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Does Health Insurance Reduce Consumption Risk?

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Abstract

We investigate the impact of health insurance on consumption by leveraging the variation arising from state-level decisions regarding Medicaid expansion in 2014. The effect of health insurance on consumption is ex-ante ambiguous due to the presence of unpaid medical debt and option to receive charity care directly from healthcare providers. Using a combination of difference-in-differences and changes-in-changes specifications, our study finds that there is no statistically significant effect of this health insurance expansion on consumption, even at the lower end of the consumption distribution. This research contributes to the existing knowledge on the insurance value of Medicaid expansion.

1 Introduction

The presence or absence of health insurance plays a critical role in individuals' ability to mitigate the effects of health shocks on their consumption patterns. A health shock, when uninsured, can have multifaceted implications, including the accumulation of medical bills and debt, as well as the loss of income due to foregone work opportunities. The severity of these consequences may be exacerbated by delays in receiving necessary medical care. However, the United States' healthcare system, characterized by a vast network of charity care and substantial levels of unpaid medical debt, adds complexity to how health-related financial shocks may become consumption shocks.

To investigate the impact of health insurance expansion on consumption, our study uses state-level variations in the expansion of Medicaid. By employing difference-in-differences and changes-in-changes models, we analyze the consumption patterns of individuals affected by Medicaid expansion and compare them to individuals residing in states without such expansion. Our analysis uses comprehensive consumption expenditure data and relevant demographic variables to refine the studied samples.

Prior research demonstrates that charity care provided by hospitals can play a crucial role in mitigating the impact of health shocks on consumption in the United States. For example, Dranove et al. (2016) shows that uncompensated care provided by hospitals decreased as a function of the 2014 Medicaid expansions. Additionally, some individuals may opt for bankruptcy as a means to discharge medical debt, which can provide them with a fresh start and potentially allow for a resumption of normal consumption patterns. There is empirical evidence to support this channel: Gross and Notowidigdo (2011) finds that Medicaid expansions in the 2004–2010 period led to an 8 percent reduction in personal bankruptcy, with no effect (as expected) on business-related bankruptcies. Also, Mahoney (2015) provides evidence supporting personal bankruptcy as implicit health insurance by showing for example that individuals facing a higher financial cost of bankruptcy make higher out-of-pocket medical payments for the same type of care as those facing a lower financial cost of bankruptcy.

We note that while charity care, bankruptcy, and unpaid medical debt can provide relief for some individuals, they do not eliminate the financial consequences. Even with charity care or unpaid debt, individuals may still face long-term repercussions such as damaged credit scores or limited access to credit, which can indirectly affect their consumption opportunities. Prior research shows that Medicaid expansion decreased the balance individuals had in debt collections by over $1,000 for those who obtained coverage (Hu et al. 2018). Other studies also find substantial effects of health insurance on financial shocks as estimated by Medicaid expansions (Mazumder and Miller 2016; Miller et al. 2021).

We note that health shocks can reduce well-being more generally. For example, Dobkin et al. (2018) finds that among both the insured and uninsured non-elderly, hospitalizations lead to a substantial decline in earnings relative to the out-of-pocket spending increase, along with greater likelihoods of unpaid medical bills, bankruptcy, and more. The paper also finds that the earnings loss is not too insured prior to the individual reaching normal retirement age for Social Security benefits. The paper finds that those who are insured experience fewer financial setbacks, however, motivating a new benefit for programs like Medicaid. There is also evidence that health shocks can forward retirement decisions McGeary (2009), suggesting important linkages between the major entitlement programs in our current system.

In what follows, we empirically examine the effect of Medicaid expansion on per-capita consumption. A key challenge in studying consumption is measurement error in household reports, which we mitigate by using the subtotal of well-measured consumption as developed in Meyer and Sullivan (2023).

2 Empirical Strategy

Our analysis uses difference-in-differences (DID) and changes-in-changes (CIC) models. These estimation approaches help us identify the causal effects of Medicaid expansion on the mean and on different quantiles of consumption, which is important given that our hypotheses are centered on the most vulnerable individuals at the left tail of the distribution.

