Does Health Insurance Reduce Consumption Risk? Evidence from Medicaid Expansions*

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Abstract

We assess the consumption insurance value of Medicaid expansions. While Medicaid expansions improve physical and financial health, they may not smooth consumption risk because a great deal of uninsured medical spending is financed with bad debt and charity care. Using multiple methods, we find only small effects of Medicaid expansion throughout the consumption distribution. Our estimates, combined with an assumed utility function, imply near-zero insurance value to the uninsured from Medicaid expansion. While our estimates are statistically noisy, we can nevertheless rule out the possibility that a large share of Medicaid's value comes from reductions in consumption risk.

Keywords: Medicaid expansion, insurance, quantile difference-in-differences, changes-in-changes, risk premium

JEL codes: I13, H51, G52

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1 Introduction

The US health care landscape is unique in its financing structure—patients face high prices for care, high cost sharing, and high rates of uninsurance. As a result, medical debt is both pervasive and frequently delinquent. The Consumer Financial Protection Bureau recently estimated that medical debt in collections totaled over $88 billion, affecting over one-fifth of the adult population. Policy at the highest levels has targeted medical debt, with proposals including mass forgiveness and bans on reporting to credit agencies (Consumer Financial Protection Bureau, 2023). In part to combat this financial burden, many states expanded access to Medicaid following the implementation of the Affordable Care Act (ACA) in 2014.

By many metrics, Medicaid expansion has been an effective policy. Expansion brought large numbers of low-income and nonelderly people into the program, which now covers over 80 million people and is the largest means-tested program in the country (Donohue et al., 2022). Prior work has shown that states' post-ACA Medicaid expansions delivered an array of positive benefits for the physical and financial health of the newly eligible. Guth et al. (2020) provide a comprehensive review of the household-side effects of the ACA. The ACA and especially the Medicaid expansions increased Medicaid coverage and all-source health insurance (e.g., Miller and Wherry 2017; Kaestner et al. 2017; Frean, Gruber and Sommers 2017). This greater coverage, in turn, increased health care utilization, including primary care, preventive care, behavioral care, and, possibly, emergency department use (e.g., Simon, Soni and Cawley 2017; Soni et al. 2018; Meinhofer and Witman 2018; Miller and Wherry 2017; Nikpay et al. 2017; Duggan, Gupta and Jackson 2022). Recent work has found important health improvements, in particular mortality reductions, from the Medicaid expansions (Miller et al., 2021; Wyse and Meyer, 2023) and from ACA Marketplace coverage (Goldin, Lurie and McCubbin, 2021). The ACA has also improved financial well-being, reducing bankruptcy, medical debt, and mortgage delinquency and improving credit scores and terms of credit (Gross and Notowidigdo, 2011; Mazumder and Miller, 2016; Hu et al., 2018; Brevoort, Grodzicki and Hackmann, 2020; Gallagher et al., 2020; Dodini, 2023).

Despite this array of positive evidence, little is known about how well the Medicaid expansions perform their core insurance function: smoothing the marginal utility of consumption across states of the world (Finkelstein, Mahoney and Notowidigdo, 2018). Understanding this aspect of Medicaid expansion is important because in standard models, equalizing marginal utility is the reason that insurance creates value. Our paper fills this gap by providing the first direct evidence on the impact of Medicaid expansions on the consumption distribution, and quantify the insurance value implied by this distributional impact.

Despite its importance, the consumption-smoothing insurance value of Medicaid expansion remains an open question in the literature. First, existing research does not provide direct evidence on how health insurance coverage affects the distribution of consumption in general and consumption risk in particular. Of the more than 400 papers studying the effects of Medicaid expansion following the ACA reviewed in Guth et al. (2020), only one studies the effects of Medicaid on consumption: Levy, Buchmueller and Nikpay (2019). That paper, however, examines only average effects, not the effects across the distribution. The literature instead focuses on the effects of Medicaid expansion on health, health care utilization, and financial outcomes. Closely related to our study, Finkelstein, Hendren and Luttmer (2019) and Shupe (2023) estimate the insurance value of Medicaid to beneficiaries. They do not, however, estimate the effect of Medicaid on the consumption distribution, instead inferring this outcome from the impact of Medicaid on out-of-pocket medical spending.

Other evidence suggests that the impact of Medicaid expansion on the consumption distribution is ambiguous. On the one hand, reductions in bankruptcy might suggest that some households avoid the worst consumption outcomes. Other evidence, however, shows that the benefits of health insurance coverage flow not only to households in the form of increased consumption but also to health care providers and financial institutions via reductions in uncompensated care—specifically bad debt (i.e., debt deemed unrecoverable) and charity care.

Such uncompensated care is an important source of health care financing for the uninsured, who pay only a small fraction of their health care bills (Mahoney, 2015). Health insurance expansions therefore end up benefiting health care providers, especially hospitals (Dranove, Garthwaite and Ody, 2016; Garthwaite, Gross and Notowidigdo, 2018; Duggan, Gupta and Jackson, 2022). Thus, greater health insurance coverage does not automatically imply reduced exposure to health care spending risk among households; instead, improvements to coverage reduce the spending risk borne by providers. Indeed, Finkelstein, Hendren and Shepard (2019) finds that the willingness to pay for health care among recipients of subsidized health insurance is below their own costs, and Finkelstein, Hendren and Luttmer (2019) finds that the value of Medicaid to beneficiaries is well below the program's cost.

To quantify the consumption insurance value of Medicaid expansion, we estimate the distributions of consumption with and without the expansion. Following Finkelstein, Hendren and Luttmer (2019), we define the insurance value of Medicaid as the willingness to pay for the expansion in excess of the increase in average consumption. Similarly to much work in the literature, our empirical strategy takes advantage of the uneven adoption of Medicaid expansion, comparing states that did and did not expand Medicaid under the ACA. We depart from this literature, however, in that we estimate not only average but also *distributional* effects: We measure the impact of Medicaid expansion on the entire household consumption distribution, using quantile difference-in-differences (DID) and changes-in-changes (CIC) methods (Athey and Imbens, 2006).

We measure consumption using the Consumer Expenditure Survey. We use the subset of "well-measured consumption" (Meyer and Sullivan, 2023), which is comprised of regular, recurring expenses rather than one-off purchases and is less vulnerable to measurement error. Following Kaestner et al. (2017), we focus on and nonelderly adults and adults with low education—those most likely to have become newly eligible for Medicaid under the ACA expansion, and we limit the analysis to 2008–2019 to avoid the complex health and consumption effects from COVID-19. We also scale our effects by the estimated Medicaid eligibility in the targeted groups.

Our main finding is that the impact of the Medicaid expansions on consumption risk was small and is sufficiently precisely estimated to rule out large benefits. Looking across the consumption distribution, we estimate that the Medicaid expansion increased consumption by a small, insignificant, and approximately constant amount between the 15th and 85th percentiles of consumption among likely Medicaid-eligible households. We find no increase at the bottom of the distribution and a small, noisy decrease at the top of the distribution. We further quantify the implied insurance value under an assumed expected utility function, finding a value of $85 per person per year. Although this estimate is imprecise, the 95 percent confidence intervals allow us to confirm that it falls far below two important benchmarks: the government costs of providing that coverage ($1,500 per person per year) and the coverage's mortality-reducing benefits ($750 per person per year). The estimate is also much smaller than we would expect if the uninsured were to pay for all their health care. Although small, this consumption insurance value is consistent with other estimates from the literature that do not use consumption data directly (Shupe, 2023; Finkelstein, Hendren and Luttmer, 2019) and with the possibility that health care for the uninsured is often financed by charity care and bad debt, with small consumption consequences for the uninsured. Overall, our findings suggest that Medicaid expansion's main value comes not from its consumption insurance component, but from its direct effects on health.

These findings contribute to and complement the literature discussed above on the effects of the Medicaid expansion. We also contribute to a smaller literature measuring the insurance value of health insurance. Finkelstein, Hendren and Luttmer (2019) develops a framework for measuring this value and applies it to the Oregon Health Insurance Experiment, accounting for benefits not only from reduced consumption risk but also from improved health and greater consumption levels. That paper does not, however, directly estimate the impact of Medicaid on consumption risk. The authors find that the value to beneficiaries is smaller than the program's cost and that the insurance value derived is sensitive to the exact method of estimation. Also related is Lockwood (2024), which argues that the insurance value of health insurance is low or even negative because of the interaction between health insurance and other aspects of the social safety net, especially uncompensated care. While that paper studies a wide variety of insurance programs, not just Medicaid, it does not use exogenous variation in program coverage to identify their impact on the consumption distribution. Shupe (2023) estimates the impact of the Medicaid expansion on the distribution of medical spending and uses this estimate to back out an insurance value but does not look at consumption responses directly. Similarly, Dodini (2023) estimates the impact of the ACA's premium and cost-sharing subsidies (for private coverage, not Medicaid) on the distribution of financial outcomes such as debt and bankruptcy and uses the distributional estimates along with a utility function to obtain an insurance value. Relative to these papers, our contribution is to use direct measures of consumption responses to insurance expansion, to estimate how exogenous variation in health insurance affects the consumption distribution, and to recover the implied insurance value from the ACA Medicaid expansions in particular.[1]

The rest of this paper proceeds as follows. Section 2 details the theoretical basis for our estimation, Section 3 explains the empirical strategy, Section 4 provides an overview of the data, Section 5 presents the results, and Section 6 concludes.

2 Insurance Value of Medicaid Expansions

2.1 Health care spending among the uninsured

Two features of the US health care financing system are key to understanding our research question and our findings. The first feature—as well as a key part of the motivation for

[1]Also relevant are papers by Dague (2014) and Finkelstein, Hendren and Shepard (2019), which use enrollment choices to estimate the value of subsidized insurance coverage to enrollees and find that a sizable fraction of beneficiaries have low willingness to pay. In contrast to us, these papers do not specifically estimate the insurance value of this coverage, but their approach requires weaker assumptions, such as revealed preference rather than a specific utility function.

the ACA (Obama, 2016)—is that uninsured Americans have historically incurred enormous medical bills. To illustrate the high health care costs faced by the uninsured, Panel A of Figure 1 shows the distribution of medical charges faced in 2008–2013 by uninsured Americans with income below 138% of the poverty line—the group that would become eligible for Medicaid under the ACA's expansion.[2] Charges here are the amount *billed*, not necessarily the amount paid. While most experience near-zero charges, there is a long right tail, with 10% facing charges of $7,400 or more. Few uninsured, low-income people can afford to pay such charges—for example, nearly half of US households report that they could not come up with $2,000 within a month if needed (Lusardi, Schneider and Tufano, 2011).

The second key feature of US health care financing is that few people actually pay these high charges. Panel A of the figure also shows the distribution of the amount paid, which is shifted substantially to the left. The difference between the amount charged and the amount paid is uncompensated care. This uncompensated care comprises a combination of hospital-provided charity care and care financed by medical debt; much of the latter is eventually deemed unrecoverable and thus becomes bad debt. This bad debt shows up on households' balance sheets and is reflected in the high levels of medical debt in the US (Kluender et al., 2021).

How this uncompensated care affects consumption is difficult to measure directly. If most uncompensated care reflects charity care or bad debt and households are not otherwise borrowing or saving, then uncompensated care should have little impact on consumption. If uncompensated care reflects bad debt that is repaid while dragging down credit scores, then it may have a large impact on the consumption distribution. We illustrate two extreme scenarios in Panel B of Figure 1. If uncompensated care has no impact on consumption, then Medicaid expansion should have a relatively modest impact on the consumption distribution. On the other hand, if households end up financing uncompensated care with their own consumption (by slowly paying down their debt, for example), then Medicaid expansion

[2] For details on the construction of the figure, see Appendix B.

should have a much larger impact, especially at the lower tails of the distribution. Because it is challenging to determine to what extent uncompensated care affects consumption, our approach is to directly estimate the impact of the post-ACA Medicaid expansion on the consumption distribution.

