likely not economically substantial. Consequently, all main outcomes are reported in the preferred IV specification for precision and OLS results are additionally provided for completeness.

For the group targeted by the ACA expansion, public insurance eligibility reduced mean non-premium OOP medical spending by an average of \$133 annually, with the stronger contribution stemming from intensive margin reductions. Conditional on having positive non-premium OOP, ACA Medicaid entitlement reduced the mean OOP burden

Table 3: Marginal Effects of Medicaid Eligibility on OOP Non-Premium Costs

	Extensive Margin		Intensive Margin		Overall Effect
	(OLS)	(Probit)	(OLS)	(GLM)	(Two-Part Model)
	(1)	(2)	(3)	(4)	(5)
	Panel A: Treating Eligibility as Exogenous				
Medicaid×Post	-0.041**	-0.043**	-147.443*	-159.936***	-124.108***
	(0.014)	(0.017)	(74.366)	(36.045)	(23.850)
	Panel B: Treating Eligibility as Endogenous (Simulated IV)				
Medicaid×Post	-0.040**	-0.043**	-152.739**	-174.390***	-132.668***
	(0.013)	(0.016)	(73.396)	(34.460)	(22.803)
First stage F-stat			1239.47***		
Second stage p-value	0.457	0.774	0.102	0.000	0.774/0.000
Observations	51,548	51,548	36,396	36,396	51,548/36,396

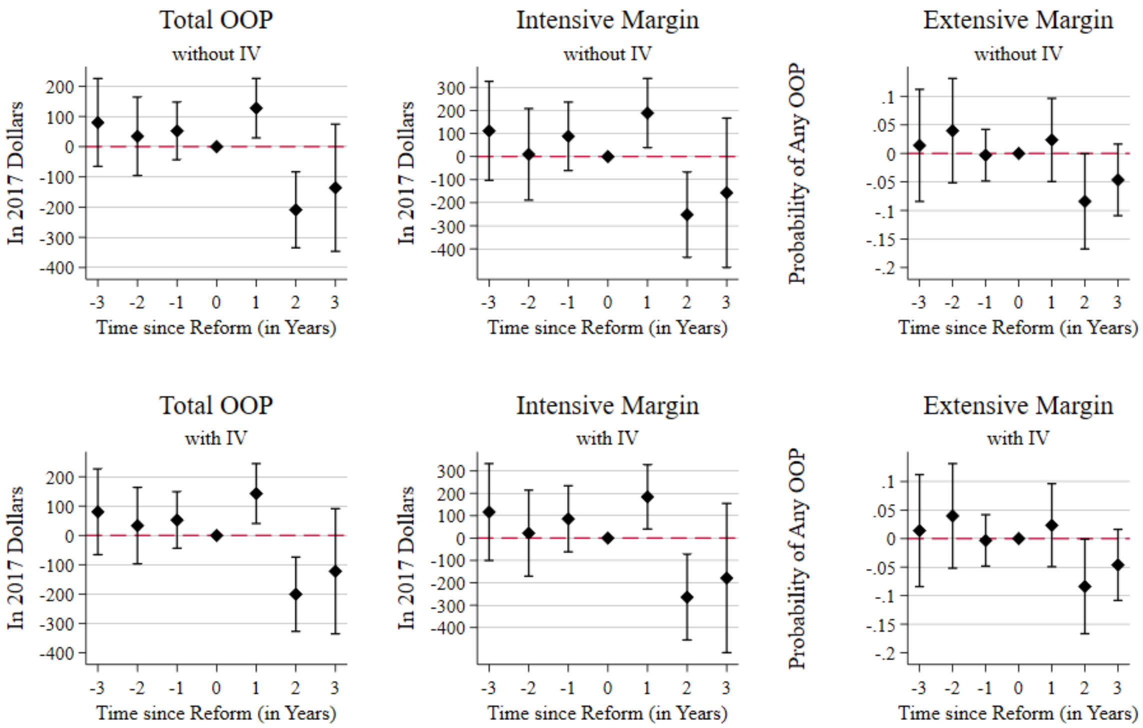
Notes: MEPS cross-sectional data 2007-2016. Weighted regression results using household sample weights. All regressions contain the full set of controls listed in Equation 1. Columns (1) and (2) present marginal effects of the probability to have any OOP expenses, columns (3)-(5) show the marginal effect in 2017 dollars, CPI-med adjusted. Columns (3) and (4) consider only positive values of OOP. Column (5) provides an overall result from a two-part model using probit and glm with a log link function and gamma distribution. Standard errors are clustered at the state level and estimated using the delta method. P-values of the residuals from the first stage equation in the second stage provide a direct test of exogeneity of Medicaid eligibility.

by \$174 annually. Given a pre-reform mean OOP expenditure of \$956.59 (Table 1), the ITT estimate corresponds to an 18.2% savings for eligible households. At the extensive margin, eligible households also experienced a 4.3 percentage point (6.2%) decrease in the probability of having any out-of-pocket costs.

Dynamic ITT Effects Turning to results of the dynamic, event study specification, Figure 3 shows the ITT marginal effects both with and without the simulated instrument for Medicaid eligibility. Two additional insights emerge from the event study results. First, Figure 3 provides evidence of the absence of pre-trends in OOP spending in the pre-reform years for the population that would later become Medicaid-eligible. Second, OOP expenditures actually increase in the first year after Medicaid expansion and then decrease in the second and third years post reform, with the largest (nearly 30%) reduction materializing the second year after implementation. The increase immediately after the reform may indicate pent-up demand that outweighs the subsidy in the first year.

Spending Components Taking a closer look at which components of medical goods and services are driving the overall OOP reduction, Figure A.1 disentangles the marginal effects on fees for emergency room (ER) visits, non-ER hospital visits, office-based visits, prescription drugs, and dental and vision costs. It documents reductions in both ER- and

Figure 3: Marginal Effects on Non-Premium OOP by Year, Event Study Analysis



Notes: Marginal effects (θ_t) from Equation 2 on yearly non-premium OOP expenditures using MEPS household weights. Effects are estimated on the main specification with a full set of controls using the two-part model. The left panel shows marginal effects in the working sample and the right panel shows results omitting early expansion states and counties. Standard errors are clustered at the state level and estimated using the delta method.

non-ER hospital expenses as well as prescription drugs, conditional on having any OOP expenses. At the extensive margin, the probability of having any out-of-pocket costs for office-based visits decreased by 7 percentage points, a 11.3% reduction from pre-reform levels, and the probability of incurring any out-of-pocket ER costs decreased by 4.7%.

Coverage, Access and Utilization Channels OOP payments present a 'downstream' outcome in the sense that the most direct expected impact from increased eligibility is on enrollment in Medicaid. Once individuals chose to enroll, changes in quantity (utilization), prices (the share they personally pay out of pocket) or both may influence this outcome. Figure C.5 demonstrates that the ACA Medicaid expansion led to a 19 percentage point increase in coverage. However, this increase in coverage did not translate into an increase in most types of medical visits for the average newly eligible household. Examining the impact of Medicaid eligibility on the number of and probability of having any visits to the ER, outpatient facilities, physician offices or inpatient stays reveals that eligibility increased the propensity to visit an ER by 15.7%, but had no effect on the other categories of visits (See Table C.7). Persistent barriers to access provide one possible explanation for these findings. For instance, Medicaid eligibility reduced the likelihood of reporting having foregone or delayed necessary medical or dental care or the purchase of prescription medication due to financial constraints by 17.5% (See Figure C.6). At the same time, eligibility did not change the likelihood that a respondent reported lacking access to a usual care provider or having to travel more than 30 minutes to reach one. Lack of a convenient alternative may explain why individuals were *more* likely to visit an ER post-reform. Appendix C provides a thorough discussion of these adjustment channels as well as how they compare to the literature that has focused on changes in utilization responses to Medicaid expansions.

Controlling for Exposure to Private Insurance Subsidies The causal effects in this analysis should be interpreted as being *in addition to* any impact from underlying changes to the regulatory environment or insurance mandate penalties, which affected both treatment and control groups.[21] Beyond these changes that impacted both treatment and control groups, one policy provision was introduced simultaneously with Medicaid expansion and only affected the control group: non-Medicaid eligible individuals with income below 400% of FPL qualify to receive an alternative treatment, namely private insurance exchange subsidies. If insurance subsidies reduced OOP for the control group, controlling for their exposure to this alternative treatment allows for the interpretation of causal effects from public insurance expansion to be compared to a counterfactual in which the control group is neither eligible for public insurance nor exchange subsidies. Appendix D provides a detailed analysis controlling for exposure to private exchange subsidies in a robustness specification. The overall ITT remains virtually unchanged, albeit with a somewhat higher intensive margin and weaker extensive margin impact.

Heterogeneity and Pre-Existing Conditions Medicaid expansion was expected to have larger effects on childless adults with a pre-existing medical condition due to both higher than average total costs for medical needs associated with poor health and barriers to insurance access stemming from the lack of community rating and guaranteed issue. The MEPS data enable identification of many of the most common chronic conditions used by insurance companies prior to the ACA in order to price discriminate among

[21] Some substantial aspects of the ACA reform, such as requiring community rating and guaranteed issue, cannot be disentangled from Medicaid expansion, as the former present a time series change without exogenous variation in exposure among the population. Guaranteed issue refers to the prohibition of insurance companies from denying coverage to eligible individuals, regardless of pre-existing conditions. Community rating obliges insurance companies to offer one price for individuals of the same age and location, regardless of sex or pre-existing conditions.

customers or to deny coverage altogether.[22] Indeed, the heterogeneity analysis finds a larger absolute reduction among the subsample of households with a chronic condition, in the order of \$234 annually, conditional on incurring any OOP costs (Panel 1 of Table B.5).