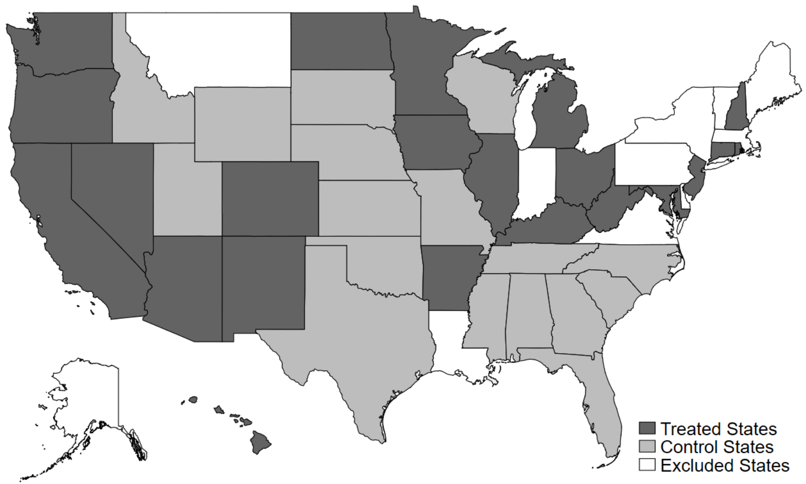
Figure 1 shows the source of identifying variation, which comes from state decisions on whether to extend Medicaid coverage to most non-elderly adults with incomes up to 133 percent of the federal poverty line. For brief background, Medicaid is a jointly funded federal-state program that provides health coverage to low-income individuals and certain eligible groups. The total amount spent on Medicaid can vary each year due to factors such as changes in enrollment, healthcare costs, and state policies. In fiscal year 2020, the total Medicaid spending in the United States was approximately $639 billion, with the federal government contributing about 61 percent of that amount and states covering the remaining 39 percent.

The state decisions about whether to expand Medicaid went into effect on January 1, 2014, generating a partition of our data into pre- and post-treatment periods. Our analysis contains 39 states, of which 22 are in the treated group and 17 are in the control group. The remaining 11 states, including Massachusetts, New York, and Pennsylvania, are excluded from our analysis as they expanded Medicaid at a point either earlier or later than January 1, 2014.

Estimating Equations: We implement the DID specification in a standard manner, with the binary treatment variable capturing whether the observation is from a state that expanded Medicaid on January 1, 2014. The DID equation is thus:

$$Consumption_{it} = Treated_{s(i)} \times Post_t + State_i + Year_i + \epsilon_{it}, \tag{1}$$

Figure 1: Map of Treated and Control States



where i is the household and t is the quarter-of-year when using the Consumer Expenditure Interview Survey data or year when using the NielsenIQ Homescan Consumer Panel data. We report two sets of bootstrapped standard errors — one set is robust and clustered at the state (treatment) level, and the other set is only bootstrapped. All regressions are weighted by the sample weights provided in the data.

We obtain CIC estimates following Athey and Imbens (2006). Here, the average treatment effect is obtained by:

$$\tau^{CIC} = E[Y_{11}] - E[F^{-1}_{Y,01}(F_{Y,00}(Y_{10}))], \tag{2}$$

where the first subscript denotes 1 (treated) and 0 (control) and the second subscript denotes 1 (post treatment period) and 0 (pre treatment period). The first element in this equation is the realized outcome, while the second element is a counterfactual outcome obtained by mapping the change in consumption of the implied percentile in the control distribution.