2.2 Consumption insurance value of Medicaid

We develop a simple model to show how we use data on the consumption distribution to estimate the insurance value of Medicaid expansion. Consider two economies indexed by $m \in \{0, 1\}$, where $m = 0$ corresponds to an economy without Medicaid expansion and $m = 1$ to one with Medicaid expansion. There is a mass of households indexed by i that are eligible for Medicaid when $m = 1$. Households earn income y_i and may experience health shocks, resulting in health costs h_i. These health costs may be paid by the households themselves or by a third party. Third-party transfers include private insurance, government insurance (in the Medicaid state of the world), and payment by the health care providers themselves via uncompensated care. The joint distribution of income, health shocks, and health care financing induces a distribution over consumption.

As we focus on the consumption insurance value of Medicaid expansion, we assume that Medicaid expansion is relevant for households only via the consumption distribution F_m. We can therefore write the expected utility of a household in economy m as

$$EU_m = \int_c u(c) dF_m(c),$$

where $F_m(c)$ is the distribution of consumption in economy m (would-be eligibles) and u is the utility function. We take the expected utility over the entire consumption distribution (among eligible households), so consumption variability reflects both risk from uninsured medical expenses and permanent differences in income. EU_m therefore represents expected utility from behind the veil of ignorance among the Medicaid-eligible population, and improvements in EU_m represent improvements in "ex ante welfare," in the sense of Hendren (2021).[3]

Following Finkelstein, Hendren and Luttmer (2019), we define the willingness to pay for Medicaid expansion γ as the amount of consumption an individual would forgo in the economy with Medicaid to be just indifferent to having Medicaid access in the economy without Medicaid. That is, γ solves

$$\int_c u(c+\gamma)dF_1(c) = \int_c u(c)dF_0(c). \tag{1}$$

We define the insurance value of Medicaid expansion as the difference between γ and the expected consumption gain:

$$\pi = \gamma - \left(\int_c cdF_1(c) - \int_c cdF_0(c) \right). \tag{2}$$

The second term in Equation (2) is the difference in expected consumption between the two economies, which is approximately equivalent to the transfer component of the value of Medicaid (Finkelstein, Hendren and Luttmer, 2019) because it represents the net transfer to Medicaid-eligible households.[4]

While the transfer component is not a net welfare gain (it represents a cost borne elsewhere in the economy), the insurance premium is a welfare benefit from Medicaid expansion. This benefit arises for the traditional reason that insurance improves welfare: Risk-averse households are happy to accept lower average consumption at the cost of a reduction in consumption risk, i.e., an improvement in the lower tail of the consumption distribution. Thus,

[3]In our empirical approach, we sometimes incldue controls. Results from those specifications should be interpreted as reflecting an interim utility level, after skill endowments are realized but before health shocks are realized.

[4]Our model differs from the setup in Finkelstein, Hendren and Luttmer (2019) in that we do not account for the health gains from Medicaid. This simplifies our estimation of insurance value but also means that the mean consumption gain in our model is not the same as the transfer component in Finkelstein, Hendren and Luttmer (2019).

the insurance value of Medicaid depends on how Medicaid expansion affects the consumption distribution and, in particular, on whether the expansion increases consumption in the lower tail.

Our empirical goal, therefore, is to estimate the impact of a change in Medicaid access on the consumption distribution and recover the implied insurance value of Medicaid. We estimate the distribution of consumption F_1 in Medicaid expansion states and recover the counterfactual distribution F_0. Armed with the estimates $\hat{F}_1$ and $\hat{F}_0$, we can calculate $\hat{\gamma}$ and $\hat{\pi}$ for any assumed utility function.

2.3 Model limitations

Broader value of Medicaid. Because we focus on estimating the *insurance value* of Medicaid following Finkelstein, Hendren and Luttmer (2019), we abstract from several potentially important channels whereby Medicaid may generate value, such as improvements in beneficiary physical and mental health (e.g., Finkelstein et al. (2012)) and reductions in mortality (Miller et al., 2021; Wyse and Meyer, 2023). Improvements in financial health may also matter for beneficiaries in ways not captured by the consumption distribution.[5]

Behavioral responses to Medicaid. To simplify the model, we abstract from two potentially important behavioral responses to Medicaid: household labor supply, which would affect income, and health care utilization, which would affect health. Reassuringly, prior evidence suggests that the post-ACA Medicaid expansions have not generated substantial labor supply responses (Kaestner et al., 2017; Leung and Mas, 2018).[6] The ACA has, how-

[5]In principle, it is possible to estimate the overall value of Medicaid by specifying a utility function that depends on many such inputs (Finkelstein, Hendren and Luttmer, 2019). However, doing so would add complexity to the model and would require us to measure causal effects on many inputs.

[6]The ACA has generated substantial responses in *taxable income* as households adjust their reported income levels to qualify for subsidized coverage (Kucko, Rinz and Solow, 2018; Heim et al., 2021), but this appears to reflect changes purely in reporting rather than in earnings. The evidence on the labor supply effects of Medicaid coverage pre-ACA is mixed; for example, Garthwaite, Gross and Notowidigdo (2014) finds large employment effects of Medicaid disenrollment in Tennessee, but Dague, DeLeire and Leininger (2017) find smaller effects in Wisconsin.

ever, had a large impact on health care utilization—which was one of the intended effects of the Medicaid expansion.[7] While we do not directly account for these changes in health care utilization in our insurance value model, we do benchmark the value that we obtain to the value of these health improvements.

Incomplete Medicaid take-up. Our model focuses on a Medicaid-eligible population, but not everyone eligible for Medicaid takes up coverage (e.g., Decker, Abdus and Lipton (2022)). We might expect Medicaid to have no impact on people who are eligible but not enrolled, but in fact the risk-reducing benefits of Medicaid extend to this group through *retroactive coverage*.[8] To consider incomplete take-up, however, we do scale some of our estimates by approximately 50% to reflect the insurance value for the newly eligible who actually enroll.

Precautionary saving. Our model abstracts from saving, but one response to health expenditure risk is precautionary saving. For example, De Nardi, French and Jones (2010) shows that this mechanism is important post-retirement (especially among those not likely to be eligible for social insurance programs such as Medicaid). If present, these savings represent a welfare loss because they generate permanently lower consumption; we suspect, however, that precautionary saving is relatively unimportant in our context because the low-income population that we study generally has little scope for saving.

3 Empirical Strategy

Our goal is to estimate the insurance value of Medicaid expansions, the empirical analog of π. This parameter is determined by the consumption distribution under Medicaid expansion, $F_1(c)$, and the counterfactual distribution, $F_0(c)$. We recover these objects using data

[7] While early evidence found little impact on overnight hospitalizations or doctor visits (Miller and Wherry, 2017), the more recent work reviewed in Guth et al. (2020) has found positive impacts on a range of preventive care measures, including, for example, immunizations and cancer screenings (Simon, Soni and Cawley, 2017) and tobacco cessation (Maclean, Pesko and Hill, 2019; Cotti, Nesson and Tefft, 2019).

[8] See, e.g., https://www.kff.org/medicaid/issue-brief/medicaid-retroactive-coverage-waivers-implications-for-beneficiaries-providers-and-states/.

on consumption—described below—and a research design levering the uneven adoption of Medicaid expansion across states.

3.1 Recovering the counterfactual consumption distribution with a Medicaid expansion design

While the ACA originally directed all states to expand their Medicaid program to cover all adults with income up to 138% of the poverty line, the Supreme Court ruled that the federal government could not force states to expand Medicaid. When the main provisions of the ACA went into effect in 2014, 21 states expanded their Medicaid programs. Five states (and Washington, DC) expanded coverage earlier than 2014, and an additional eight states did so between 2015 and 2019. As of 2019, the end of our sample period, 17 states had not yet expanded Medicaid. Our empirical strategy takes advantage of this uneven expansion, following a large literature investigating the effects of the Medicaid expansion.[9] Figure A.1 shows the timing of state expansion adoptions. While the expansion states are spread throughout the country, the never-expanders are concentrated in the southeast and Great Plains.

Much of the literature focuses on estimating the average impact of Medicaid expansion, largely by means of DID models comparing the difference in mean outcomes between expansion states and nonexpansion states before and after the expansions. Our interest, by contrast, lies in estimating the distributional impacts. To this end, we turn to two natural alternatives to DID. The first is quantile regression (in particular, quantile DID or QDID), which requires that the parallel trends assumption hold within quantiles rather than across means. However, as Athey and Imbens (2006) explain, this application has some unappealing features. They propose an alternative method, changes-in-changes (CIC). We use both

[9] Within this literature, there is some inconsistency on how states' expansion decisions should be classified and dated. We follow the classification in Miller, Johnson and Wherry (2021).

approaches and find very similar results.[10]

We introduce some notation to explain our approach. Let $t = 1, 2$ denote time periods (where $t = 1$ before an expansion and $t = 2$ after), and let $C_{i,t}$ denote the consumption of household i in period t. We assume for the moment that states (s) either expand Medicaid at the end of period 1 (denoted by $D_{s(i)} = 1$) or never do so ($D_{s(i)} = 0$). We relax this assumption below. We let $C_{i,t}(0)$ and $C_{i,t}(1)$ denote potential consumption without and with expansion.

The Medicaid expansion literature usually focuses on the average effect of expansion among expanders in the post period:

$$\tau_2 = E\left[C_{i,2}(1) - C_{i,2}(0) \middle| D_{s(i)} = 1\right].$$

While $E\left[C_{i,2}(1) \middle| D_{s(i)} = 1\right]$ is directly observed, researchers recover the missing mean potential outcome, $E\left[C_{i,2}(0) \middle| D_{s(i)} = 1\right]$, by invoking the parallel trends assumption,

$$E\left[C_{i,2}(0) - C_{i,1}(0) \middle| D_{s(i)} = 1\right] = E\left[C_{i,2}(0) - C_{i,1}(0) \middle| D_{s(i)} = 0\right],$$

and a no-anticipation assumption,

$$E\left[C_{i,1}(0) \middle| D_{s(i)} = 1\right] = E\left[C_{i,1}(1) \middle| D_{s(i)} = 1\right],$$

which yields the average untreated potential outcome in the post period as a function of observed quantities:

$$E\left[C_{i,2}(0) \middle| D_{s(i)} = 1\right] = E\left[C_{i,1}(1) \middle| D_{s(i)} = 1\right] + E\left[C_{i,2}(0) - C_{i,1}(0) \middle| D_{s(i)} = 0\right].$$

[10] A third approach would be to estimate unconditional quantile regressions (Firpo, Fortin and Lemieux, 2009), which would measure how Medicaid affects the unconditional consumption distribution. This distribution includes cross-state differences in consumption levels, and so is not the object of interest for us.

Our approach diverges from the methods used in prior work recovering average effects in that we are interested not in drawing causal contrasts but in directly characterizing the distribution of untreated potential outcomes, which (as we explain below) is key to recovering the insurance value of Medicaid.