Robustness to Sample Specification and Eligibility Measure Appendix B explores the sensitivity of the OOP results to several robustness sample specifications and summarizes these results in Table B.5. In order to ease interpretation of the ITT in the event study specification, the main sample excluded late expansion states. Panel 2 of Table B.5 shows that results are very similar when including late expansion states in the sample. Second, in order to reconcile the mean reductions in OOP presented in this paper with previous work that has compared low-income populations in expansion and non-expansion states, I run two additional analyses to highlight the effect of measuring eligibility at the individual rather than state level. The first repeats the main analysis retaining pre-ACA Medicaid eligible households in the control group. The second conducts a traditional expansion versus non-expansion state treatment analysis on a subsample of households below 138% of FPL. Individual identification of eligibility leads to smaller estimates of OOP reductions compared to the expansion vs. non-expansion analysis of adults below 138% of FPL, partially due to spillover effects from individuals already eligible for Medicaid prior to the ACA. This finding complements work by Frean et al. (2017), who identify spillover effects of the ACA Medicaid expansion on the enrollment into Medicaid of previously eligible populations.

4.2 Welfare Analysis

The preceding results document a substantial reduction in the payment burden of medical care among households eligible for public insurance. But how efficient is the Medicaid expansion compared to alternative interventions that seek to provide affordability and risk protection for targeted groups? In order to answer this question, the welfare analysis draws on the framework from Hendren (2016), Hendren and Sprung-Keyser (2020) and Finkelstein and Hendren (2020) to define a Marginal Value of Public Funds (MVPF) for the ACA Medicaid expansion, which can be compared to the MVPF of other programs. Building on Okun's leaky bucket experiment,[23] the MVPF does not measure whether a

[22]These conditions include: heart attack, coronary heart disease, angina, other heart disease condition, stroke, emphysema, diabetes, arthritis, high blood pressure, asthma, high cholesterol, pregnancy, and extreme obesity (BMI$\geq$40). For a more complete discussion and list of conditions see, for example, Fehr et al. (2018).

[23]The experiment asks how large of a resource loss society is willing to accept to transfer resources from one person to another (Okun, 1975).

policy pays for itself in the sense of a cost-benefit analysis, but rather whether the resource transfer associated with the policy is larger or smaller than an alternative policy that has a similar objective.[24]

For in-kind benefits such as public insurance, the value of one government dollar spent on Medicaid can be defined as follows:

$$MVPF = \frac{Beneficiaries' \; WTP}{Net \; Cost \; to \; Government} = \frac{Beneficiaries' \; WTP}{Mechanical \; Cost + Fiscal \; Externality} \tag{5}$$

where the mechanical cost (MC) includes the direct cost of expansion and fiscal externalities (FE) encompass effects from behavioral changes that have an indirect impact on the public budget, such as disemployment effects or health benefits. Previous papers find no significant effects of the ACA Medicaid expansion on either of these outcomes.[25] This paper therefore focuses on a positive fiscal externality inherent in the motivation for insurance: protection against risk. The reduction of risk exposure among the Medicaid eligible population arguably carries a positive social externality due to the potential long-run impacts on beneficiaries' financial health and consumption. In the following, Section 4.2.1 examines the impact of Medicaid expansion on the mechanical cost, or the cost shifting from beneficiaries to taxpayers. Section 4.2.2 calculates the risk protection from Medicaid eligibility and estimates the willingness to pay for beneficiaries. Section 4.3 brings together these components to formulate the MVPF.

4.2.1 Cost Shifting

Table 4 shows descriptive statistics of the total expenditures for medical goods and services paid on behalf of Medicaid-eligible households from any source before and after the reform. Total expenditures may be paid by one of three mutually exclusive categories: household OOP, private insurance and any public source, including Medicaid, Medicare and some charity care.[26] To examine the causal impact of Medicaid expansion on the shifting of payment burdens within the healthcare system, I run the same analysis from Equation 1

[24]The MVPF framework builds off of previous work by Mayshar (1990) on the Marginal Excess Burden, Slemrod and Yitzhaki (2001) on the Marginal Cost of Funds and Kleven and Kreiner (2006) on the Marginal Cost of Public Funds. See Hendren (2016) for a comparison of these concepts.

[25]For evidence of a lack of short-run health effects, see Wherry and Miller (2019), Miller and Wherry (2017), Courtemanche et al. (2018a), Courtemanche et al. (2018b) and Sommers et al. (2015). Heath improvements from Medicaid expansion may be expected to appear in a longer-run analysis than is presently possible and should be monitored carefully going forward. For employment effects, see Gooptu et al. (2016), Kaestner et al. (2017), Mas and Leung (2018) and Duggan et al. (2019) among others.

[26]Expenditures for charity care are imperfectly measured in the MEPS, as they only appear in the data if the service utilization event triggered a charge, either to the individual, another party, state or federal program. Therefore, some charity care is captured in the public source payment variable. It excludes zero charge charity care.

with Y_h equal to the total amount of expenditures paid by an source as well as the share paid by each category in four separate regressions. Table 5 displays the marginal effects of Medicaid eligibility on these payment shares.

Results point to cost shifting from Medicaid-eligible households and private insurance toward formal public insurance programs, with the payment burden to the taxpayer increasing by 16.5 percentage points, or 47.1% from the baseline share of 0.35 on account of Medicaid expansion. Using the amount of CPI-adjusted pre-reform expenditures from Table 4, the mechanical cost of Medicaid amounts to \$2,797.98 annually. This increase in taxpayer burden is the net effect of a decrease in other state programs and charity care and an increase in Medicaid. Appendix Tables A.3 and A.4 can be used to calculate the mechanical cost for the subset of households with at least one pre-existing condition, which amounts to \$3,253.94.[27] Figure A.2 shows the absence of pre-trends in the source of payment variables using the event study specification. Table A.2 further demonstrates that results are robust to treating eligibility as exogenous (OLS specification) and controlling for exposure to private insurance subsidies.

Despite the increase in total expenditures in the descriptive statistics, the causal analysis does not find that average total costs for the group of newly eligible households increased on account of Medicaid. Rather, Medicaid expansion shifted the payment burden without directly increasing total costs in the system beyond any deadweight loss distortions associated with funding the program. Table 5 further documents evidence of some crowd-out of private insurance by public sources, as the share of total expenditures covered by private insurance decreased by 17% from baseline. Figure A.2 shows the dynamic effects of eligibility on these cost-shifting outcomes from the event study specification. The lack of pre-trends in these outcomes lends support to the empirical strategy.

[27]Marginal effects shown in A.4 are comparable to those in the full sample, but baseline expenditures and the share paid by public sources are higher for households with a pre-existing condition.

Table 4: Total Expenditures and Payment Burdens: Conditional Means

	According to the ACA Medicaid Rules from 2014-2016:			
	Medicaid Eligible 2007-2013	Medicaid Eligible 2014-2016	Not Eligible 2007-2013	Not Eligible 2014-2016
	(1)	(2)	(3)	(4)
- Total expenditures	5,940.50	6,483.18	5,886.49	5,778.52
	(13648.75)	(14073.74)	(12703.14)	(12907.92)
- Share paid by public source	0.35	0.54	0.09	0.11
- Share paid by private ins.	0.27	0.24	0.51	0.54
- Share paid out of pocket	0.32	0.20	0.37	0.32
Observations	5,017	2,402	30,560	13,612

Source: Weighted means using household sample weights in the MEPS cross-sectional data 2007-2016. Column (1) presents the average value for households that would have been eligible according to the ACA rules, had the reform been implemented between 2007-2013. Column (2) presents the average value for the treatment×post group that actually became eligible for Medicaid through the ACA expansion. Columns (3) and (4) show weighted means for households that would not have met eligibility criteria for the ACA Medicaid expansion in any year. Standard deviations in parentheses.

Table 5: Sources of Payment for Household Medical Expenditures: Marginal Effects

	Total	*Share of total expenditures paid by:*		
	Expenditures	OOP	public sources	private ins.
	(1)	(2)	(3)	(4)
Medicaid×post	62.279	-0.081***	0.165***	-0.055***
	(431.698)	(0.015)	(0.019)	(0.014)
Observations	51,548	38,654	38,654	38,654

Source: MEPS cross-sectional data 2007-2016. Simulated IV results from Equation 1 with the same control variables as in Table 3. Column (1) is estimated as a two-part model with a probit first stage and GLM with log-link function and gamma distribution in the second stage. Columns (2)-(4) use OLS to estimate the log share from each source. Standard errors are clustered at the state level for all regressions and calculated using the delta method for marginal effects in column (1).

4.2.2 Willingness to Pay and Risk Protection

The Model In order to estimate the willingness of beneficiaries to pay for Medicaid eligibility, I employ a similar approach to that used in previous work evaluating the welfare gains from Medicare and other pension and insurance programs (Feldstein and Gruber, 1995; Finkelstein and McKnight, 2008; Engelhardt and Gruber, 2011; Limwattananon et al., 2015; Shigeoka, 2014; Barcellos and Jacobson, 2015). Assuming risk aversion, the basic model involves a one-period CRRA utility maximization problem subject to the household budget constraint:

$$u(c) = \frac{c^{1-\rho}}{1-\rho}; c = y - m^{oop} \qquad (6)$$

where non-health consumption, c, is defined as household income, y, less OOP medical expenditures, m^{oop}. m^{oop} is a random variable with a probability density function $f(m^{oop})$ along the support of $[0,\bar{m}^{oop}]$:

$$\int_0^{\bar{m}^{oop}} u(y - m^{oop}) f(m^{oop}) dm^{oop} \tag{7}$$

The value a household places on the risk protection of Medicaid insurance is captured by the risk premium, π, which quantifies the household's willingness to pay in order to completely insure itself against the random variable m^{oop}.