3 Data and Summary Statistics

We use two sources of consumption data for our analysis. Both sources of data provide information at the household-level, so we use an equivalence scale following Meyer and Sullivan

(2023) and Citro et al. (1995) to obtain per-capita outcomes that account for differences in family size and composition. This method allows for (i) differences in consumption between adults and children and (ii) diminishing marginal costs of consumption with each additional adult equivalent. Therefore, we divide household consumption by:

$$(A + 0.7K)^{0.7} \tag{3}$$

where A is the number of adults in the family and K is the number of children. To focus our analysis on those who may be affected by Medicaid expansion, we restrict our sample in each dataset to those aged 22–64 with education less than or equal to high school. We also restrict our analysis to states that expanded Medicaid in 2014 or never expanded Medicaid.[1] In what follows, we do not extend our data to 2020 or further to avoid complexities in the analysis arising from the COVID-19 pandemic, which greatly affected both health needs and consumption patterns.

Our data contain 48,471 households in the CEX data and 45,678 households in the Nielsen data.

Consumer Expenditure Surveys: We use the quarterly 2008–2019 Consumer Expenditure Interview Surveys (CE) to examine categories of well-measured consumption. Our focus on well-measured consumption follows Meyer and Sullivan (2023), which shows by comparing to national accounts that there is substantial measurement error in total consumption. These categories include spending on food at home, rent (for renters), rental equivalent (for homeowners or those in government or subsidized housing), utilities, service flows from owned vehicles, and spending on gasoline and motor oil. The original categories of well-measured consumption as laid out in Bee et al. (2015) also include communication, so we add telecommuting consumption (telephone and cable) to the total of well-measured

[1] Kaestner et al. (2017) shows that those with low education/low income were more likely to gain insurance coverage following the 2014 Medicaid expansions.

consumption.

The CE are a series of surveys conducted by the US Bureau of Labor Statistics to collect detailed information on household spending patterns and expenditures. The surveys aim to provide a comprehensive picture of consumer expenditures, income, and demographic characteristics at the national level. A key use of the CE is to calculate the Consumer Price Index on an ongoing basis.

The CE surveys employ a rotating panel design, where households are selected to participate in the survey for a specific period of time, typically lasting one year. The selected households are then interviewed every quarter during this period to gather data on their expenditures, income sources, and various demographic factors. The surveys cover a wide range of both recurring and occasional expenditures including housing, transportation, food, healthcare, education, and entertainment.

Meyer and Sullivan (2023) converts the reported expenditures in the CE into consumption metrics using a series of adjustments. For example, vehicle spending is converted to a monthly flow using the depreciated market value of the car. Housing spending is also converted to a monthly flow for homeowners using mortgage and property tax information. As we fully adopt that paper's methodology, we refer readers to that source for detailed information on the conversion of expenditure to consumption. For our analysis, we use the replication dataset provided for that paper in Sullivan and Meyer (2022).

NielsenIQ Homescan Consumer Panel: Our secondary measure of consumption comes from the annual 2008–2019 NielsenIQ Homescan Consumer Panel (Nielsen). Our motivation in studying the Nielsen data is to examine a subset of consumption, food, that is perhaps more vulnerable to fluctuation than other category of consumption. A drawback of this data, however, is that it is not likely to be well-measured given that much of retail and food consumption is relatively small and irregular.

The Nielsen data includes about 61,000 households (refreshed annually) that are randomly selected via a stratified scheme. Households in the survey scan all of their household's purchases each week; we use an annual aggregation of these purchases. We obtained the Nielsen data from the Kilts Center for Marketing at Chicago Booth. We look at both total consumption in the Nielsen data as well as food-specific consumption.[2]

Summary Statistics: Table 1 shows the distribution of consumption (in 2017 dollars) across the two datasets, pre- and post- Medicaid expansion, for the treated and control states. We show both the mean metrics as well the summary at the 5^{th}, 10^{th}, 25^{th}, 50^{th}, and 75^{th} percentiles, following our focus on changes across the consumption distribution. Beginning with the CE dataset, we observe that the mean quarterly well-measured consumption is slightly higher in treated states both pre- and post- Medicaid expansion, across the consumption distribution. The mean pre-period consumption is about \$3,466 in treated states, ranging from \$1,391 at the 5^{th} percentile to \$4,284 at the 75^{th} percentile.