To estimate the distribution of untreated potential outcomes, we invoke parallel trends assumptions for quantiles rather than expectations. Specifically, let $P_{qgt}(0)$ and $P_{qgt}(1)$ be the qth percentile of consumption for expansion group g in period t and state of the world 0 (nonexpansion) or 1 (expansion). Then, for all quantiles q, we assume

$$P_{q12}(0) - P_{q11}(0) = P_{q02}(0) - P_{q01}(0). \tag{3}$$

We call this assumption *parallel trends in percentiles*. This assumption lets us recover the counterfactual untreated consumption distribution, $F_0(q) = P_{q11}(0) + P_{q02}(0) - P_{q01}(0)$.

To implement this identification approach, we estimate quantile regressions of consumption on indicators for the post-expansion period and for the state's having ever expanded Medicaid and their interaction, as in the standard DID model—hence, the name *quantile* DID. In some specifications, to improve the precision of our estimates, we include controls (indicators for education and for household size, top-coded at 6, as well as income and age). We estimate the QDID model at a set of quantiles denoted by $p_1, \ldots, p_N$. In practice, we estimate the impacts for 20 evenly spaced quantile bins, starting at the 2.5th percentile. We perform inference via the bootstrap, described below.

The assumption of parallel trends in quantiles makes QDID a simple and intuitive application of DID ideas to quantiles rather than means. However, this simplicity comes at the cost of some unappealing features, as Athey and Imbens (2006) explains. QDID recovers a counterfactual quantile (for $D_i = 1$) by adding the observed change in quantile q for $D_i = 0$. To justify this additive approach, we would have to assume that time effects are the same between $D_i = 0$ and $D_i = 1$, which limits our ability to leverage cross-group heterogeneity.[11] Athey and Imbens (2006) therefore develops change-in-changes, an alternative approach to extending DID to estimate distributional impacts that avoids these unappealing features of QDID.

We estimate both CIC and QDID models, which, reassuringly, yield very similar estimates. To implement CIC, we recover estimates for 20 uniformly spaced counterfactual quantiles, as in our QDID implementation. Estimating CIC requires repeatedly evaluating empirical distribution functions at each point in the support of the outcome. This is computationally demanding for continuous outcomes taking on many values, as our outcome variable does. We therefore coarsen our outcome measure slightly, rounding consumption amounts to the nearest \$1. We use the CIC implementation developed by Kranker (2016), again using the bootstrap for inference.

3.2 From consumption distributions to insurance value

Our CIC and QDID estimates give us the factual and counterfactual consumption distributions for the post period in Medicaid expansion states. Denote these distributions $\hat{F}_1$ and $\hat{F}_0$. Our CIC and QDID estimations recover the percentile $p_1, ..., .p_N$. Denote the value of consumption under distribution F_j at these quantiles as c_{im}, so that, for example, c_{10} is the p_1 percentile of consumption in the nonexpansion state of the world.

To translate these percentiles to the insurance value of Medicaid, we assume that the consumption distribution has N points of support and that utility is of the constant relative risk aversion class with risk aversion ρ (following Finkelstein, Hendren and Luttmer (2019)).

[11] An additional unappealing feature of additive separability is that it is generally not invariant to alternative scalings of outcomes; if the level of consumption satisfies the (additive) assumption of parallel trends in quantiles, the log of consumption does not. Of course, DID suffers from this problem, as well (e.g., Roth and Sant'Anna (2023)).

We can therefore estimate expected utility in each state of the world:

$$\hat{EU}_m = \sum_{i=1}^{20} (p_i - p_{i-1}) \frac{c_{im}^{1-\rho}}{1-\rho}. \tag{4}$$

To recover $\hat{\gamma}$, we find the consumption offset that equalizes expected utility between both states of the world. That is, $\hat{\gamma}$ solves

$$\sum_{i=1}^{N} (p_i - p_{i-1}) \frac{(c_{i1} - \hat{\gamma})^{1-\rho}}{1-\rho} = \sum_{i=1}^{N} (p_i - p_{i-1}) \frac{c_{i0}^{1-\rho}}{1-\rho}. \tag{5}$$

Finally, to estimate the insurance value π, we subtract off the difference in expected consumption:

$$\hat{\pi} = \hat{\gamma} - \sum_{i=1}^{N} (p_i - p_{i-1}) (c_{i1} - c_{i0}). \tag{6}$$

We report estimates of $\hat{\pi}$ for different levels of ρ. In implementation, we have $N = 20$ uniformly spaced percentiles.

3.3 Accounting for staggered adoption

Until now, we have assumed that all states either expanded Medicaid at the same time or not at all. In fact, states expanded at different times. Pooling groups with different treatment timings generally leads to bias in DID-type models (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021), but dropping late expanders would reduce power. To account for states' staggered timing of expansion, we follow the logic of Callaway and Sant'Anna (2021). That is, we first estimate all parameters separately by expansion timing and then aggregate the estimates to obtain an overall average effect.

In the first step, we divide the data into timing groups, defined by the year when each state expanded Medicaid. Let g index these groups, and let $\hat{F}_m^g$ refer to the estimated (factual and counterfactual) timing group–specific distributions. We estimate $\hat{F}_1^g$ directly from the data, and we recover $\hat{F}_0^g$ using QDID or CIC, with never-expanders (as of 2020) as the control group for timing group g. For all the timing groups, our data start in 2008 and end in 2019. We use this range to preserve the widest symmetric window for 2014 expanders while avoiding the complex impacts of the COVID-19 pandemic on health and consumption. From $\hat{F}_0^g$ and $\hat{F}_1^g$, we recover $\hat{\gamma}^g$ and $\hat{\pi}^g$ using Equations (5) and (6).

In our second step, we aggregate the timing group–specific parameters to overall averages. To do so, we average them together, weighting each timing group by the share of the post-expansion population that it contains. That is,

$$w^g = \frac{\sum_i w_{it} \cdot 1\{\text{timing} = g\} \cdot 1\{g \leq t\}}{\sum_{g'} \sum_i w_{it} \cdot 1\{\text{timing} = g'\} \cdot 1\{g' \leq t\}}, \tag{7}$$

$$\hat{F}_m = \sum_g w^g \hat{F}_m^g \tag{8}$$

$$\hat{\pi} = \sum_g w^g \hat{\pi}^g, \tag{9}$$

where w_{it} is the survey weight of observation i in year t. These weighted averages are analogous to the average treatment on the treated parameter. For example, $\hat{\pi}$ is the weighted average insurance value experienced post-expansion, accounting for the uneven post-period lengths and (potentially) unequal insurance values across timing groups.

3.4 Inference via the block bootstrap

We conduct inference via the block bootstrap, resampling states. We use the bootstrap because our ultimate object of interest, π, is defined as an implicit function of the estimated objects and because we are not aware of a cluster-robust variance estimator for CIC.

We implement our bootstrap as follows. First, we draw a bootstrap sample of states, resampling with replacement. Second, we estimate timing group–specific distributions and insurance values for the resampled timing groups. Third, we recalculate the timing group weights within the bootstrap iteration and obtain bootstrap-specific estimates $\hat{\pi}_b$ and $\hat{F}_{m,b}$.[12] We repeat this procedure 1,000 times. We then report bootstrap confidence intervals as the 2.5th and 97.5th percentiles of the bootstrap estimates.

4 Data

Our analysis requires well-measured, comprehensive consumption data featuring state identifiers and covering much or all of the nation and years before and after 2014.[13] We turn to the Consumer Expenditure (CE) survey, a long-running, nationally representative survey of household expenditures, for our primary analysis sample.[14] A limitation of the CE survey is that it measures overall consumption expenditures with error, primarily because household respondents have difficulty recalling all of their purchases. Such measurement error may be especially problematic in the tails of the distribution, on which we focus. To minimize any bias from measurement error, our analysis focuses on "well-measured consumption" (Meyer and Sullivan, 2022), a construct developed in Meyer and Sullivan (2023), although we also investigate the effects of the Medicaid expansions on overall consumption. To construct well-measured consumption, Meyer and Sullivan (2023) takes the subcategories of consumption for which underreporting seems lowest (in the sense that, for these subcategories, the implied aggregate spending aligns with aggregate spending in the national accounts (Bee, Meyer and

[12] Our bootstrap procedure does not stratify on timing group, so some bootstrap samples exclude some timing groups. Thus, the variability across bootstrap iterations reflects, in part, variability in the timing group, and our bootstrap confidence intervals account for uncertainty in which states expanded when, as they should in a design-based approach to uncertainty.

[13] Several data sources meet some of these requirements, but few meet all of them. Consumption data derived from credit and debit card transactions, as in, for example, Baker (2018), cover neither all consumption nor all households, and in particular, they may miss the low-income households most likely to have benefited from the Medicaid expansions. Household scanner data such as the Nielsen Household Panel provide approximately representative, high-quality data but mainly measure food and grocery consumption. Likewise, the Current Population Survey asks some consumption-related questions in its food security module but lacks comprehensive consumption measures. The Panel Study on Income Dynamics has national coverage and comprehensive consumption measures but is too small to estimate state-level models.

[14] Although the CE survey is nationally representative, its sampling scheme does not result in every state being included in the sample.

Sullivan, 2015). They exclude expenditures closer to investments than to consumption—health, education, and pension expenditures and outlays for retirement. To translate spending to consumption, Meyer and Sullivan (2023) converts expenditures such as new vehicle purchases and housing expenditures into flows of vehicle services and housing services.[15]

The resulting well-measured consumption consists of food at home, the flow value of housing (rent and the rental value of owner-occupied housing), utilities, the flow value of owned vehicles, gas and motor oil expenses, and communications. Intuitively, well-measured consumption reflects common, recurring consumption plus the flow value of very large durable expenditures (housing and car purchases). The components of well-measured consumption are measured in the Quarterly Interview Survey, so our consumption measures are quarterly. We construct inflation-adjusted measures using the CPI-U, and following Meyer and Sullivan (2023), we adjust for differences in household composition using the equivalence scale suggested in Constance F. Citro and Robert T. Michael (1995), $(A + 0.7K)^{0.7}$, where A and K are the number of adults and children in the household, respectively. With this adjustment, we can interpret all effects on a per-person (rather than a per-household) basis.[16]

Because the components of well-measured consumption are either difficult to adjust or inferior goods (e.g., food at home), it might seem unlikely that this indicator would respond to uninsured health expenditure shocks or to Medicaid expansion. Our results using all consumption are reassuring on this point. We note that this concern is premised on the assumption that households pay for unanticipated health care shocks exclusively through a large, one-time decrease in consumption. However, medical debt is an important financing

[15] Another limitation of the CE survey is its reduced ability to capture effects on eviction, which is relevant for the most vulnerable people in our study. For example, Allen et al. (2019) uses California data to show that the state's early Medicaid expansion reduced eviction by approximately 10%, with larger effects in counties with higher rates of pre-expansion uninsurance. Relatedly, Collinson et al. (2024) shows that financial distress and hospital visits are predictors of imminent eviction. The CE survey design is derived from the Census Bureau's Master Address File, which fails to capture people with no address; if people transition to homelessness or eviction over the course of the survey, we may observe an empirical signature in the form of a reduction in the reported housing cost or survey exit.

[16] Despite our using Meyer and Sullivan's (2022) data, our implementation of well-measured consumption differs from theirs in that we include communication expenses, which they drop because of changes in communication technology over the 60-year period that they study.

mechanism. Paying down the principal and interest on medical debt can reduce consumption for several years, giving households time to adjust not only their consumption of nonnecessities but also their food, housing, or transportation consumption.