The total beneficiary WTP is a combination of the utility gained from expected reductions in the mean and variance of OOP spending, i.e. the difference in the certainty equivalence (CE) of non-health consumption and expected consumption in two possible states of the world: one in which the household is eligible for Medicaid, $s = 1$, and one in which it is not, $s = 0$. The CE and risk premium for each household π_h are then implicitly defined by the following equation:

$$u(CE_s) = u(y - E[m_s^{oop}] - \pi_s) = \int_0^{\bar{m}_s^{oop}} u(y - m_s^{oop}) f(m_s^{oop}) dm_s^{oop};\ s = 0, 1 \tag{8}$$

Predictions of OOP Spending Distributions In order to first estimate the right-hand side of Equation 8 for each household, I use unconditional quantile regression based on the re-centered influence function (RIF, Firpo et al. (2009)) to predict the out-of-pocket distribution of expenditures with Medicaid eligibility, $\hat{m}_{1,h}^{oop}$, and without, $\hat{m}_{0,h}^{oop}$ for each household in the sample, at each percentile p of the unconditional OOP distribution. Applying the RIF to Equation 1, I make a linear prediction of $\hat{m}_{0,h}^{oop}$ using the coefficients from the quantile regressions at each $p = 1/99$ percentile:

$$\hat{m}_{0,h}^{oop,p} = \hat{\alpha}^p + \hat{\beta}^p ELIG_h^{ACA} + \hat{\beta}_{st}^p + \hat{\xi}^p \boldsymbol{X}_h \tag{9}$$

where, as in Equation 1, $ELIG_h^{ACA}$ defines household eligibility according to the ACA rules from 2014-2016, $\boldsymbol{X}_h$ is a matrix containing the same observable household characteristics as in the main analysis and β_{st} includes a full set of state-year fixed effects. Predicted out-of-pocket expenditures *with* Medicaid eligibility, $\hat{m}_{1,h}^{oop,p}$ then equate to:

$$\hat{m}_{1,h}^{oop,p} = \hat{\alpha}^p + \hat{\beta}^p ELIG_h^{ACA} + \hat{\theta}^p (ELIG_h^{ACA} \times POST) + \hat{\beta}_{st}^p + \hat{\xi}^p \boldsymbol{X}_h, \tag{10}$$

in which $\hat{\theta}^p$ captures the quantile treatment effects of the policy interaction term for the ACA Medicaid expansion. Figure A.3 plots these coefficients from the quantile regressions and shows that mean OOP reductions and the variance of reductions are highest in the upper tail of the distribution.

Willingness to Pay Using the predicted distributions in the treated and counterfactual situations, we can now calculate Equation 8 empirically for π_0 and π_1:

$$u(y - \bar{\hat{m}}_{s,h} - \hat{\pi}_s) = \frac{1}{99}\sum_{p=1}^{99} u(y - \hat{m}_s^p);\ s = 0, 1 \tag{11}$$

where $\bar{\hat{m}}_{s,h}$ is the mean of predicted OOP based on 99 predictions for each household and state of the world s. Assuming a CRRA utility function with risk aversion parameters of $1, 3, 5$ allows one to solve this equation for $\hat{\pi}_{s,h}$.[28] Equipped with this last parameter, the willingness to pay of each household for risk protection of Medicaid can be calculated as the sum of $\Delta\pi_h$ and $\Delta\bar{\hat{m}}_h$, which together define the change in the certainty equivalence of consumption with and without Medicaid eligibility:

$$\Delta CE = (\hat{\pi}_0 - \hat{\pi}_1) + (\bar{\hat{m}}_0^{oop} - \bar{\hat{m}}_1^{oop}) \tag{12}$$

Averaging over the entire sample of treated households yields a distribution of private welfare gain, or WTP, (ΔCE) from Medicaid risk protection among eligible households, summarized in Table 6.

The upper panel of Table 6 shows that beneficiaries' WTP increases with risk aversion and expected health expenditures, proxied here by the presence of a chronic condition in the household. On the one hand, it should be acknowledged that insurance is not traded in a perfectly competitive market (Einav et al., 2010) and may not be offered at an actuarially fair price. Prior to Medicaid expansion, mean OOP spending for uninsured households below 138% FPL amounted to $545 annually. Note that *even at this price*, most households are not willing to pay the expected cost they impose on the insurer. This finding adds to Finkelstein et al. (2019b), Finkelstein et al. (2019a) and Hendren and Sprung-Keyser (2020), who document a low WTP among low-income adults for health insurance in the context of the Oregon Medicaid Experiment and Massachusetts health reform.

Having a WTP below expected costs may be an entirely rational decision. Low income, eligible households have a low level of non-health consumption due to a tight budget constraint. Therefore, their marginal utility of consumption will be higher than for the average household. Second, the availability of uncompensated (charity) care may reduce the necessity to pay any amount out of pocket. In addition, however, behavioral

[28]Assuming $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, it follows that $\hat{\pi}_s = y - ((1-\gamma) \times E[u(y_h - \hat{m}_h))^{\frac{1}{1-\gamma}}]$.

Table 6: Welfare Gain from Medicaid Risk Protection

Using Quantile Estimates	Full Sample		Subpopulation w/ Chronic Condition	
***Panel A: Mean WTP (ΔCE)**, by risk aversion parameter:*				
	$\Delta\pi$	ΔCE	$\Delta\pi$	ΔCE
risk aversion:				
$\gamma = 1$	\$0.04	\$157.39	\$9.24	\$262.29
$\gamma = 3$	\$33.42	\$192.85	\$202.25	\$455.30
$\gamma = 5$	\$68.82	\$228.24	\$345.96	\$599.00
***Panel B: WTP Distribution**, risk aversion = 3*				
	$\Delta\pi$	ΔCE	$\Delta\pi$	ΔCE
25th percentile	\$1.97	\$121.40	\$35.66	\$277.48
Median	\$11.63	\$191.25	\$105.64	\$385.28
75th percentile	\$60.70	\$240.03	\$202.25	\$680.96
90th percentile	\$323.76	\$498.02	\$1042.22	\$1305.20
95th percentile	\$703.75	\$848.63	\$1,644.32	\$1,897.31
99th percentile	\$1,622.20	\$1,816.88	\$3,067.34	\$3,362.31

Source: MEPS cross-sectional data 2007-2016. Values listed in 2017 CPI-med-adjusted dollars. Calculations are based on RIF quantile regressions at each percentile of the unconditional OOP non-premium distribution, with a full set of controls listed in Equation 1.

biases may also play an important role in reducing private WTP, as previous research has found that individuals underestimate the likelihood of adverse events (Moore and Healy, 2008; Mullainathan and Shafir, 2014). Identifying the relative contribution of each of these factors in low-income insurance markets remains an important area for future research.

Risk Protection The bottom panel of Table 6 holds the risk aversion parameter constant at 3 and separately disentangles the portion of ΔCE attributable to the change in risk exposure, $\Delta\pi$. The remainder is the redistributive component, mean OOP costs. Results document that the insurance component comprises only 17% of the private WTP at the mean, but 89% at the top of the distribution and it is higher for households with a chronic condition. Importantly, the impact of Medicaid on risk exposure is highest for this group, i.e., the positive fiscal externality of $\Delta\pi$ increases with expected OOP medical payments. Comparing the reductions in risk exposure to the baseline level of risk without insurance (π_0) for large OOP reveals that the reduction of risk exposure in the economy due to Medicaid eligibility amounts to 6.6% from baseline at the 75th percentile ($\pi_0 =$

\$924.21), 27.5% at the 90th (π_0 = \$1,177.09) and 82.2% at the 99th (π_0 = \$1,972.78).

4.3 The Marginal Value of Public Funds for Medicaid Expansion

Section 4.2.1 estimated the direct, mechanical cost of Medicaid expansion to be \$2,797.98 annually per eligible household in the full sample and \$3,253.94 among households with a pre-existing condition. The risk protection analysis in Section 4.2.2 produced a distribution for the monetary value of Medicaid insurance access in terms of both beneficiaries' willingness to pay (ΔCE) and the positive fiscal externality of risk protection ($\Delta\pi$), both of which increase with expected OOP costs. Table 7 calculates the corresponding distribution of MVPF, inserting the values from Table 6 into Equation 5, where $MVPF = \frac{\Delta CE}{MC - \Delta\pi}$ for different levels of ΔCE and $\Delta\pi$. Values for the MVPF of expanding Medicaid eligibility are lower than those calculated for previous insurance expansions to low-income adults (0.40-1.63) (Hendren and Sprung-Keyser, 2020), as the present estimates relate to the value of providing the average, low-income childless household access to insurance rather than the value of gaining access among a population that asked to become enrolled (Oregon Experiment).

Table 7: Marginal Value of Public Funds (per Dollar Spent)

	Full Sample	Subpopulation w/ Chronic Condition
Mechanical Cost	\$2,797.98	\$3,253.94
MVPF		
25th percentile	0.06	0.09
Median	0.07	0.12
Mean	0.07	0.14
75th percentile	0.09	0.22
95th percentlie	0.41	0.59

Source: MEPS cross-sectional data 2007-2016. Calculations are based on RIF quantile regressions at each percentile of the unconditional OOP non-premium distribution, with a full set of controls listed in Equation 1. MVPF stated in dollars.

The preceding exercise shows that the efficiency of public funds spent on Medicaid expansion varies by household and is highest among target groups with high expected OOP, for example households with pre-existing conditions. This MVPF for different groups can then be compared to other potential policies that seek to lower OOP medical spending and risk exposure among low-income adults. Examples of such comparative interventions include: subsidization of health providers who relocate to low-income or rural areas; behavioral nudges to encourage households to seek more preventive care at publicly funded community centers, thus limiting more expensive urgent care; a single-payer system with more regulated pricing, and many others.