Consumption in the Nielsen dataset is reported at the annual level. Note that it is much smaller than that of well-measured consumption across the distribution (when the CE measures are multiplied by four to convert them to annual numbers), which is not surprising given that Nielsen does not capture important sources of well-measured consumption such as housing, vehicle, or utilities, for example. In the Nielsen data, we observe smaller differences between the treated and control states in both the pre- and post-periods. Turning to food consumption, we observe that the mean per-capita consumption (for treated states, pre-period) is \$1,500, ranging from \$456 at the 5^{th} percentile to \$1,918 at the 75^{th} percentile.

[2]We categorize food expenditures in Nielsen as those that are sourced at locations coded as "Bakery," "Beverage Store," "Bodega," "Butcher," "Candy Store," "Cheese Stores," "Coffee Store/Gourmet Coffee Shop," "Convenience Store," "Coop/Farm/Feed," "Dairy Store," "Delicatessen," "Fish Market," "Fruit Stand," "Health Food Store," "Liquor Store," "Pizzeria," "Quick Serve Restaurants," "Restaurant," and "Grocery."

Table 1: Summary Statistics of Consumption

	Well-Measured Consumption (CE)				Total Consumption (Nielsen)			
	Pre		Post		Pre		Post	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
Mean	3465.50	3232.64	3825.76	3514.48	2495.29	2453.33	2411.93	2438.93
p5	1391.00	1382.86	1544.59	1419.59	751.28	701.95	735.96	733.38
p10	1692.05	1651.14	1884.27	1765.09	973.45	926.35	937.92	936.05
p25	2289.65	2203.00	2543.69	2389.74	1439.38	1382.07	1379.37	1386.16
p50	3164.58	2984.62	3505.93	3221.64	2166.95	2107.84	2082.09	2102.40
p75	4283.92	3989.68	4719.52	4289.15	3157.71	3112.26	3053.61	3098.74
Observations	48,471				150,436			
					Food Consumption (Nielsen)			
Mean					1500.49	1433.64	1644.66	1645.31
p5					455.64	415.39	467.56	469.65
p10					611.70	573.11	632.78	621.27
p25					924.65	868.50	959.91	955.08
p50					1365.57	1300.74	1460.07	1460.12
p75					1918.25	1846.87	2099.06	2114.07
Observations					152,148			

4 Results

Table 2 shows the DID and CIC results for well-measured consumption from the CE data. Here, we find that Medicaid expansions do not exert a protective effect over consumption even at the left tail of the distribution. In column (1), the mean DID estimate is $50, though the estimate is noisy. We observe that the CIC estimates are not statistically significant at all points of the consumption distribution. The same is true for the logged specification in column 2.