We limit our sample to households likely to have benefited from the Medicaid expansions. Our primary analysis sample is constructed on the basis of the inclusion criteria of Kaestner et al. (2017). We restrict the sample to people aged 22–64 with no college education. Restricting on the basis of education rather than income per se is helpful for two reasons. First, some high-income households may experience health shocks and become eligible for Medicaid; the consumption insurance value includes its value to these households. Second, we avoid sample selection bias that could arise from a response of income to the Medicaid expansions. Throughout, we use 2008–2019, setting the end of the sample period before 2020 to avoid complexities in the analysis arising from the COVID-19 pandemic, which greatly affected both health needs and consumption patterns. The analysis sample consists of 58,314 observations.

Table A.1 reports summary statistics on income and consumption for our sample separately by state expansion status. Income and consumption are higher in expansion than in nonexpansion states. In our sample of less-educated households, real annual income averages approximately $25,000 (after we adjust by the equivalence scale). Quarterly consumption is approximately $4,365 and well-measured consumption is about four-fifths of overall consumption. The most important component of well-measured consumption is housing, followed by food at home and gas and motor oil.

5 Results

We begin our discussion of the results by showing trends in the distribution of well-measured consumption in Figure 2. The figure plots percentiles of this indicator from 2008 to 2019 for nonexpansion states and for states that expanded in 2014.[17] Several trends are apparent in the figure. First, even in our relatively homogeneous sample, consumption is fairly dispersed, with a 90/10 ratio of approximately 3. Second, consumption is higher at each percentile in expansion states than in nonexpansion states. Third, consumption fell throughout the distribution in the great recession, although it fell more sharply at higher percentiles. Consumption did not return to its 2008 levels until 2019.

Most critically, prior to the Medicaid expansions, at each percentile, consumption moved roughly in parallel for expansion and nonexpansion states. Individuals at high percentiles of consumption experienced a sharp consumption decline from 2008 to 2009 in both expansion and nonexpansion states. Those at low percentiles experienced more modest declines. The figure also shows some divergence in consumption across percentiles after the Medicaid expansions. The median, 75th, and 90th percentiles all appear to have diverged somewhat, falling in nonexpansion states but holding steadier in expansion states. These results suggest that the Medicaid expansions increased consumption more in the middle of the distribution than in the lower tail.

The estimates in Figure 3 confirm this impression: The Medicaid expansions increased consumption in the middle of the distribution but not in the tails. The figure plots the estimated factual and counterfactual distributions (for expansion states, post expansion) and the estimated quantile treatment effects. The estimation approach underlying this exercise uses all timing groups: We estimate distributional effects separately by timing group, and average the estimates. The figure shows positive impacts of expansion throughout the distribution, except at the very top quantile. The estimates for the lower tail are positive but smaller, and the estimate for the top of the distribution is almost zero. Overall, the average impact is an increase in quarterly consumption of $111. Few of the estimates are statistically significant. While this figure reports the results obtained with QDID, CIC produces very

[17] We focus on the 2014 expansion states here to avoid the problems from pooling them with later adopters. We show analogous plots for states that expanded later (2015, 2016, 2017, and 2019) in Appendix Figures A.2–A.5. Note that no states expanded in 2018.

similar results, as Appendix Figure A.6 shows.

We use the estimated consumption distributions, along with an assumed utility function, to estimate the insurance value of the Medicaid expansion. We report these estimates in Table 1, along with their 95% and 50% confidence intervals. With a risk aversion parameter of 3, we estimate a small insurance value: \$21 per quarter or \$85 per year. With risk aversion of 1, we have essentially zero insurance value, and with risk aversion of 5, we estimate an annual insurance value of \$179—higher, but still low relative to the program costs or health benefits, as we will explain in a moment.[18] The estimates from lower values of risk aversion are likely more plausible because Chetty (2006) reports that labor supply choices rule out values of risk aversion above 2 and point toward values closer to 1.

Overall, we estimate a low insurance value of Medicaid expansion. Of course, this result does not necessarily imply that Medicaid has low or no value to recipients. Recall that our estimate reflects the *insurance* component of the value of Medicaid, not the transfer or nonconsumption components (such as health improvements or prevention of stress from bankruptcies), which our model does not consider. Indeed, Medicaid expansion increases consumption throughout much of the distribution, resulting in a (quarterly) transfer value of approximately \$100 (the mean consumption effect reported in Figure 3). Intuitively, the reason that the estimated *insurance* value is low is that the consumption increase is larger in the middle of the distribution than in the lower tail. Like the individual percentile estimates, our estimate of the insurance value is statistically insignificant, with an annual 95% confidence interval of (-202, 282).

Despite this wide confidence interval, our estimate of the insurance value is informative and smaller than some important benchmark values. To illustrate the uncertainty in our estimates and their relation to these benchmarks, we plot our insurance premium estimate (conditional on covariates, and annualized) and its 95% confidence interval in Figure 4 as

[18] We report insurance values for risk aversion parameters of 3, 1, and 5 so that our results can be compared to those in Finkelstein, Hendren and Luttmer (2019), the mostly closely related prior work.

a function of the assumed risk aversion parameter. We overlay on the figure several benchmarks.[19] The figure shows, first, that regardless of the magnitude of risk aversion, Medicaid's consumption insurance value is small relative to program outlays (Decker, Abdus and Lipton, 2022), and our confidence intervals let us reject that the insurance value is equal to the program outlays (or even a quarter of those outlays, at $\rho = 3$). We can also reject that the consumption insurance value is as large as the value of the mortality-reducing benefits of Medicaid expansion (Miller et al., 2021; Wyse and Meyer, 2023), which are themselves a subset of the total health benefits. At plausible risk aversion levels (3 or lower), we can reject that the consumption insurance value is half as large as the mortality-reducing benefit.

Finally, we compare our estimates to other estimates of the insurance value of Medicaid expansion. One useful benchmark is the insurance value that we would find if the uninsured paid for all their care. We calculate this value using data from the Medical Expenditure Panel Survey (MEPS; see Appendix B); it ranges from \$200 to \$1,000, depending on risk aversion. We can always reject that our estimates are even half as large as this value. The literature provides a small number of other estimates of the insurance value of Medicaid expansion. Finkelstein, Hendren and Luttmer (2019) report a high and a low estimate. We cannot quite reject their high estimate (at $\rho = 3, p \approx .05$). We do not reject—and our point estimates are largely consistent with—other estimates from the literature that fall on the small side. In particular, Finkelstein, Hendren and Luttmer (2019) report a lower estimate of approximately \$30/year, and Shupe (2023) estimates a consumption insurance value of approximately \$20 per year.

Overall, therefore, we find that the consumption insurance value of Medicaid expansion is small, though consistent with lower estimates from the literature and with what we would expect if the uninsured never bore the cost of uncompensated care. Our finding of a small insurance value is not especially sensitive to the consumption measure, the estimator, the sample, or the exclusion of covariates, as the results in Table 1 show. Working with overall

[19] Appendix C provides more detail on how we calculate these benchmarks.

consumption instead of well-measured consumption (Panel C) produces similar point estimates but wider confidence intervals, consistent with the greater noise in the former than the latter indicator. The CIC estimates in Panel D are very similar to the results from QDID. In Panel E, we restrict the sample to individuals with income low enough to be eligible for Medicaid in expansion states.[20] In this sample, we find larger point estimates, with a (quarterly) insurance value of approximately \$20–\$100. The estimates are much less precise, however, with a 95% confidence interval ranging from -\$200 to \$250 (or wider). Thus, these estimates are largely uninformative: They are consistent with our main estimates, with zero or negative insurance value, and with a substantial insurance value.[21] Finally, our estimates are not sensitive to the exact coding of expansion status or handling of consumption. Excluding California or Wisconsin does not meaningfully change our estimates; nor does working with a 50-point grid of the consumption distribution.

6 Conclusion

Theory suggests that a first-order benefit of insurance is its consumption-smoothing effect. This paper investigates the impact of several US states' post-ACA expansion of Medicaid on the consumption distribution using household-level data on well-measured expenditures. While our point estimates suggest that the Medicaid expansion increased consumption in the middle of the distribution, these estimates are imprecise, and we find no evidence of increased consumption at the bottom of the distribution. Combining these distributional estimates with a utility function, we estimate an insurance value of the Medicaid expansion

[20] In the results so far, we have considered a sample that is likely to benefit from Medicaid expansion, but not everyone in our sample is necessarily eligible for Medicaid.

[21] Although our main sample includes people not currently eligible, we nonetheless believe that our main estimates are informative about the insurance value of Medicaid because Medicaid eligibility is fluid and retroactive; indeed, people regularly churn in and out of Medicaid (Einav and Finkelstein, 2023). Thus, people with moderately high current income may have previously been eligible for Medicaid, and should they be hospitalized, we might expect a large fall in income (Dobkin et al., 2018), triggering Medicaid eligibility.

of \$85 per person per year. This point estimate is small relative to the overall government expenditures on the expansion population and relative to the program's mortality-reducing benefits. It is also much smaller than the value we would expect if uninsured Americans were to pay for all of their health care. Although our estimated insurance value is uncertain, our 95% confidence intervals allow us to rule out the possibility that the insurance value is a large fraction of either the overall outlays or the value from reduced mortality.

Taken together, our results suggest that the consumption risk–reducing benefits of Medicaid expansion are not the main source of its value. A caveat is that, by design, we measure one component of the value of insurance. Although the consumption insurance value of Medicaid expansion is theoretically important, recent evidence has found a range of other benefits, including improved health (including reduced mortality, as shown in Wyse and Meyer 2023; Miller et al. 2021), and improved hospital finances. Our approach does not capture these benefits, but our findings suggest that they are important determinants of the overall value of Medicaid given how small the consumption insurance value is by comparison.

References

Allen, Heidi L, Erica Eliason, Naomi Zewde, and Tal Gross. 2019. "Can Medicaid expansion prevent housing evictions?" *Health Affairs*, 38(9): 1451–1457.

Athey, Susan, and Guido W Imbens. 2006. "Identification and inference in nonlinear difference-in-differences models." *Econometrica*, 74(2): 431–497.

Baker, Scott R. 2018. "Debt and the response to household income shocks: Validation and application of linked financial account data." *Journal of Political Economy*, 126(4): 1504–1557.

Bee, Adam, Bruce D Meyer, and James X Sullivan. 2015. "The Validity of Consumption Data." *Improving the Measurement of Consumer Expenditures*, 74: 204.

Brevoort, Kenneth, Daniel Grodzicki, and Martin B Hackmann. 2020. "The credit consequences of unpaid medical bills." *Journal of Public Economics*, 187: 104203.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of econometrics*, 225(2): 200–230.

Chernozhukov, Victor, Iván Fernández-Val, and Blaise Melly. 2022. "Fast algorithms for the quantile regression process." *Empirical Economics*, 1–27.

Chetty, Raj. 2006. "A new method of estimating risk aversion." *American Economic Review*, 96(5): 1821–1834.

Collinson, Robert, John Eric Humphries, Nicholas Mader, Davin Reed, Daniel Tannenbaum, and Winnie Van Dijk. 2024. "Eviction and poverty in American cities." *The Quarterly Journal of Economics*, 139(1): 57–120.

Constance F. Citro, and Editors Robert T. Michael. 1995. *Measuring poverty: A new approach.* National Academies Press.

Consumer Financial Protection Bureau. 2022. "Medical Debt Burden in the United States." https://files.consumerfinance.gov/f/documents/cfpb_medical-debt-burden-in-the-united-states_report_2022-03.pdf.

Consumer Financial Protection Bureau. 2023. "CFPB Proposes to Ban Medical Bills from Credit Reports." Accessed: 2024-08-29.

Cotti, Chad, Erik Nesson, and Nathan Tefft. 2019. "Impacts of the ACA Medicaid expansion on health behaviors: Evidence from household panel data." *Health Economics*, 28(2): 219–244.