5 Conclusion

This study examined the short-run impact of the ACA Medicaid expansion on OOP medical spending and risk protection among low-income eligible households as well as the incidence of the cost of providing insurance. I find that Medicaid expansion improved affordability of care for eligible households by reducing non-premium OOP by 18.2% among households with positive expenditures and reducing the probability of having any OOP cost by 6.2%. Affordability improved most strongly for eligible households with at least one pre-existing condition. In addition to decreases in mean spending, risk exposure to very high OOP events among target households decreased substantially. At the top of the expected OOP distribution, public insurance eligibility reduced risk exposure among low-income households by 27.5-82.2%.

Importantly, reductions in OOP spending were not accompanied by significant increases in total expenditures paid on behalf of eligible households. This finding indicates a lack of increased moral hazard spending attributable to Medicaid. Rather, public insurance expansion shifted the cost burden of medical care from beneficiary households and private insurance (17.0% reduction) to public insurance (47.1% increase). In line with this result, the analysis of the channels of adjustment identifies a 19 percentage point increase in coverage and a 15.7% increase in the likelihood of visiting an ER, but no substantial growth in other margins of utilization. The documented persistent access constraints to a usual care provider help to explain these findings. Finally, a replication exercise using only state-level variation shows that utilization is increasing more in expansion states compared to non-expansion states, but not on account of public insurance alone.

Notably, the private WTP for expanded access to insurance falls well below the expected OOP costs, even without taking the value of risk protection into account. This result corroborates findings from similar health reform contexts in Oregon and Massachusetts that document a low willingness to pay for health insurance among low-income adults (Finkelstein et al., 2019a,b; Hendren and Sprung-Keyser, 2020). The present study emphasizes the importance, given the fiscal externality of risk protection, of better understanding the drivers of this low WTP for insurance. The corresponding MVPF of expanding Medicaid is lower than that calculated in the context of the Oregon Medicaid Experiment and the reasons for this difference carry important policy implications in the current health reform debate. Estimates of the MVPF of Medicaid expansion in this study range between 0.06-0.59 and are based on the ITT estimates that may be of particular interest when anticipating potential costs of expansion in non-expansion states. The cost of providing implicit insurance to the average low-income, childless household through Medicaid eligibility is likely much lower than the costs associated with the average lottery participant in the Oregon Experiment. The average targeted household in the ACA expansion is healthier, has a lower health care demand and a higher likelihood of private insurance coverage than the exclusively uninsured population that actively signed up for the Oregon Experiment.

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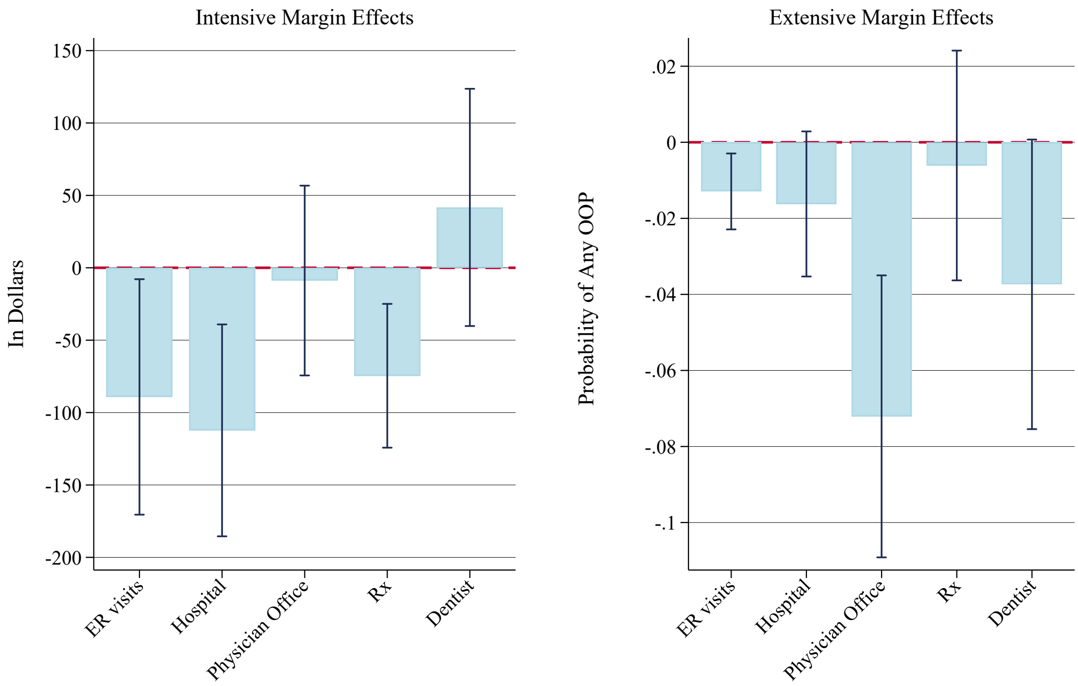
A Appendix A: Additional Tables and Figures

Table A.1: Sample Characteristics of Treatment and Control Households, 2007-2016

	According to the ACA Medicaid Rules from 2014-2016:			
	Medicaid Eligible 2007-2013	Medicaid Eligible 2014-2016	Not Eligible 2007-2013	Not Eligible 2014-2016
	(1)	(2)	(3)	(4)
Household Head:				
- Age 18-25	0.34	0.32	0.18	0.18
- Age 26-39	0.20	0.21	0.26	0.28
- Age 40-49	0.14	0.13	0.17	0.14
- Age 50-64	0.32	0.34	0.39	0.40
- White	0.79	0.78	0.81	0.79
- Black	0.18	0.18	0.16	0.18
- Hispanic	0.11	0.12	0.12	0.14
Household Context:				
- Singles	0.91	0.92	0.71	0.73
- Couples w/o children	0.08	0.08	0.29	0.27
- Larger households	0.01	0.001	0.003	0.004
- Total HH income ($)	36,060.87	32,780.90	67,350.35	68,257.62
	(49650.97)	(44862.02)	(56213.65)	(56108.84)
Household Insurance Coverage:				
- Any private insurance, share	0.33	0.33	0.70	0.74
- Public only, share	0.29	0.51	0.06	0.09
- Uninsured, share	0.38	0.16	0.24	0.17
Observations	5,017	2,402	30,560	13,612

Notes: Weighted means using household sample weights in the MEPS cross-sectional data 2007-2016. Column (1) presents the average value for households that would have been eligible according to the ACA rules, had the reform been implemented between 2007-2013. Column (2) presents the average value for the treatment×post group that actually became eligible for Medicaid through the ACA expansion. Columns (3) and (4) show weighted means for households that would not have met eligibility criteria for the ACA Medicaid expansion in any year. Standard deviations in parentheses.

Figure A.1: Marginal Effects by Medical Spending Component, Pooled Specification



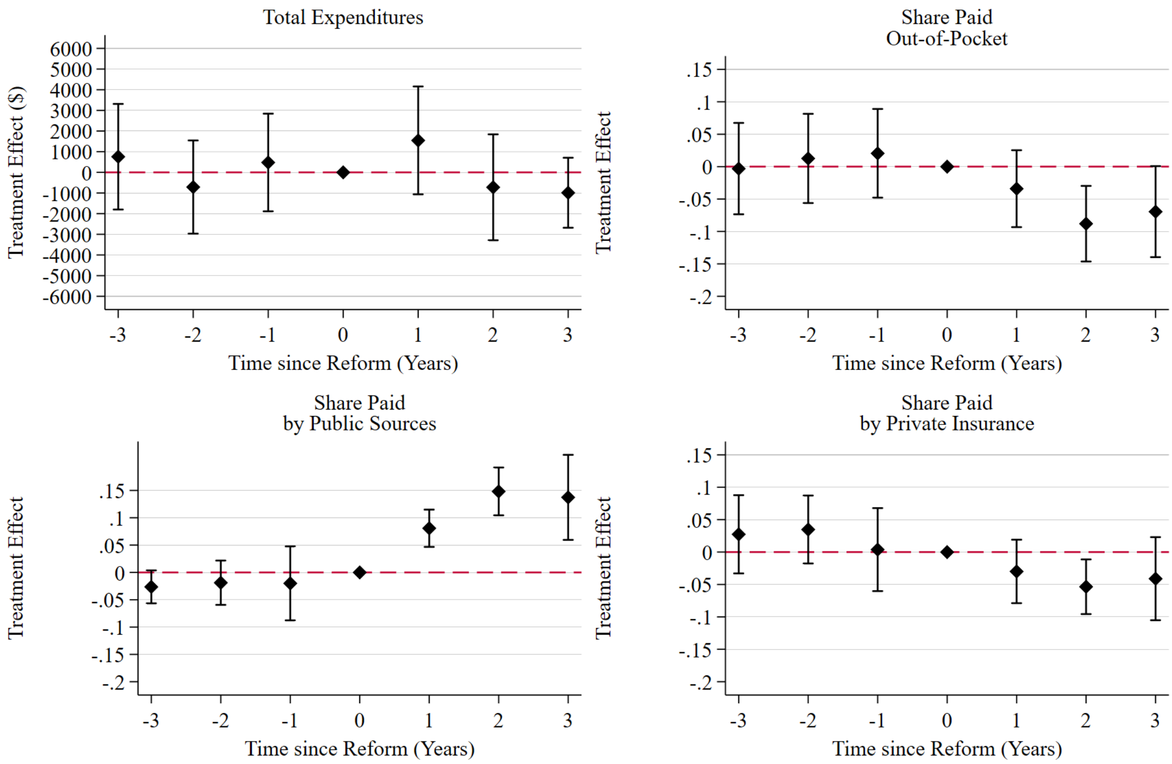
Source: MEPS 2007-2016 with household weights and a full set of controls. *Notes:* Rx = prescription medications. Hospital visits combines inpatient and outpatient observations. The bar marks the estimated marginal effects of the impact of $Medicaid \times Post$ from Equation 1 on each component of non-premium OOP expenditures in separate regressions. A 95% confidence interval is shown in whiskers. Intensive margin effects on positive values of OOP in each component are estimated as a GLM, corresponding to column (4) of Table 3. Extensive marginal effects are estimated using a probit estimation on the indicator variable equal to one if the household spends any money out of pocket in the given category, corresponding to column (2) of Table 3. Standard errors are estimated using the delta method.