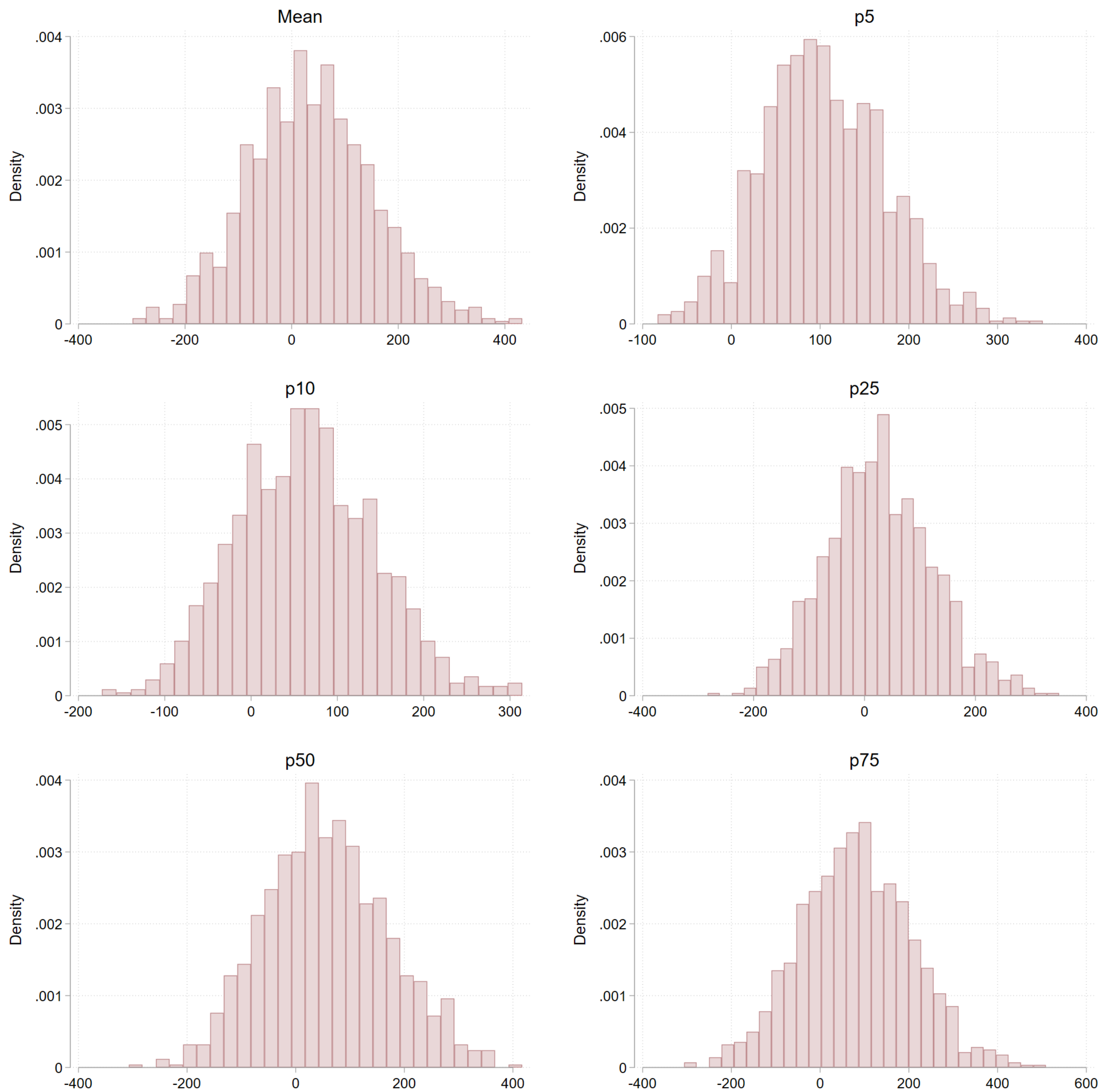
Table 2: DID and CIC: Well-measured Consumption

	(1)	(2)
	A. Difference-in-Differences	
	Well-measured Consumption	Log
β	50.37	0.01
	(84.50)	(0.03)
	B. Changes-in-Changes	
	Well-measured Consumption	Log
mean	45.00	0.01
	[-181.07, 272.27]	[-0.05, 0.08]
p5	109.65	0.06
	[-25.69, 248.98]	[-0.02, 0.16]
p10	81.65	0.04
	[-85.00, 222.36]	[-0.05, 0.12]
p25	55.28	0.02
	[-159.98, 230.42]	[-0.06, 0.09]
p50	80.97	0.02
	[-149.90, 285.56]	[-0.04, 0.08]
p75	98.74	0.02
	[-164.85, 331.10]	[-0.03, 0.07]

Notes: State-clustered standard errors (95 percent) in parentheses; these are only provided for the DID model. Bootstrapped and state-clustered confidence intervals (95 percent) in brackets are provided for the CIC models.