Dague, Laura. 2014. "The effect of Medicaid premiums on enrollment: A regression discontinuity approach." *Journal of Health Economics*, 37: 1–12.

Dague, Laura, Thomas DeLeire, and Lindsey Leininger. 2017. "The effect of public insurance coverage for childless adults on labor supply." *American Economic Journal: Economic Policy*, 9(2): 124–154.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review*, 110(9): 2964–2996.

Decker, Sandra L, Salam Abdus, and Brandy J Lipton. 2022. "Eligibility for and enrollment in Medicaid among nonelderly adults after implementation of the Affordable Care Act." *Medical Care Research and Review*, 79(1): 125–132.

De Nardi, Mariacristina, Eric French, and John B Jones. 2010. "Why do the elderly save? The role of medical expenses." *Journal of Political Economy*, 118(1): 39–75.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J Notowidigdo. 2018. "The economic consequences of hospital admissions." *American Economic Review*, 108(2): 308–352.

Dodini, Samuel. 2023. "Insurance Subsidies, the Affordable Care Act, and Financial Stability." *Journal of Policy Analysis and Management*.

Donohue, Julie M, Evan S Cole, Cara V James, Marian Jarlenski, Jamila D Michener, and Eric T Roberts. 2022. "The US Medicaid program: coverage, financing, reforms, and implications for health equity." *JAMA*, 328(11): 1085–1099.

Dranove, David, Craig Garthwaite, and Christopher Ody. 2016. "Uncompensated care decreased at hospitals in Medicaid expansion states but not at hospitals in nonexpansion states." *Health Affairs*, 35(8): 1471–1479.

Duggan, Mark, Atul Gupta, and Emilie Jackson. 2022. "The impact of the Affordable Care Act: evidence from California's hospital sector." *American Economic Journal: Economic Policy*, 14(1): 111–151.

Einav, Liran, and Amy Finkelstein. 2023. "The risk of losing health insurance in the United States is large, and remained so after the Affordable Care Act." *Proceedings of the National Academy of Sciences*, 120(18): e2222100120.

Finkelstein, Amy, Nathaniel Hendren, and Erzo FP Luttmer. 2019. "The value of Medicaid: Interpreting results from the oregon health insurance experiment." *Journal of Political Economy*, 127(6): 2836–2874.

Finkelstein, Amy, Nathaniel Hendren, and Mark Shepard. 2019. "Subsidizing health insurance for low-income adults: Evidence from Massachusetts." *American Economic Review*, 109(4): 1530–67.

Finkelstein, Amy, Neale Mahoney, and Matthew J Notowidigdo. 2018. "What does (formal) health insurance do, and for whom?" *Annual Review of Economics*, 10: 261–286.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P Newhouse, Heidi Allen, Katherine Baicker, and Oregon Health Study Group. 2012. "The Oregon health insurance experiment: evidence from the first year." *The Quarterly Journal of Economics*, 127(3): 1057–1106.

Firpo, Sergio, Nicole M Fortin, and Thomas Lemieux. 2009. "Unconditional quantile regressions." *Econometrica*, 77(3): 953–973.

Frean, Molly, Jonathan Gruber, and Benjamin D Sommers. 2017. "Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act." *Journal of Health Economics*, 53: 72–86.

Gallagher, Emily A, Radhakrishnan Gopalan, Michal Grinstein-Weiss, and Jorge Sabat. 2020. "Medicaid and household savings behavior: New evidence from tax refunds." *Journal of Financial Economics*, 136(2): 523–546.

Garthwaite, Craig, Tal Gross, and Matthew J Notowidigdo. 2014. "Public health insurance, labor supply, and employment lock." *The Quarterly Journal of Economics*, 129(2): 653–696.

Garthwaite, Craig, Tal Gross, and Matthew J Notowidigdo. 2018. "Hospitals as insurers of last resort." *American Economic Journal: Applied Economics*, 10(1): 1–39.

Goldin, Jacob, Ithai Z Lurie, and Janet McCubbin. 2021. "Health insurance and mortality: Experimental evidence from taxpayer outreach." *The Quarterly Journal of Economics*, 136(1): 1–49.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.

Gross, Tal, and Matthew J Notowidigdo. 2011. "Health insurance and the consumer bankruptcy decision: Evidence from expansions of Medicaid." *Journal of Public Economics*, 95(7-8): 767–778.

Guth, Madeline, Bradley Corallo, Robin Rudowitz, and Rachel Garfield. 2021. "Medicaid Expansion Enrollment and Spending Leading up to the COVID-19 Pandemic." Accessed: 2024-08-26.

Guth, Madeline, Rachel Garfield, Robin Rudowitz, et al. 2020. "The effects of Medicaid expansion under the ACA: updated findings from a literature review." *Kaiser Family Foundation*, 37(6): 944–50.

Heim, Bradley T, Gillian Hunter, Adam Isen, Ithai Z Lurie, and Shanthi P Ramnath. 2021. "Income responses to the affordable care act: Evidence from a premium tax credit notch." *Journal of Health Economics*, 76: 102396.

Hendren, Nathaniel. 2021. "Measuring ex ante welfare in insurance markets." *The Review of Economic Studies*, 88(3): 1193–1223.

Hu, Luojia, Robert Kaestner, Bhashkar Mazumder, Sarah Miller, and Ashley Wong. 2018. "The effect of the affordable care act Medicaid expansions on financial wellbeing." *Journal of Public Economics*, 163: 99–112.

Kaestner, Robert, Bowen Garrett, Jiajia Chen, Anuj Gangopadhyaya, and Caitlyn Fleming. 2017. "Effects of ACA Medicaid expansions on health insurance coverage and labor supply." *Journal of Policy Analysis and Management*, 36(3): 608–642.

Kearsley, A. 2024. "HHS Standard Values for Regulatory Analysis, 2024." Accessed: 2024-08-26.

Kluender, Raymond, Neale Mahoney, Francis Wong, and Wesley Yin. 2021. "Medical debt in the US, 2009-2020." *JAMA*, 326(3): 250–256.

Kranker, Keith. 2016. "Effects of Medicaid disease management programs on medical expenditures: evidence from a natural experiment in Georgia." *Journal of Health Economics*, 46: 52–69.

Kucko, Kavan, Kevin Rinz, and Benjamin Solow. 2018. "Labor market effects of the Affordable Care Act: Evidence from a tax notch." *Available at SSRN 3161753*.

Leung, Pauline, and Alexandre Mas. 2018. "Employment effects of the affordable care act medicaid expansions." *Industrial Relations: A Journal of Economy and Society*, 57(2): 206–234.

Levy, Helen, Thomas Buchmueller, and Sayeh Nikpay. 2019. "The impact of Medicaid expansion on household consumption." *Eastern Economic Journal*, 45: 34–57.

Lockwood, Lee M. 2024. "Health Insurance and Consumption Risk."

Lusardi, Annamaria, Daniel J Schneider, and Peter Tufano. 2011. "Financially fragile households: Evidence and implications." National Bureau of Economic Research.

Maclean, Johanna Catherine, Michael F Pesko, and Steven C Hill. 2019. "Public insurance expansions and smoking cessation medications." *Economic Inquiry*, 57(4): 1798–1820.

Mahoney, Neale. 2015. "Bankruptcy as implicit health insurance." *American Economic Review*, 105(2): 710–746.

Mazumder, Bhashkar, and Sarah Miller. 2016. "The effects of the Massachusetts health reform on household financial distress." *American Economic Journal: Economic Policy*, 8(3): 284–313.

Meinhofer, Angélica, and Allison E Witman. 2018. "The role of health insurance on treatment for opioid use disorders: Evidence from the Affordable Care Act Medicaid expansion." *Journal of Health Economics*, 60: 177–197.

Meyer, Bruce D, and James X Sullivan. 2022. "Replication Data for: Consumption and Income Inequality in the US since the 1960s." Harvard Dataverse, https://doi.org/10.7910/DVN/587F9Z.

Meyer, Bruce D, and James X Sullivan. 2023. "Consumption and Income Inequality in the United States since the 1960s." *Journal of Political Economy*, 131(2): 247–284.

Miller, Sarah, and Laura R Wherry. 2017. "Health and access to care during the first 2 years of the ACA Medicaid expansions." *New England Journal of Medicine*, 376(10): 947–956.

Miller, Sarah, Luojia Hu, Robert Kaestner, Bhashkar Mazumder, and Ashley Wong. 2021. "The ACA Medicaid expansion in Michigan and financial health." *Journal of Policy Analysis and Management*, 40(2): 348–375.

Miller, Sarah, Norman Johnson, and Laura R Wherry. 2021. "Medicaid and mortality: new evidence from linked survey and administrative data." *The Quarterly Journal of Economics*, 136(3): 1783–1829.

Nikpay, Sayeh, Seth Freedman, Helen Levy, and Tom Buchmueller. 2017. "Effect of the Affordable Care Act Medicaid expansion on emergency department visits: Evidence from state-level emergency department databases." *Annals of emergency medicine*, 70(2): 215–225.

Obama, Barack. 2016. "United States health care reform: progress to date and next steps." *Jama*, 316(5): 525–532.

Roth, Jonathan, and Pedro HC Sant'Anna. 2023. "When is parallel trends sensitive to functional form?" *Econometrica*, 91(2): 737–747.

Shupe, Cortnie. 2023. "Public health insurance and medical spending: The incidence of the ACA Medicaid expansion." *Journal of Policy Analysis and Management*, 42(1): 137–165.

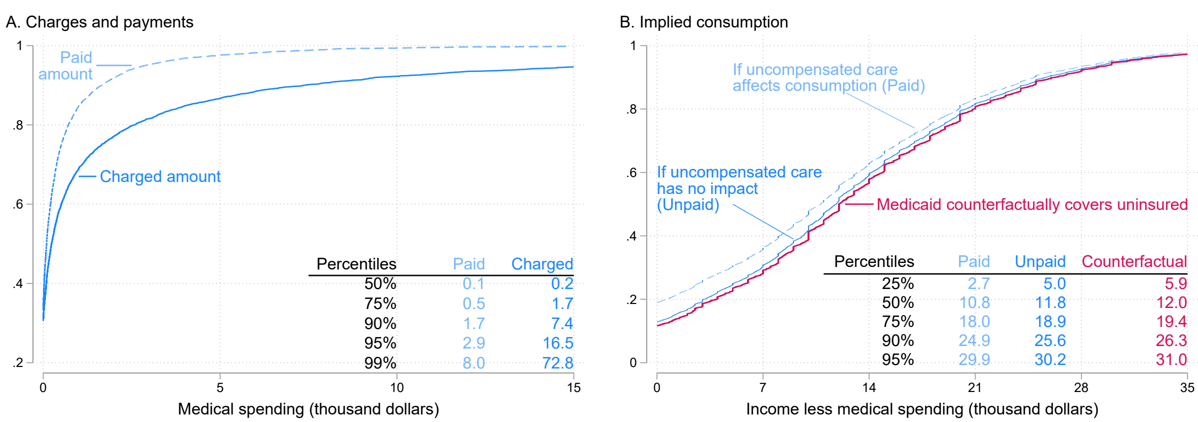
Simon, Kosali, Aparna Soni, and John Cawley. 2017. "The impact of health insurance on preventive care and health behaviors: evidence from the first two years of the ACA Medicaid expansions." *Journal of Policy Analysis and Management*, 36(2): 390–417.