Table A.2: Sources of Payment for Household Medical Expenditures: Marginal Effects, Alternative Specifications

	Total	*Share of total expenditures paid by:*		
	Expenditures	OOP	public sources	private ins.
	(1)	(2)	(3)	(4)
Medicaid×post				
A. Treating eligibility	56.777	-0.066***	0.152***	-0.058***
as exogenous	(407.292)	(0.015)	(0.019)	(0.014)
B. Panel A. with	125.903	-0.078***	0.163***	-0.058***
subsidy controls	(408.078)	(0.015)	(0.019)	(0.014)
C. Simulated IV with	62.279	-0.081***	0.165***	-0.055***
subsidy controls	(431.698)	(0.015)	(0.019)	(0.014)
Observations	51,548	38,654	38,654	38,654

Source: MEPS cross-sectional data 2007-2016. Results from Equation 1 with the same control variables as in Table 3. Column (1) is estimated as a two-part model with a probit first stage and GLM with log-link function and gamma distribution in the second stage. Columns (2)-(4) use OLS to estimate the log share from each source. Standard errors are clustered at the state level for all regressions and calculated using the delta method for marginal effects in column (1).

Figure A.2: Marginal Effects on Source of Payment, Event Study Specification



Notes: MEPS 2007-2016 with household weights and a full set of controls from Equation 2. Simulated IV results are marked by the diamond and 95% confidence intervals with whiskers. Total expenditure outcome is estimated as a two-part model with a probit first stage and GLM with log-link function and gamma distribution in the second stage. Shares paid by each source use OLS to estimate the log share from each source. Standard errors are clustered at the state level for all regressions and calculated using the delta method for marginal effects on total expenditures.

Table A.3: Total Expenditures and Payment Burdens by Pre-Existing Condition Status

	According to the ACA Medicaid Rules from 2014-2016:			
	Medicaid Eligible 2007-2013	Medicaid Eligible 2014-2016	Not Eligible 2007-2013	Not Eligible 2014-2016
	(1)	(2)	(3)	(4)
	Panel A: Households with at least one pre-existing condition:			
- Total expenditures	9,608.94	9,773.40	8,789.01	8,537.48
	(16810.00)	(16850.06)	(15295.43)	(15518.66)
- Share paid by public source	0.44	0.62	0.10	0.13
- Share paid by private ins.	0.23	0.19	0.53	0.54
- Share paid out of pocket	0.27	0.16	0.34	0.30
Observations	2,816	1,437	17,916	7,850
	Panel B: Households without any pre-existing condition:			
- Total expenditures	1,369.89	1,482.51	1,669.27	1,591.57
	(5358.99)	(5122.85)	(5088.83)	(4992.55)
- Share paid by public source	0.16	0.35	0.05	0.07
- Share paid by private ins.	0.35	0.34	0.48	0.54
- Share paid out of pocket	0.44	0.29	0.44	0.37
Observations	2,201	965	12,644	5,762

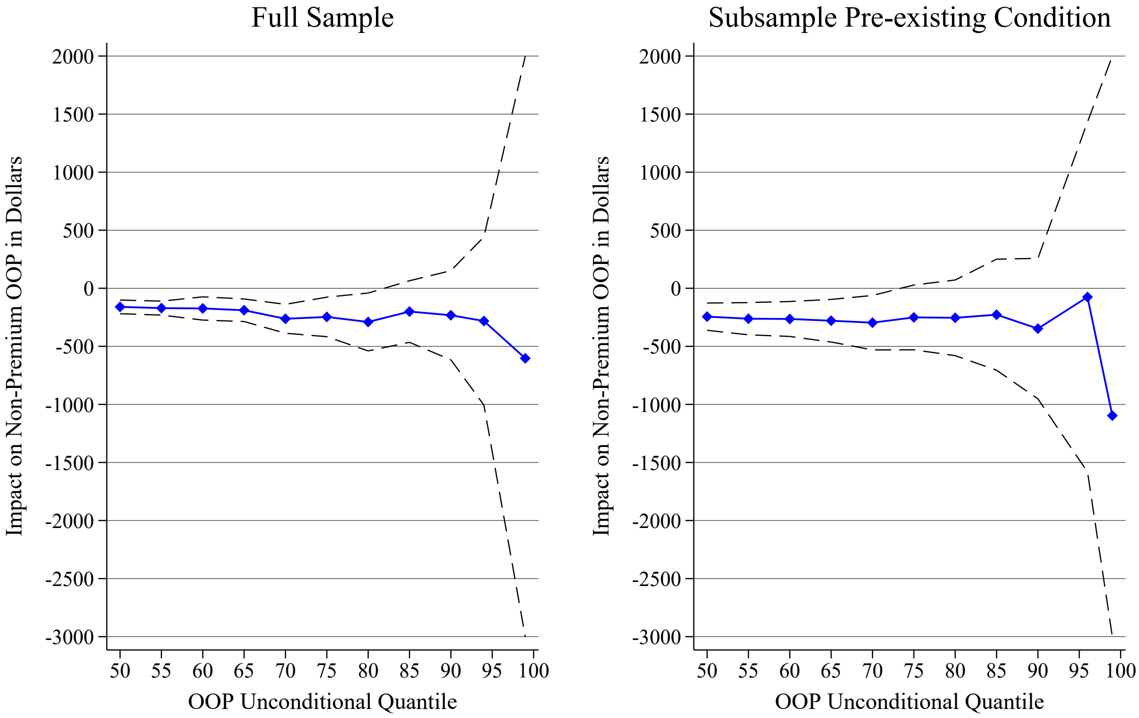
Notes: MEPS cross-sectional data 2007-2016. Panels show weighted means for split samples according to the presence of at least one pre-existing condition in the household. Column (1) presents the average value for households that would have been eligible according to the ACA rules, had the reform been implemented between 2007-2013. Column (2) presents the average value for the group that actually became eligible for Medicaid through the ACA expansion. Columns (3) and (4) show weighted means for households that would not have met eligibility criteria for the ACA Medicaid expansion in any year. Standard deviations in parentheses.

Table A.4: Sources of Payment for Household Medical Expenditures: Marginal Effects, Subsample with Pre-Existing Condition

	Total	*Share of total expenditures paid by:*		
	Expenditures	OOP	public sources	private ins.
	(1)	(2)	(3)	(4)
Medicaid×post	-325.501	-0.058***	0.149***	-0.061***
	(674.065)	(0.015)	(0.020)	(0.018)
Observations	29,458	26,673	26,673	26,673

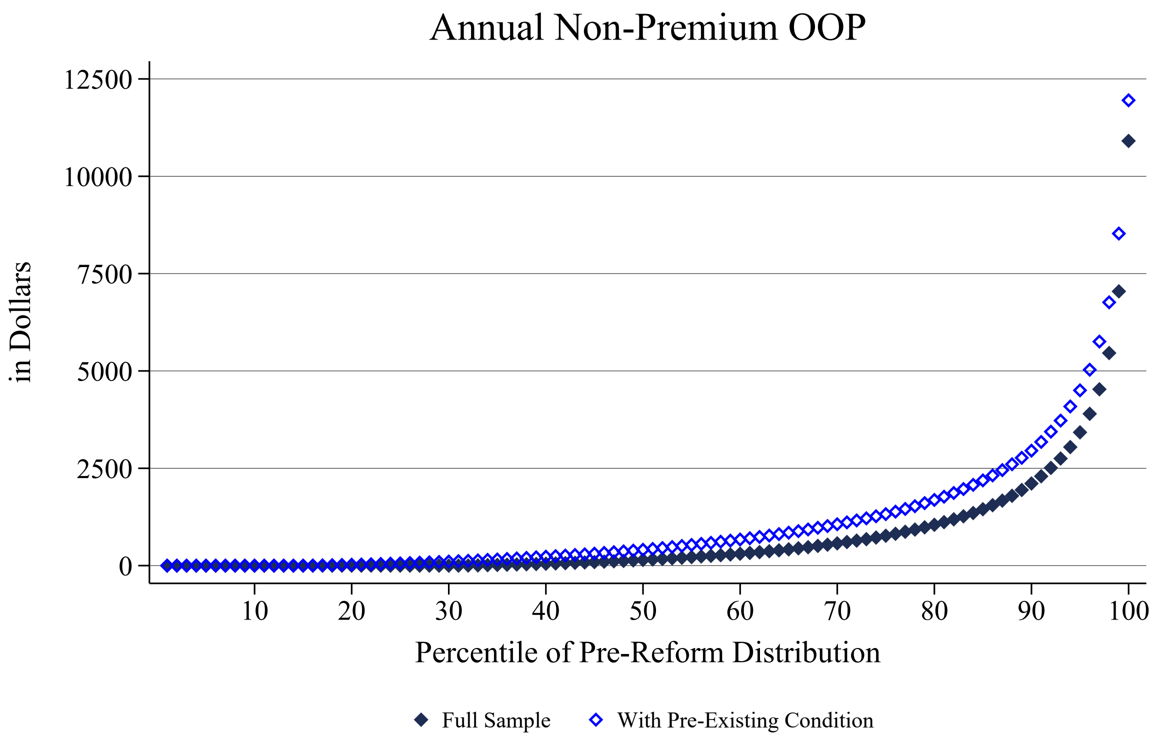
Source: MEPS cross-sectional data 2007-2016, using a subsample of households with at least one pre-existing condition. Simulated IV results from Equation 1 with the full set of controls. Column (1) is estimated as a two-part model with a probit first stage and GLM with log-link function and gamma distribution in the second stage. Columns (2)-(4) use OLS to estimate the log share from each source. Standard errors are clustered at the state level for all regressions and calculated using the delta method for marginal effects in column (1).