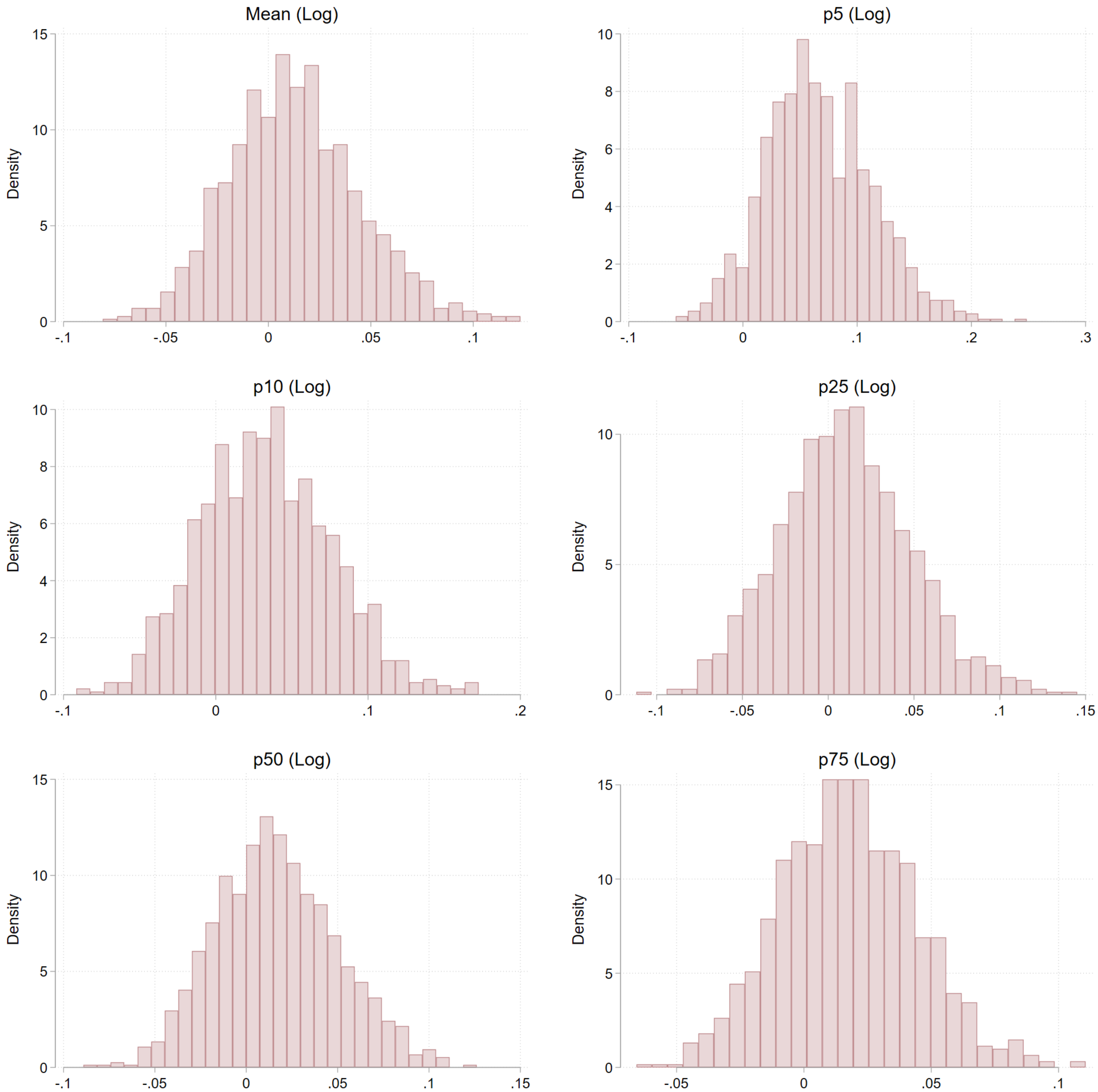
Figure 2 shows the distributions of the CIC estimates from resampled data at the mean and at different percentiles of the consumption distribution. Figure 3 shows the analogous estimate distribution plots for the log of well measured consumption. We observe that there is a positive effect of the Medicaid expansions on consumption at especially the left tail of the consumption distribution (5^{th} and 10^{th} percentiles).