Soni, Aparna, Kosali Simon, John Cawley, and Lindsay Sabik. 2018. "Effect of Medicaid expansions of 2014 on overall and early-stage cancer diagnoses." *American Journal of Public Health*, 108(2): 216–218.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199.

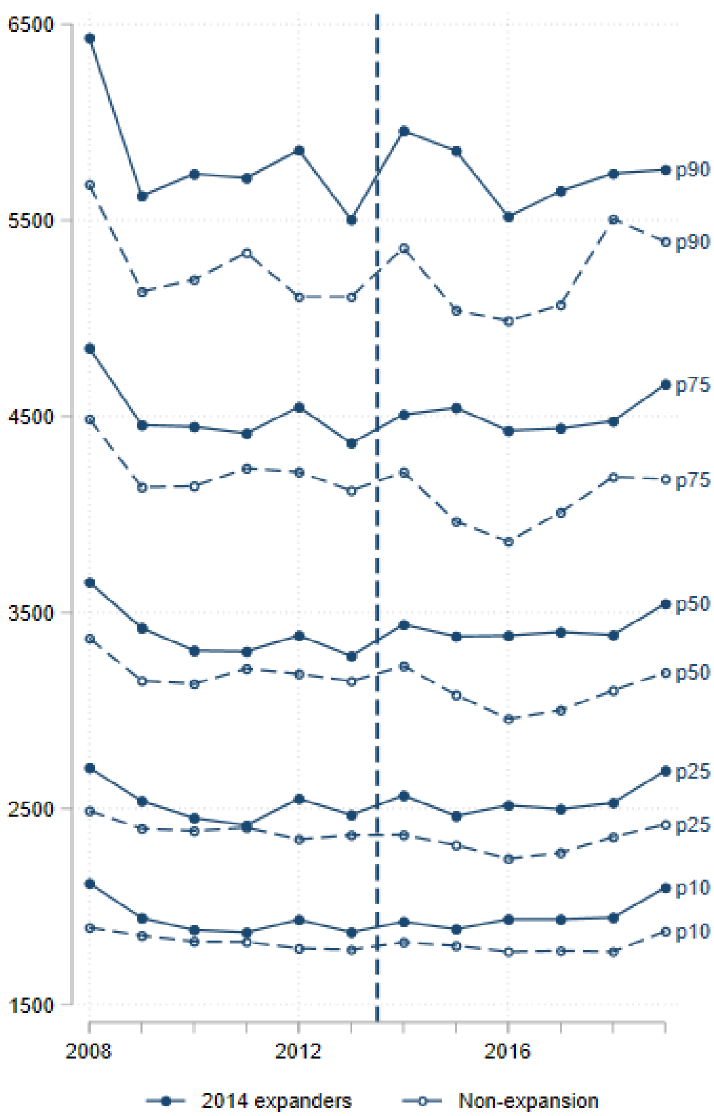
Wyse, Angela, and Bruce Meyer. 2023. "Saved By Medicaid: New Evidence on Health Insurance and Mortality from the Universe of Low-Income Adults."

Figure 1: Medical spending and implied consumption among would-be Medicaid eligibles



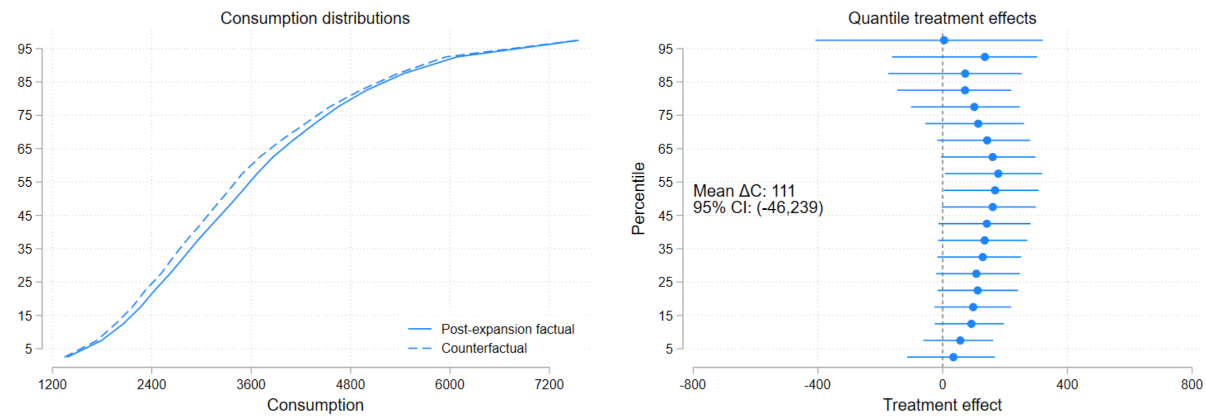
Notes: Panel A presents the cumulative density functions of both the actual medical spending paid and the amount charged among the uninsured. Panel B shows the empirical Cumulative Density Function (CDF) of the implied consumption for (i) those who paid their medical expenses, (ii) those who never paid, and (iii) those who were uninsured but were counterfactually covered by Medicaid. See Appendix B for details.

Figure 2: Parallel trends in percentiles of well-measured consumption



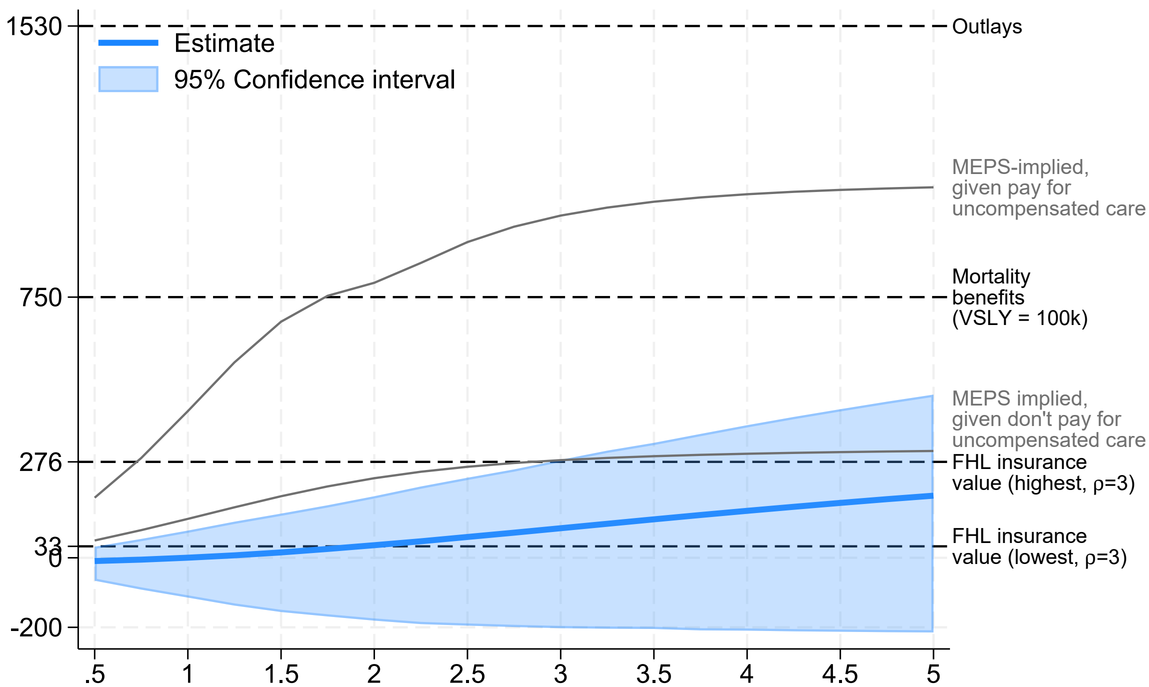
Notes: The figure plots the indicated percentiles of well-measured consumption for the states that expanded Medicaid in 2014 (solid line) and the states that never expanded (dashed line). The sample is defined in the notes to Table A.1.

Figure 3: Impact of Medicaid expansion on the consumption distribution



Notes: The figure plots the estimated factual and counterfactual consumption distributions (left panel) and the quantile treatment effects (right panel) estimated with quantile difference-in-differences with covariates (dummies for education, dummies for household size, top-coded at 6, income, and age) with 95% confidence intervals calculated via the bootstrap (with resampling of states). The 'qrprocess' command in the STATA is used for a faster algorithm for the quantile regression (Chernozhukov, Fernández-Val and Melly, 2022). We estimate effects separately for each timing group, and the figure reports the weighted average effect. Distributional effects are estimated with quantile difference-in-differences with covariates (dummies for education, dummies for household size (top-coded at 6), income, and age). The sample is defined in the notes to Table A.1.

Figure 4: Consumption insurance value of Medicaid and some benchmarks



Notes: The figure plots our estimated consumption insurance value with its 95% confidence interval. We also report benchmarks for the value of Medicaid expansion, as described in Appendix C. MEPS is the Medical Expenditure Panel Survey.

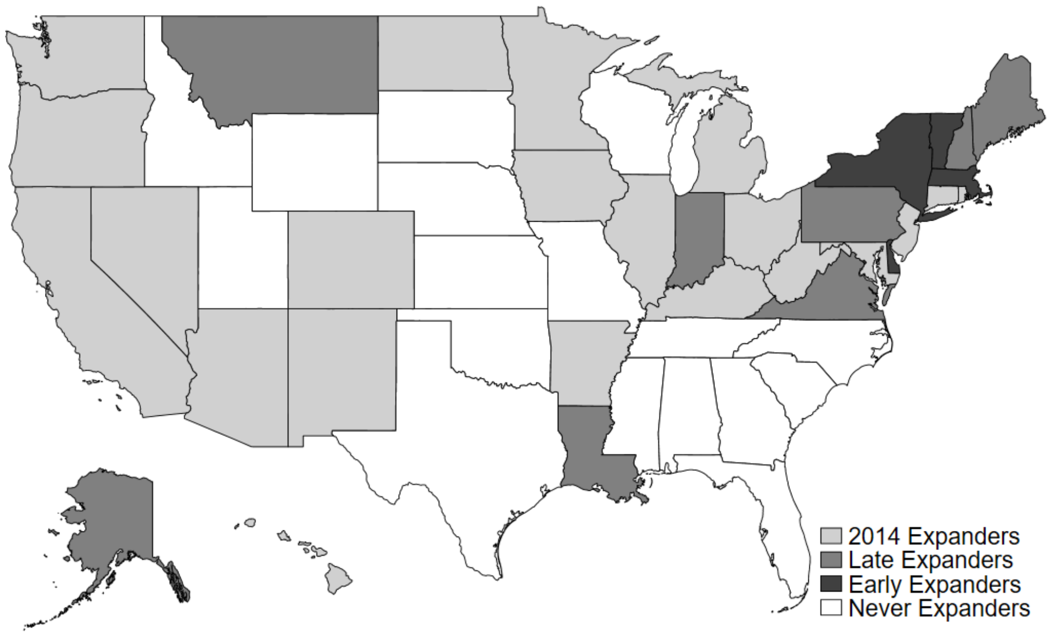
Table 1: Insurance value of Medicaid expansion