Figure A.3: Unconditional Quantile Treatment Effects



Source: MEPS 2007-2016. Unconditional quantile treatment effects estimated using Equation 1 and the RIF with the full set of controls. Unlike in the main analysis, the risk analysis and this figure are based on the unwinsorized OOP spending in order to capture outliers that are relevant for risk exposure. Treatment effects are stated in 2017 constant medical dollars. Point estimates display the effect of Medicaid eligibility, θ, with a 95% confidence interval based on bootstrapped standard errors with 200 repetitions. The left panel contains the main analysis sample and the right panel presents results from a separate regression using only the subsample of households with at least one pre-existing condition.

Figure A.4: OOP Non-Premium Spending 2007-2013



Source: MEPS 2007-2016. Total non-premium OOP during pre-reform years. Separate distributions shown for the main analysis sample ("Full Sample") and a subsample of households with at least one pre-existing condition.

B Appendix B: Robustness to Sample Specifications

In an effort to compare results from the present paper with related work on the ACA Medicaid expansions and mean OOP reductions, this section discusses robustness to alternative sample definitions. Table B.5 provides estimates comparable to those in the main results table, Table 3, with these alternative samples. Because the main sample does not include late expanding states, the second panel of Table B.5 shows results retaining these 5 states, which are very similar to the baseline results. The third panel illustrates the effect of retaining previously eligible adults as additional controls for the newly eligible. Finally, the fourth panel allows for a comparison of results using the individual level definition of eligibility with those defining eligibility at the state level.

Panel 4 provides the closest comparison to estimates by Abramowitz (2018) and Buchmueller et al. (2019), who compare OOP in expansion compared to non-expansion states among households with income below 138% of FPL. Panel 4 presents results from the following difference-in-difference specification for expansion and non-expansion states:

$$Y_h = \alpha + \beta(Expand^{ACA}_{hst} \times Post_t) + \beta_s + \beta_t + \gamma X_{hst} + \varepsilon_h \qquad \text{(B.1)}$$

Table B.5: Marginal Effects of Medicaid Eligibility on OOP Non-Premium Costs

	Extensive Margin		Intensive Margin		Overall Effect
	(OLS)	(Probit)	(OLS)	(GLM)	(Two-Part Model)
Medicaid×Post	(1)	(2)	(3)	(4)	(5)
1) Households with	-0.029**	-0.028	-172.696**	-234.154***	-191.991***
a chronic condition	(0.012)	(0.020)	(75.432)	(32.421)	(26.526)
Observations	30,019	30,019	25,649	25,649	29,679/25,649
2) Retaining late	-0.043**	-0.043**	-155.667**	-166.544***	-129.361***
expanders	(0.013)	(0.016)	(66.283)	(33.189)	(22.257)
Observations	57,200	57,200	40,613	40,613	40,613/57,200
3) Retaining previously	-0.038**	-0.041**	-129.274*	-142.186***	-112.256***
eligible as control	(0.015)	(0.018)	(69.134)	(37.763)	(25.200)
Observations	52615	52615	37040	37040	52615/37040
4) Expansion vs. non-	-0.011**	-0.011***	-386.523***	-289.289***	-161.676***
expansion below 138% FPL	(0.004)	(0.003)	(12.103)	(15.012)	(7.821)
Observations	22,950	22,950	14,538	14,538	22,950/14,538

Notes: MEPS cross-sectional data 2007-2016. Weighted regression results using household sample weights. All regressions contain the full set of controls listed in Equation 1 and use the simulated IV specification. Columns (1) and (2) present marginal effects of the probability to have any OOP expenses, columns (3)-(5) show the marginal effect in 2017 dollars, CPI-med adjusted. Columns (3) and (4) consider only positive values of OOP. Column (5) provides an overall result from a two-part model using probit and glm with a log link function and gamma distribution. Standard errors are clustered at the state level.

Equation B.1 is analogous to Equation 1, with the exception of the treatment variable and lack of state-time interaction terms. In the above, $Expand^{ACA}_{hst}$ refers to residing in an expansion state.[29] Buchmueller et al. (2019) uses household income and Abramowitz (2018) income at the health insurance unit for the means-tested cut-off threshold for their sample. Both of these income concepts fall at or above the income level of the Medicaid household, leading to a likely underestimation of eligibility. This difference helps to explain the stronger evidence of reductions in OOP seen in panel 4 compared to these two papers.[30] All of these estimates will include spillover effects from households previously eligible for Medicaid, which is one explanation for the larger estimated effects using the expansion vs. non-expansion comparison rather than exclusively identifying the newly eligible.

[29]Expansion states include AR, AZ, CA, CO, CT, DC, DE, HI, IA, IL, KY, MA, MD, MI, MN, NH, NJ, NM, ND, NV, NY, OH, OR, RI, WA and WV. By 2015, PA, IN and AK also expanded Medicaid and MT and LA followed suit in 2016. For these states, $Expand^{ACA}_{hst}$ takes the value of one beginning in the year in which the state expanded. Non-expansion states include: AL, FL, GA, ID, KS, IN, ME, LA, MS, MO, NC, NE, OK, SC, SD, TN, TX, UT, VA, WI and WY.

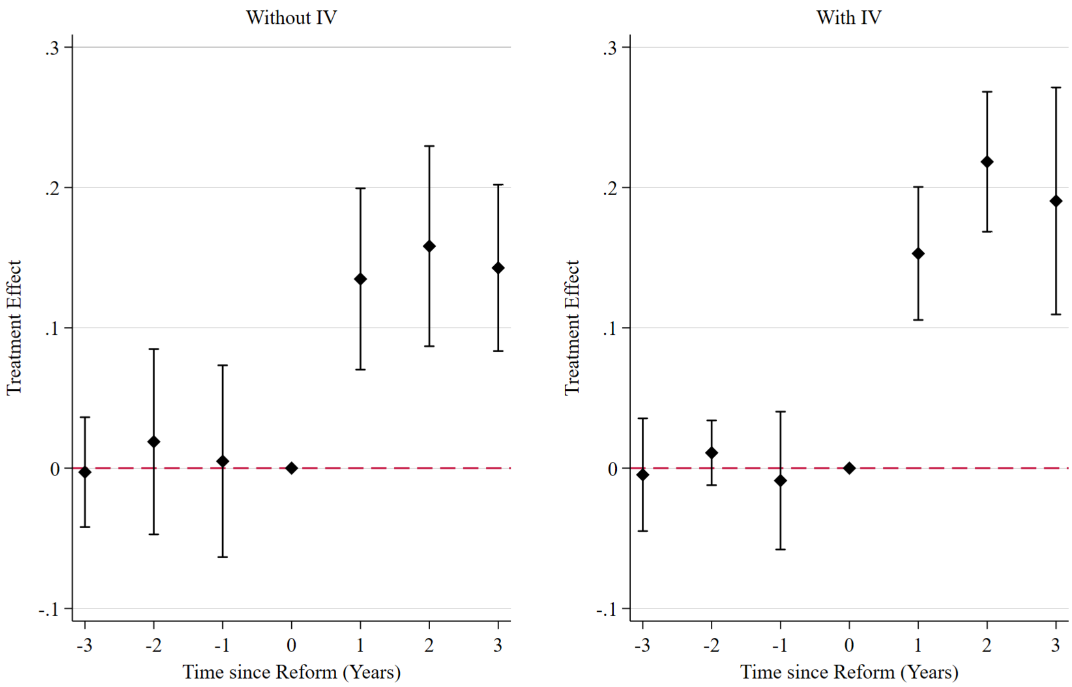
[30]Abramowitz (2018) finds a reduction in the probability of having no OOP two years after the reform, but no impact on the intensive margin and Buchmueller et al. (2019) find only marginally significant reductions, but in the same ballpark as those of panel 4.

C Appendix C: Adjustment Channels

C.1 Medicaid Insurance Coverage

Figure C.5 displays marginal effects of new Medicaid eligibility on enrollment. It offers evidence of a common pre-trend in enrollment and shows that eligibility, on average, increases the likelihood of Medicaid coverage by roughly 19 percentage points (IV specification) in the post-reform period. While the MEPS does not follow the same households over the pre- and post-reform period, conditional means of insurance coverage for treatment and control groups (Table A.1) suggest that the increase in coverage likely stems predominately from those who were previously uninsured.

Figure C.5: Marginal Effects of Medicaid Eligibility on Enrollment, Event Study Analysis



Notes: MEPS 2007-2016. Marginal effects of Medicaid eligibility (θ_t) from Equation 2 on the probability of being covered by Medicaid. The outcome variable of interest is whether anyone in the household is covered by Medicaid. Effects are estimated using probit on the main sample with a full set of controls and a control function approach for the IV results in the right panel. Standard errors are clustered at the state level and estimated using the delta method.