Figure 2: Well-measured Consumption



Notes: Figure 2 shows the distribution of CIC estimates by resampling 33 states with replacements. The outcome variable is the well-measured consumption (mean, p5, p10, p25, p50, and p75). The intervals between the bottom 2.5 percent and the top 2.5 percent represent the state-clustered bootstrap confidence intervals.

Figure 3: Log of Well-measured Consumption



Notes: Figure 3 shows the distribution of CIC estimates by resampling 33 states with replacements. The outcome variable is the log of the well-measured consumption (mean, p5, p10, p25, p50, and p75). The intervals between the bottom 2.5 percent and the top 2.5 percent represent the state-clustered bootstrap confidence intervals.

Table 3 shows the DID and CIC results for the Nielsen data. Here, we find some results contradicting our hypothesis, though we highlight that this analysis is less reliable given the lack of parallel trends in the pre-period (see Appendix XX[3]). The Nielsen-based results here suggest that Medicaid expansion had a *negative* effect on both the food and total categories of consumption available.

Table 3: DID and CIC: Nielsen

	A. Difference-in-Differences			
	Food	Total	Log(Food)	Log(Total)
	(1)	(2)	(3)	(4)
β	-68.32	-69.62	-0.06	-0.04
	(19.19)	(26.42)	(0.02)	(0.01)
	B. Changes-in-Changes			
	Food	Total	Log(Food)	Log(Total)
mean	-80.86	-64.64	-0.06	-0.04
	[-95.55, -27.85]	[-110.78, 11.25]	[-0.06, -0.02]	[-0.05, -0.01]
p5	-34.86	-40.13	-0.07	-0.05
	[-68.18, -11.02]	[-88.40, -8.52]	[-0.12, -0.02]	[-0.10, -0.01]
p10	-33.78	-37.91	-0.05	-0.04
	[-71.23, -20.25]	[-83.77, -9.91]	[-0.10, -0.03]	[-0.08, -0.01]
p25	-62.87	-68.18	-0.06	-0.05
	[-75.62, -16.71]	[-98.23, -6.94]	[-0.07, -0.02]	[-0.06, -0.00]
p50	-77.26	-85.53	-0.05	-0.04
	[-81.92, -8.40]	[-112.46, 12.95]	[-0.05, -0.01]	[-0.05, 0.01]
p75	-107.23	-93.10	-0.05	-0.03
	[-135.65, -49.91]	[-164.16, -0.65]	[-0.06, -0.02]	[-0.05, -0.00]

Notes: State-clustered standard error (95 percent) in parentheses; these are only provided for the DID model. Bootstrapped and state-clustered confidence intervals (95 percent) in brackets are provided for the CIC models.

4.1 Heterogeneity by Race and Ethnicity

Tables 4 and 5 provide the subsample results for those reporting to be White non-Hispanic, Black non-Hispanic, and Hispanic. We hypothesized that there might be differences in the main effect on this dimension tied to baseline economic vulnerability. We do not observe any such differences, however. This result is not surprising in the context of there being no detectable protective effect of Medicaid on overall consumption as shown in the main result.

[3] Forthcoming.

Table 4: DID and CIC: Well-measured Consumption

	A. Difference-in-Differences					
	White, non-Hispanic		Black, non-Hispanic		Hispanic	
	Consump.	Log	Consump.	Log	Consump.	Log
β	93.52	0.02	94.74	0.00	25.01	0.01
	(103.45)	(0.03)	(145.04)	(0.04)	(62.23)	(0.02)
# of Obs.	23607	23604	7090	7088	15175	15171
	B. Changes-in-Changes					
	Consump.	Log	Consump.	Log	Consump.	Log
mean	68.56	0.02	60.09	0.01	38.43	0.02
	[-49.85,186.98]	[-0.01,0.05]	[-114.07,234.26]	[-0.04,0.07]	[-51.99,128.84]	[-0.01,0.04]
p5	42.88	0.02	75.30	0.02	93.72	0.06
	[-57.00,142.76]	[-0.04,0.09]	[-82.98,233.59]	[-0.17,0.21]	[-14.90,202.35]	[-0.02,0.13]
p10	3.41	-0.00	200.24	0.12	95.79	0.05
	[-107.12,113.93]	[-0.06,0.05]	[46.14,354.34]	[-0.01,0.24]	[4.91,186.67]	[0.00,0.10]
p25	67.45	0.02	-17.79	-0.01	101.28	0.04
	[-22.36,157.27]	[-0.02,0.06]	[-161.37,125.79]	[-0.08,0.05]	[13.94,188.63]	[0.00,0.08]
p50	175.14	0.04	47.90	0.01	48.94	0.02
	[47.62,302.66]	[0.01,0.08]	[-130.03,225.82]	[-0.05,0.07]	[-54.53,152.42]	[-0.01,0.05]
p75	43.45	0.01	-29.17	-0.01	-8.63	-0.00
	[-124.83,211.72]	[-0.02,0.04]	[-336.83,278.49]	[-0.07,0.05]	[-144.14,126.87]	[-0.04,0.03]