Risk aversion	$\rho = 3$	$\rho = 1$	$\rho = 5$
A. Well-measured consumption, QDID, Sample ($\leq$ HS, aged 22–64), with covariates			
Insurance value	21.3	0.1	44.7
95% CI	(-50.6, 70.5)	(-28.6, 19.6)	(-53.7, 117.4)
50% CI	(-2.4, 35.8)	(-9.1, 5.7)	(11.8, 66.7)
B. Without covariates			
Insurance value	21.9	-0.0	43.7
95% CI	(-41.2, 96.1)	(-26.0, 30.9)	(-43.3, 146.4)
50% CI	(1.1, 46.3)	(-9.0, 10.3)	(16.3, 76.0)
C. Alt consumption measure: All consumption excluding health insurance			
Insurance value	1.2	-7.8	19.2
95% CI	(-101.9, 68.7)	(-53.3, 21.9)	(-115.2, 109.3)
50% CI	(-33.0, 21.1)	(-23.9, 0.8)	(-23.4, 47.5)
D. Alt estimator: CIC, Without Covariates			
Insurance value	17.0	-2.0	37.9
95% CI	(-54.6, 94.4)	(-32.4, 30.1)	(-56.1, 142.7)
50% CI	(-3.9, 44.1)	(-11.1, 9.8)	(9.2, 71.5)
E. Alt sample: $\leq$ 138% FPL, aged 18–64			
Insurance value	78.4	16.0	110.8
95% CI	(-70.7, 164.1)	(-24.1, 49.7)	(-97.5, 226.6)
50% CI	(17.2, 96.0)	(-0.4, 23.7)	(27.6, 135.7)
F. Excluding CA (given its early expansion)			
Insurance value	-4.4	-9.2	8.4
95% CI	(-60.3, 55.1)	(-32.8, 15.8)	(-66.3, 95.8)
50% CI	(-23.1, 19.0)	(-16.8, -0.1)	(-15.3, 41.9)
G. Excluding WI (given its high coverage)			
Insurance value	15.6	-2.3	38.3
95% CI	(-54.5, 60.8)	(-29.3, 15.9)	(-57.5, 103.6)
50% CI	(-9.7, 29.5)	(-12.2, 3.1)	(3.5, 57.8)
H. Finer grid (50-point, instead of 20-point grid)			
Insurance value	35.3	3.9	70.6
95% CI	(-50.4, 89.7)	(-28.0, 25.0)	(-70.2, 154.7)
50% CI	(8.0, 52.8)	(-5.9, 10.4)	(25.3, 95.9)

Notes: The table reports the implied quarterly insurance value of Medicaid expansion, for the indicated risk aversion value, consumption measure, estimation approach, sample, and grid granularity. QDID is quantile difference-in-differences, and CIC is change-in-changes, and FPL is the federal poverty line. We report 95% and 50% confidence intervals, calculated via the bootstrap (with resampling of states), reported in parentheses. For Panels A, C, E, F, G, and H, covariates include dummies for education, dummies for household size (top-coded at 6), income, and age.

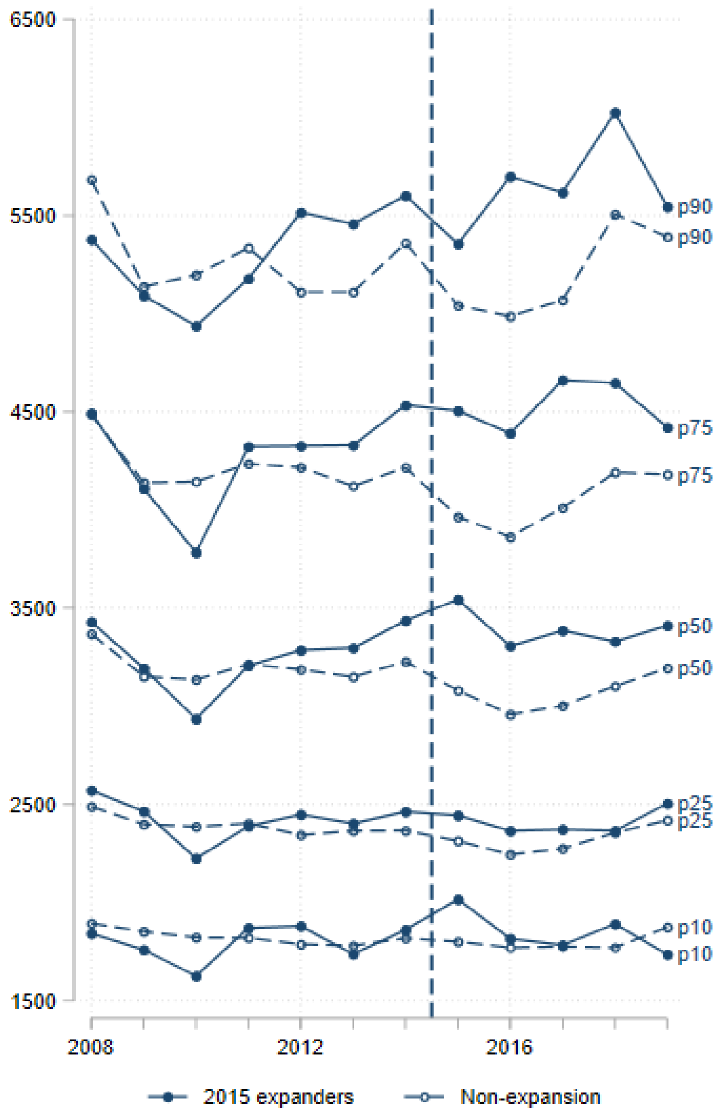
A Appendix Figures and Tables

Figure A.1: Timing of state Medicaid expansions



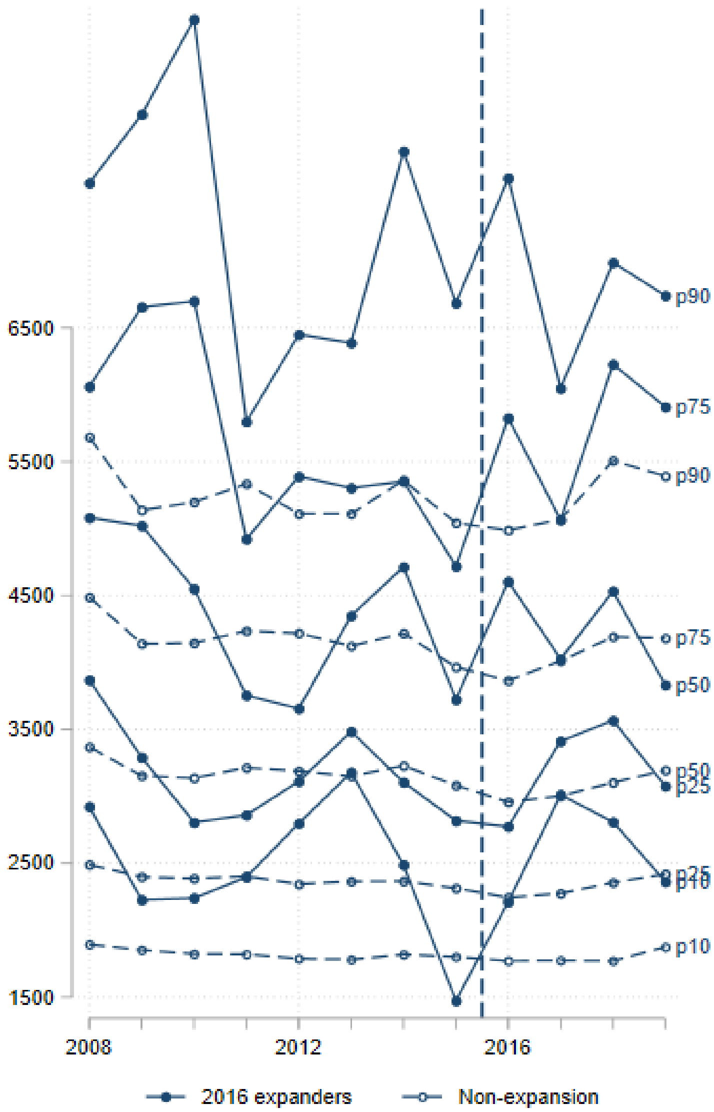
Notes: The figure indicates the timing of states' Medicaid expansion decisions as of 2019. We use the classification in Miller, Johnson and Wherry (2021). Among the late expanders, Indiana, New Hampshire, and Pennsylvania adopted the expansion in 2015, Alaska and Montana in 2016, Louisiana in 2017, and Maine and Virginia in 2019. Other states (e.g., North Carolina) expanded after our sample period ends.

Figure A.2: Percentiles of well-measured consumption, 2015 expanders



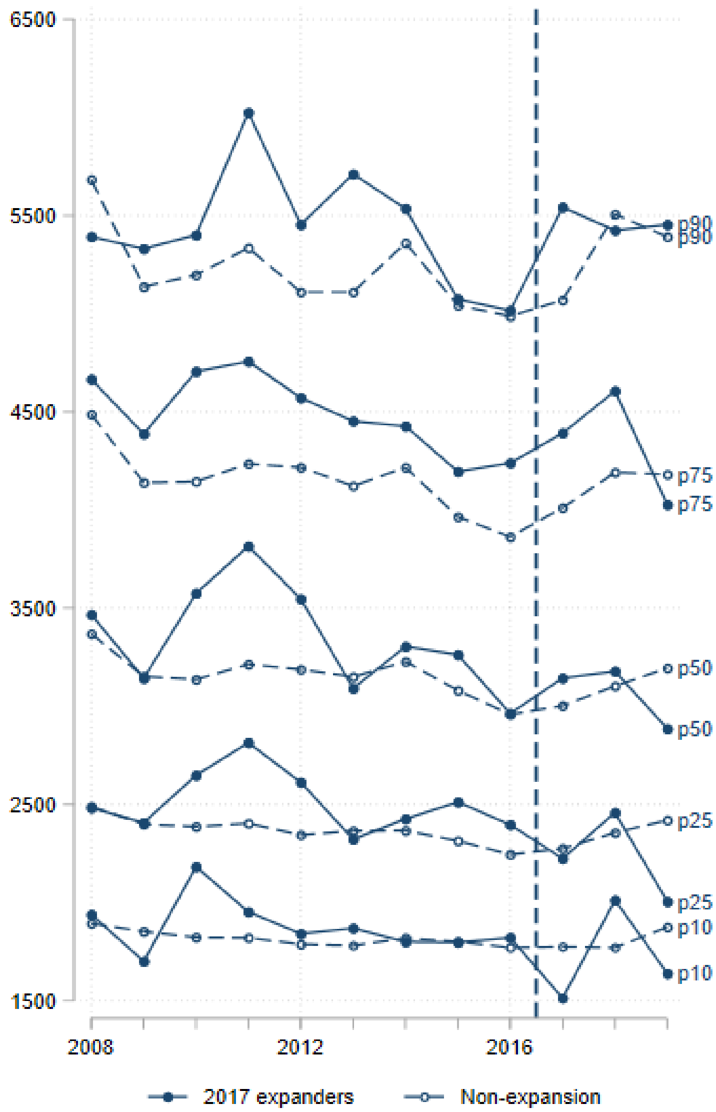
Notes: The figure plots the indicated percentiles of well-measured consumption for states that expanded Medicaid in 2015 (solid line) and states that never expanded (dashed line). The sample is defined in the notes to Table A.1.