C.2 Utilization

This section explores the extent to which the decrease in OOP medical spending among newly Medicaid eligible households can be explained by changes in health care consumption (utilization). Table C.6 shows conditional means for different types of health service utilization. Both the newly eligible and ineligible groups slightly increased their utilization in the post-reform years. The descriptive statistics display an increase in utilization in particular at the extensive margin that is higher in the treatment group after the reform. However, in the causal analysis that includes the full set of income, state, time and demographic controls, the only change that remains statistically significant is the probability of having an ER visit. Notably, this probability *increases* by 14% from baseline. Panels A and B of Table C.7 displays these marginal effects from Equation 1 for the utilization categories listed in Table C.6.[31]

Table C.6: Medical Service Utilization: Conditional Means

	According to the ACA Medicaid Rules from 2014-2016:			
	Medicaid Eligible 2007-2013	Medicaid Eligible 2014-2016	Not Eligible 2007-2013	Not Eligible 2014-2016
	(1)	(2)	(3)	(4)
- Share with any ER visit	0.21	0.24	0.15	0.16
- Number of ER visits (if> 0)	1.70	1.73	1.45	1.47
	(1.43)	(1.31)	(1.06)	(1.08)
- Share with any inpatient visit	0.09	0.08	0.07	0.06
- Number of hospital inpatient visits	1.54	1.46	1.33	1.34
	(1.20)	(0.90)	(0.80)	(0.72)
- Share with any outpatient visit	0.16	0.22	0.18	0.18
- Number of outpatient hospital visits	3.84	4.05	2.73	2.96
	(9.03)	(8.09)	(4.73)	(5.63)
- Share with any office visit	0.62	0.67	0.69	0.70
- Number of physician office visits	9.76	10.47	8.67	9.13
	(18.76)	(16.75)	(13.10)	(13.63)
Observations	5,017	2,402	30,560	13,612

Notes: MEPS cross-sectional data 2007-2016. Weighted means at the household level using household sample weights. Column (1) presents the average value for households that would have been eligible according to the ACA rules, had the reform been implemented between 2007-2013. Column (2) presents the average value for the treatment×post group that actually became eligible for Medicaid through the ACA expansion. Columns (3) and (4) show weighted means for households that would not have met eligibility criteria for the ACA Medicaid expansion in any year. ER = emergency room.

Recent research on the effect of the ACA Medicaid expansion on utilization among low-income childless adults has found indications of an increase along some dimensions. Using NHIS data on a nationally representative sample, Wherry and Miller (2019) find

[31] In unreported regressions, the event study specification for utilization outcomes yields imprecise estimates, but no clear pattern of increasing or decreasing over time.

increases in the probability of seeing a general doctor (0.052 p.p.) and the probability of seeing a specialist (0.032-0.042 p.p.), but no changes in the likelihood of an ER visit during the first three years after the expansion. These estimates, however, are based on expansion vs. non-expansion state variation without additional within state controls to account, for instance, for differential improvements in access to care in expansion compared to non-expansion states. Similarly, Sommers et al. (2016) compares utilization outcomes during the first two years after the ACA expansion between Kentucky (Medicaid expansion state), Arkansas (private option state) and Texas (non-expansion state). They find that Medicaid expansion caused reductions in ER visits and an increase in outpatient visits. Finally, using the Behavioral Risk Factor Surveillance System (BRFSS) telephone survey, Simon et al. (2017) find that low-income adults in expansion states increased their preventive care behavior compared to those in non-expansion states, which may suggest an increase in physician office visits. In order to better compare the utilization results in the current paper to this research, I repeat my analysis using only the across-state variation from Equation B.1. Panel C of Table C.7 shows that this specification yields similar results to those in Wherry and Miller (2019) and can reconcile the increase in outpatient visits found in Sommers et al. (2016) for the state of Arkansas as well as increased probability of a physician visit from Simon et al. (2017).

Prior to the ACA, previous analyses of the impact of earlier Medicaid expansions to low-income childless adults on health service utilization have found both increases and decreases in utilization. However, these results can be largely reconciled once differences in the underlying treatment and control populations are considered.[32] The finding in this paper that emergency room utilization increased on account of Medicaid expansion is generally in line with that of Taubman et al. (2014) from the 2008 Oregon Medicaid Experiment, albeit at a significantly smaller magnitude in the present paper (14% compared to 40%). As the authors acknowledge, the lottery participants in the Oregon Experiment are likely sicker and thus have a higher demand for health services than the average low-income individual in the population, for whom the ACA expanded eligibility (Finkelstein et al. (2012), Taubman et al. (2014)). Correspondingly, Taubman et al. (2014) likewise find an increase in other types of utilization, which is not corroborated in this paper.

Three main insights emerge from these comparisons. First, the low-income childless adults that were targeted by the ACA Medicaid expansion did not increase their utilization by as much as the lottery participant population in the Oregon Medicaid Experiment, likely because the the national pool of childless adults is less adversely selected compared

[32]See Kowalski (2020) for a thorough comparison of ER usage in the Oregon Medicaid Experiment and the Massachusetts Health Reform and Miller (2012) and Kolstad and Kowalski (2012) for ER utilization results from the Massachusetts Health Reform.

to those who chose to signed up for the lottery in Oregon. A second important difference between the two populations is that the control group in the Oregon Experiment was exclusively uninsured. In the case of the ACA, the control group can be uninsured or privately insured, and thus causal effects reflect differences between Medicaid eligibility and other outside options in the insurance market. Going forward, current non-expansion states weighing the costs of expansion should therefore expect fewer increases in total expenditures than those found in the Oregon Experiment and instead, a shifting of the cost burden across payers in the health care system. Third, new visits to physicians and specialists are increasing more in expansion states, but this increase may be caused by other improvements in access in these states rather than by public insurance expansion alone. Once within-state controls and state-year fixed effects are included, increases only remain for the likelihood of an ER visit. This result may indicate persistent barriers to access, in line with Miller (2012), for example for hourly wage workers seeking care outside of doctors' office hours or those residing in areas with few doctors available. The next section provides further support for this hypothesis.

Table C.7: Marginal Effects from Equation 1: Medical Service Utilization

	Emergency Room		Inpatient Stay		Outpatient Facility		Physician Office	
	Any visit	Log Nr. of visits	Any visit	Log Nr. of visits	Any visit	Log Nr. of visits	Any visit	Log Nr. of visits
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicaid×post								
A. Baseline Specification	0.030*	0.038	0.006	-0.038	0.031	-0.048	0.001	0.047
	(0.016)	(0.043)	(0.012)	(0.052)	(0.019)	(0.096)	(0.018)	(0.040)
B. Controlling for Subsidies	0.033**	0.037	0.008	-0.017	0.027	-0.015	0.009	0.043
	(0.016)	(0.043)	(0.012)	(0.052)	(0.020)	(0.105)	(0.018)	(0.041)
Observations	51,568	8,441	51,004	3,528	51,534	8,087	51,584	32,631
Expansion×post								
C. Adults below 138% FPL	0.006	0.010	-0.005	0.007	0.043*	-0.106	0.040**	0.049
	(0.015)	(0.048)	(0.010)	(0.056)	(0.019)	(0.078)	(0.014)	(0.055)
Observations	22,950	4,842	22,943	1,999	22,943	3,408	22,950	13,170

Notes: MEPS cross-sectional data 2007-2016. Weighted regression results using household sample weights. All columns refer to marginal effects for OLS estimation of Equation 1 with a full set of controls. Outcome variables are the probability of having each type of visit and the log number of each type of visit. Standard errors are clustered at the state level. Small discrepancies in the number of observations stem from missing information in a few cases on the outcome variable.

C.3 Access to Care

Table C.8 exhibits conditional means for various measures of access to care. Both eligible and non-eligible populations are less likely in the post-reform period to delay or forgo necessary medical treatment or the purchase of prescription medication. However, the share of households reporting they lack access to a usual care provider decreased by 4 percentage points between 2014-2016 in the treatment group and remained constant among ineligible households.

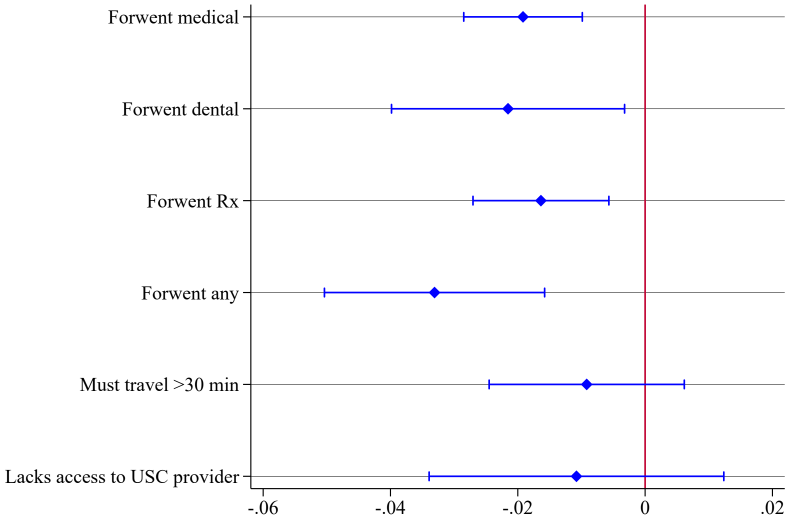
Table C.8: Access to Care: Conditional Means

	According to the ACA Medicaid Rules from 2014-2016:			
	Medicaid Eligible 2007-2013	Medicaid Eligible 2014-2016	Not Eligible 2007-2013	Not Eligible 2014-2016
	(1)	(2)	(3)	(4)
Due to cost, delayed/forwent:				
- Medical care	0.09	0.06	0.05	0.04
- Dental care	0.13	0.10	0.08	0.06
- Prescription drugs	0.08	0.06	0.04	0.03
- Any care or drugs	0.20	0.16	0.11	0.09
Access to usual care provider:				
- Must travel > 30 min. to USC provider	0.14	0.13	0.11	0.11
- Lacks access	0.13	0.09	0.07	0.07
Observations	50,17	2,402	30,560	13,612

Notes: MEPS cross-sectional data 2007-2016. Weighted means at the household level using household sample weights. Column (1) presents the average value for households that would have been eligible according to the ACA rules, had the reform been implemented between 2007-2013. Column (2) presents the average value for the treatment×post group that actually became eligible for Medicaid through the ACA expansion. Columns (3) and (4) show weighted means for households that would not have met eligibility criteria for the ACA Medicaid expansion in any year.

Results of the causal analysis are displayed in Figure C.6 and reveal that the reductions in delays to medical and dental treatment as well as that for purchasing necessary prescription drugs can be attributed to public insurance expansion whereas changes to reporting lack of access to a personal doctor cannot be interpreted as causal. Given that the physician response to the Medicaid expansion has been largely limited to health care providers who had previously already treated Medicaid patients (Neprash et al., 2018), a lack of availability of doctors in rural or poor neighborhoods may explain why ACA Medicaid eligibility did not reduce the two extensive margin measures of access: lacking access to a usual care provider and travel of more than 30 minutes to reach a usual care provider.

Figure C.6: Marginal Effects of Access to Health Care Measures



Notes: MEPS 2007-2016. Marginal effects using Equation1 to estimate separate OLS regressions for each of the six outcomes depicted. The outcome variable is the share of the household answering positively to each corresponding access constraint question in the MEPS. Control variables are the same as those found in Table 3. Whiskers represent a 95% confidence interval. Standard errors are clustered at the state level.

D Appendix D: Controlling for Exposure to ACA Private Exchange Subsidies

Private health insurance exchange subsidies offer households without Medicaid or employer-sponsored-insurance an online marketplace for purchasing private health insurance. Households with income between 100–400% of the FPL are eligible for exchange subsidies that decrease with income up to this threshold. The subsidy amount is equal to zero for households eligible for Medicaid as well as those earning at least 400% of FPL. The value of this subsidy depends on household income (MAGI) and the cost of the second-lowest premium for single coverage in the household's rating area.[33] For eligible households, the amount results from the difference between a progressive affordability cap and the second-lowest cost silver plan in the household's rating area.[34] Both the sliding scale of affordability caps and the market prices of the benchmark silver plans changed in 2015 and 2016, which are accounted for in the calculation.

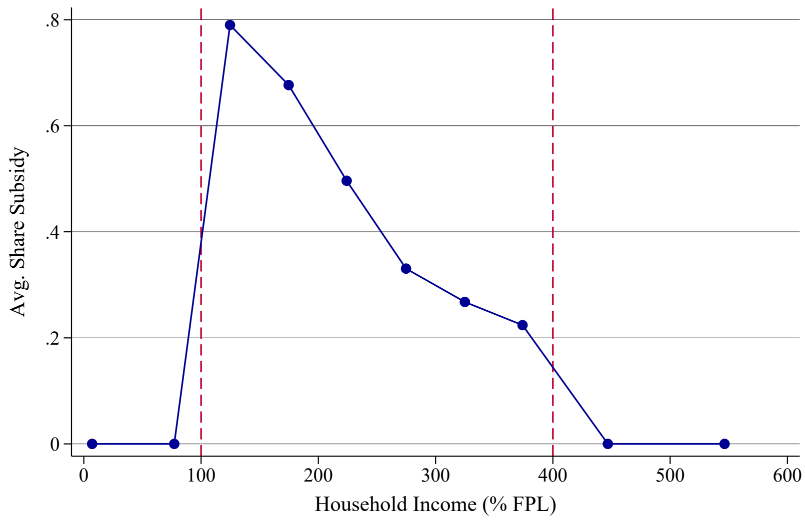
To calculate the eligible subsidy amount, I incorporate price information from the Robert Wood Johnson Foundation for the second-lowest cost silver plan on the federal

[33]Rating areas are equivalent to counties with the exception of AK, CA, ID, MA and NE, which use 3-digit ZIP codes. For these 5 states, I use the average price in the rating area.

[34]In 2014, the affordability cap as a percentage of MAGI were: 2% for households earning below 138% of FPL, 4% for those in the range of 138-150, 6.3% for 150-200% of FPL, 8.05% for 200-250% of FPL, 9% for 250-300% of FPL and 9.5% for 300-400% of FPL.

insurance exchange in each county. I supplement federal exchange prices with those from state exchanges with the help of the Kaiser Family Foundation's Marketplace Calculator.[35] Next, I apply the age adjustment curves documented by the Center for Medicare and Medicaid Services in order to account for age-based price setting. Finally, the price of the benchmark plan equates to the sum of costs for the individual plans in the household, including up to 3 children.[36] I apply these thresholds to the households in the MEPS dataset and calculate the eligible dollar amount in subsidies using the MHU composition, income and county in the MEPS.

Figure D.7: Share of Premium Cost Covered by Household Potential Subsidy



Notes: MEPS 2007-2016, Robert Wood Johnson Foundation Hix Compare and Kaiser Family Foundation Marketplace Calculator. The percentage of the second-lowest cost premium plan covered by the subsidy is calculated on the basis of household composition and income in the MEPS dataset as well as the rating area according to the MEPS county-level geocodes.

The treatment variable for exposure to subsidy eligibility is the percentage of the unsubsidized second-lowest cost premium plan in the household's rating area that would be covered by the potential subsidy amount for which each household qualifies, averaged over 2014-2016. Figure D.7 displays this subsidy rate across household income, measured as a percent of the FPL. Subsidies are largest, roughly 80% of the unsubsidized premium, for an average household earning at the FPL and then taper off as income increases up until 400% FPL. Analogously to Medicaid eligibility, subsidy eligibility is measured according to the eligibility rules from 2014-2016 applied to the county of residence, income and composition of each household in the sample in each year. An average share is taken

[35] Beginning in 2015, the Robert Wood Johnson Foundation provides price data for all states. For 2014, however, information is missing for the 14 states that relied on their own state exchanges rather than the federal exchange. I fill in this missing information manually using the Marketplace Calculator.

[36] Federal regulations stipulate that insurance coverage of the fourth and subsequent children must be offered without extra cost.

over the post-reform period and added to regression Equation 1 ($+\beta SUB_{hst}+\theta_2(SUB_{hst}\times Post_t)$).

Table D.9: Marginal Effects of Medicaid Eligibility on OOP Non-Premium Costs

	Extensive Margin		Intensive Margin		Overall Effect
	(OLS)	(Probit)	(OLS)	(GLM)	(Two-Part Model)
	(1)	(2)	(3)	(4)	(5)
Treating Eligibility as Exogenous:					
$Medicaid \times Post$	-0.038**	-0.032**	-169.265**	-182.563***	-132.079***
	(0.013)	(0.016)	(79.593)	(39.098)	(25.620)
$Subsidy \times Post$	-0.018	-0.008	-123.018	-88.869	-59.963
	(0.018)	(0.021)	(108.961)	(67.345)	(43.763)
Treating Eligibility as Endogenous:					
$Medicaid \times Post$	-0.023*	-0.021	-158.249**	-172.048***	-119.670***
	(0.014)	(0.017)	(76.532)	(38.225)	(25.347)
$Subsidy \times Post$	-0.016	-0.006	-90.107	-40.329	-26.541
	(0.018)	(0.022)	(108.961)	(67.345)	(43.763)
Observations	51,548	51,548	36,396	36,396	51,548/36,396

Notes: All notes from Table 3 apply. This table additionally controls for exposure to subsidy eligibility among the control group.

Table D.9 displays the results from the main analysis with the addition of the control variables for subsidy eligibility. Whereas Medicaid targets the lowest income households, subsidies concentrate on low-medium income households. Although the sign is negative, subsidy eligibility does not have a statistically significant impact on OOP spending for eligible households. Most importantly, however, is the observation that the effects of Medicaid expansion are quite robust to controlling for this additional policy provision (Compare results in Table 3).

E Appendix E: Model Specification Tests for GLM

The modelling choice for GLMs includes the link function and distribution family, which were chosen sequentially, as the test for the distribution family relies on a properly specified link function. Starting with the link function, a Box-Cox test applied to Equation 1 determines the scalar power (δ) of (the positive support of) the dependent variable, OOP_h, that yields the most symmetric distribution (Deb and Norton, 2018). If $\delta = 0$, the natural log-transformed link function will best fit the data generating process; a $\delta = 0.5$ indicates a square-root transformation and $\delta = 1$ would indicate a linear model best fits the data. Table E.10 shows that $\delta = 0.121$, which is closest to the log link transformation.

Following the test for the link function, a modified Park test determines the most appropriate fit for the distribution family (Park, 1966), which affects the precision of marginal effects. In a first step, I estimate Equation 1 using a GLM and a best guess for the distributional family. Based on Deb and Norton (2018), who use the same outcome variable and dataset as the present analysis, I run the initial GLM using a gamma distribution and save the log of the squared residuals as well as the predicted linear index of OOP_h. In a second step, I regress the log squared residuals on the predicted linear index with robust standard errors. The coefficient, which captures the relationship between the mean and the variance of the errors, then determines the distributional family that best fits the data. A coefficient of zero would imply that the variance is unrelated to the mean, whereas a coefficient of one indicates a proportional relationship, two indicates a gamma distribution and three an inverse Gaussian. Because Table E.10 shows this relationship to be closest to two, the analysis uses a gamma distribution family for the GLM.

Table E.10: Link Function and Distribution Family Tests for GLM

	Link Function Test (δ) (1)	Distribution Family Test (2)
	0.1210***	1.563***
	(0.002)	(0.006)
Test	Box-Cox	Park
Observations	36,396	51,548

Source: MEPS cross-sectional data 2007-2016, main analysis sample.