Figure A.3: Percentiles of well-measured consumption, 2016 expanders



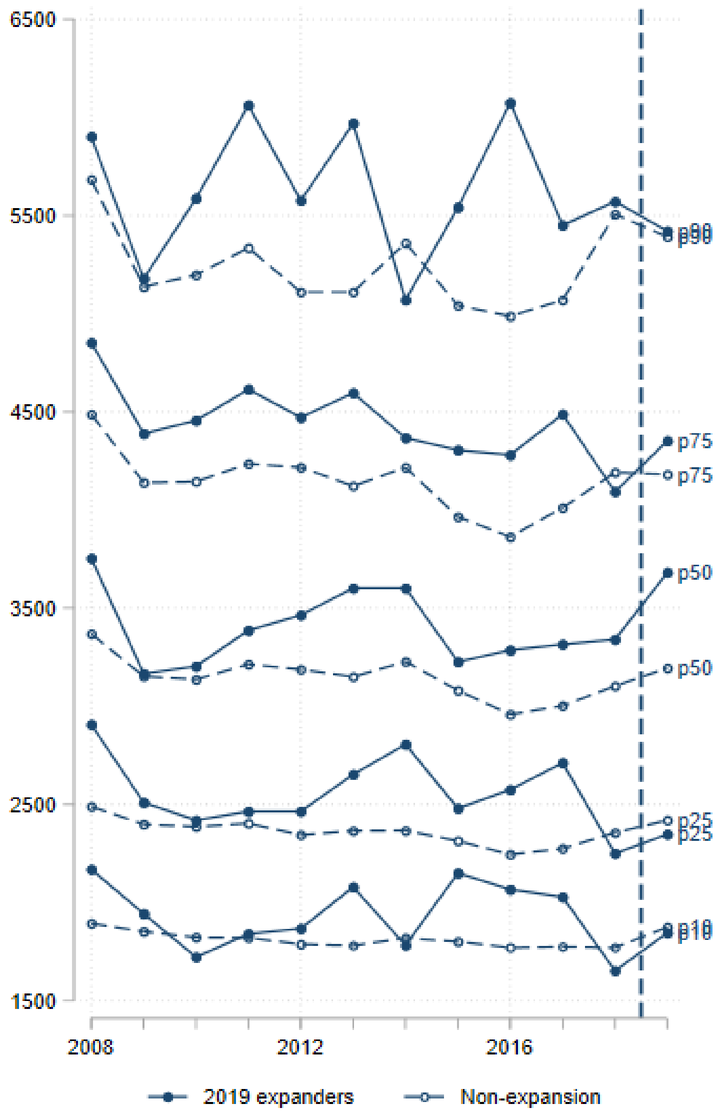
Notes: The figure plots the indicated percentiles of well-measured consumption for states that expanded Medicaid in 2016 (solid line) and states that never expanded (dashed line). The sample is defined in the notes to Table A.1.

Figure A.4: Percentiles of well-measured consumption, 2017 expanders



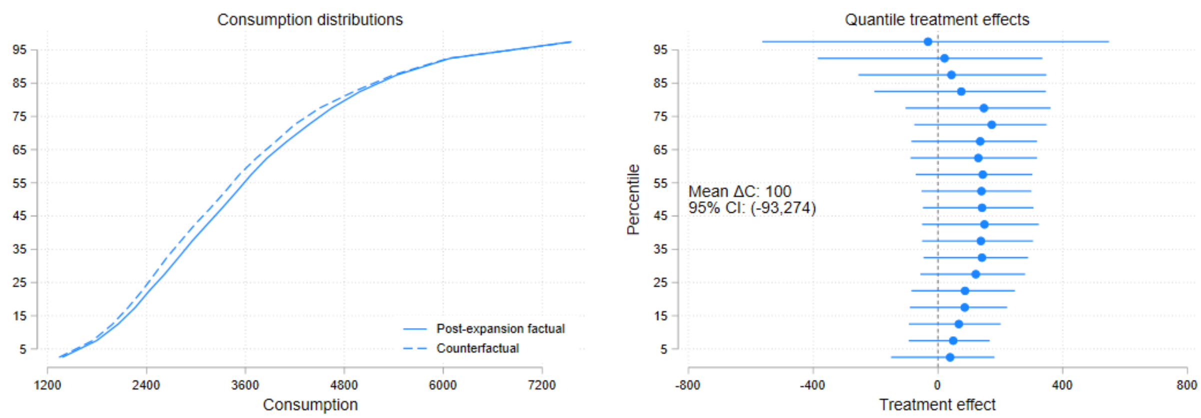
Notes: The figure plots the indicated percentiles of well-measured consumption for states that expanded Medicaid in 2017 (solid line) and states that never expanded (dashed line). The sample is defined in the notes to Table A.1.

Figure A.5: Percentiles of well-measured consumption, 2019 expanders



Notes: The figure plots the indicated percentiles of well-measured consumption for states that expanded Medicaid in 2015 (solid line) and states that never expanded (dashed line). The sample is defined in the notes to Table A.1.

Figure A.6: CIC estimates of impact of Medicaid expansion on consumption distribution



Notes: The figure is identical to Figure 3 except that we use change-in-changes (CIC) without covariates, rather than quantile difference-in-differences (QDID) to estimate the distributional effects.

Table A.1: Summary statistics on consumption

	Expansion states		Nonexpansion states	
	Mean	(SD)	Mean	(SD)
A. Overall income and consumption				
Income (annual, before tax)	25,734	(22,556)	23,558	(20,420)
Consumption (excl. health ins, quarterly)	4,503	(2,504)	4,160	(2,307)
Well-measured consumption	3,649	(1,620)	3,395	(1,491)
B. Consumption by category				
Flow value of housing	1,622	(1,030)	1,378	(876)
Food at home	642	(367)	627	(360)
Gas and motor oil	560	(532)	557	(542)
Utilities	457	(276)	464	(250)
Flow value of new vehicles	212	(274)	215	(267)
Communication	157	(121)	154	(123)
# Observations		36,387		21,927
# Households		13,506		8,319

Notes: The sample consists of households in the Consumer Expenditure Survey with no college education, 2008–2019. Expansion states include 2014–2019 expanders, and nonexpansion states include never-expanders (as of 2020). Well-measured consumption consists of the sum of the categories in Panel B.

B Details on MEPS Data

In some supplemental analyses, we use data from the Medical Expenditure Panel Survey (MEPS) to provide some evidence on uninsured health spending risk. MEPS is a high-quality, government-run survey designed to measure medical spending. We use data from 2008 to 2013, the period immediately prior to most states' adoption of their Medicaid expansions. (We use these years instead of looking at post-2014 years in nonexpansion states because the publicly available MEPS data do not contain state identifiers.) Households participate in five semiannual interviews covering two years, in which they report the insurance coverage and health care utilization of each member. MEPS officials then contact health care providers to determine amounts paid for servicesand amounts charged for services.

We use these data in two ways. First, in Figure 1, we show the distribution of spending and charges among the uninsured, potential Medicaid eligibles, prior to the Affordable Care Act (ACA). Second, we use the distribution of spending and charges among a broader set of the population to develop benchmarks for the consumption insurance value of Medicaid expansion. Here, we provide more detail.

For both approaches, we begin by shifting the data from the individual level to the household level. We use MEPS's constructed "CPS family ID" to identify individuals sharing consumption resources. We use family weights in calculating all statistics and distributions. We then construct the total paid amount for each household (h) and year (t) by summing out-of-pocket medical payments for each household member, m_{ht}. To construct billed amounts, we sum up the charged amount for uninsured members and the paid amount for insured members, b_{ht}. (We do not include charges to insured members because insurers typically negotiate prices well below charges.)

We construct two measures of baseline consumption, i.e., consumption in the absence of Medicaid:

1. c_0^{paid}: We assume that unpaid charges are paid off in the same year, and have impact on consumption, so $c_0^{paid} = y - b$.

2. c_0^{unpaid}: We make the opposite assumption, and assume that unpaid charges will never be paid off and have no consumption consequence, so $c_0^{unpaid} = y - m$, where y is family income.

3. c_0^{full}: We assume the opposite, namely, that unpaid charges are paid off in the same year, so $c_0^{full} = y - b$.

We also construct a measure of counterfactual consumption under Medicaid expansion, c_1. To construct c_1, we assume that Medicaid covers the medical expenses of individuals who are uninsured at baseline and live in households with income below 138% of the poverty line.

To measure medical spending and consumption of the uninsured (Figure 1), we limit the sample to household–years with at least one uninsured member and with income below 138% of the poverty line. These are the households most likely to have benefited from the Medicaid expansion. We then plot the distribution of paid amounts and charged amounts, as well as c_0^{paid}, c_0^{unpaid}, and c_1.

To create our benchmarks for the consumption insurance value, we focus on a MEPS sample analogous to our CE estimation sample: households with at least one member aged 22–64 with no college education. We then make the consumption measures analogous to our CE measures by dividing by our household equivalence scale. Finally, to evaluate utility functions, we impose a floor on consumption of F. We impose $F =$\$500, which is somewhat lower than the figure used by others (e.g., Finkelstein, Hendren and Luttmer (2019) sets $F =$\$2,000). However, a higher consumption floor implies that most charges are not paid (because the consumption floor is more likely to bind). The lower consumption floor is necessary for us to measure the consumption insurance value of insuring these charges.

We construct two benchmarks: the insurance value assuming that the insured do or do not pay their uncompensated care. For both benchmarks, we calculate the insurance value of Medicaid using the main approach in the text, and we take as the consumption distribution with Medicaid the empirical cumulative distribution function (CDF) of c_1. To obtain the consumption insurance value of Medicaid expansion if the uninsured do pay for their uncompensated care, we set the consumption distribution without Medicaid equal to the empirical CDF of c_0^{paid}. To obtain the insurance value if the uninsured do not pay for their uncompensated care, we set the consumption distribution without Medicaid equal to the empirical CDF of c_0^{unpaid}. In Figure 4, we plot these insurance values (as a function of risk aversion) as gray lines.

C Details on Benchmarks

In Figure 4, we compare our consumption insurance value estimates to various benchmark values. We describe the creation of the Medical Expenditure Panel Survey–related benchmarks in Appendix B. The other benchmarks are taken from the literature, which typically reports estimates per enrollee. As our sample includes both unenrolled eligibles and ineligible Americans, the average benefit and the average cost of expansion are lower in our sample than the corresponding benchmarks in other works. We therefore make simple adjustments to ensure the comparability of our estimates. Specifically, approximately half of our sample is income eligible, and approximately half of the eligibles in the expansion population actually took up Medicaid (Decker, Abdus and Lipton, 2022), so we scale down the estimates by 75%.

Below, we describe the benchmarks that we take from the literature and how we adjust for comparability.

Outlays: Guth et al. (2021) report that government outlays on the expansion population averaged \$6,110 per enrollee. We scale this down by 25% to account for both noneligibility and nonenrollment in our population, arriving at a cost per person of \$1,530 per person for our population.

Mortality reduction benefit: Wyse and Meyer (2023) estimate the impact of Medication expansion on mortality. They find that expansions increased coverage by 28.7 million coverage-years and reduced mortality by 831,890 life-years, or 0.03 life-years per enrollee-year. We value this increase at \$3,000 per enrollee-year, assuming a value of \$100,000 per life-year. This value is low relative to the government guideline for valuing life improvements, which is closer to \$500,000 (Kearsley, 2024). This low value represents a conservative choice with respect to our conclusion that the consumption insurance value is low relative to the mortality benefit. Scaling down by 75% yields a mortality reduction benefit of \$750.

Other estimates of insurance value: Finkelstein, Hendren and Luttmer (2019) and Shupe (2023) use medical spending data to estimate the insurance value of Medicaid. Finkelstein, Hendren and Luttmer (2019) estimate the insurance value of Medicaid to enrollees in the Oregon Health Insurance Experiment, using multiple approaches. Their estimates range from \$133 to \$1,106. Scaling down, we obtain our benchmarks of \$33 and \$276. Shupe (2023) estimates the insurance value of Medicaid expansion among the Medicaid eligible (but not necessarily enrolled) population, finding a value of \$0–\$70, depending on risk aversion. Scaling down for our 50% eligibility rates, we obtain benchmarks of \$0–\$20.