Notes: State-clustered standard error (95 percent) in parentheses; these are only provided for the DID model. Bootstrapped and state-clustered confidence intervals (95 percent) in brackets are provided for the CIC models.

5 Implied Risk Premium

To place our results in better context of the literature, here we discuss and show the implied consumption risk premium for Medicaid expansion. The risk premium is a measure of insurance or risk-reducing value of Medicaid expansion.

Theory Consider two states of the world, state 1 with Medicaid expansion and state 0 without. Let C_1 and C_0, random variables, be consumption in each state of the world. We assume that both have finite support taking on k values, $c_1^1, \ldots, c_1^K$ and $c_0^1, \ldots, c_0^k$. Expected utility in state of the world $j \in 0, 1$ is

$$EU_j = \sum_k p_k u(c_k^j), \tag{4}$$

Table 5: DID and CIC: Nielsen

	White, non-Hispanic		Black, non-Hispanic		Hispanic	
A. Difference-in-Differences						
	Consump.	Log	Consump.	Log	Consump.	Log
β (Food)	-54.53	-0.05	-113.81	-0.12	-102.49	-0.10
	(17.25)	(0.01)	(75.57)	(0.06)	(40.52)	(0.03)
# of Obs.	123565	123565	11633	11633	11639	11639
β (Total)	-41.42	-0.02	-200.23	-0.10	-104.25	-0.07
	(23.05)	(0.01)	(138.84)	(0.06)	(75.33)	(0.04)
# of Obs.	122242	122242	11461	11461	11479	11479
B. Changes-in-Changes						
	White, non-Hispanic		Black, non-Hispanic		Hispanic	
	Consump.	Log	Consump.	Log	Consump.	Log
a. Food						
mean	-64.62	-0.05	-163.27	-0.12	-105.88	-0.08
	[-88.19, -41.05]	[-0.06, -0.03]	[-242.77,-83.76]	[-0.17,-0.06]	[-172.10,-39.66]	[-0.13,-0.04]
p5	-35.13	-0.06	-61.81	-0.17	-26.70	-0.07
	[-50.10, -20.15]	[-0.10, -0.03]	[-110.08,-13.55]	[-0.31,-0.03]	[-73.81,20.40]	[-0.19,0.05]
p10	-25.02	-0.04	-23.35	-0.05	20.59	0.04
	[-39.59, -10.44]	[-0.06, -0.01]	[-80.89,34.18]	[-0.16,0.07]	[-29.09,70.27]	[-0.04,0.12]
p25	-41.00	-0.04	-78.91	-0.09	-49.29	-0.06
	[-59.07, -22.94]	[-0.06, -0.02]	[-129.45,-28.36]	[-0.16,-0.03]	[-113.30,14.73]	[-0.12,0.01]
p50	-58.81	-0.04	-154.60	-0.12	-86.88	-0.07
	[-77.38, -40.25]	[-0.05, -0.03]	[-226.37,-82.82]	[-0.18,-0.06]	[-169.31,-4.45]	[-0.12,-0.01]
p75	-109.82	-0.05	-272.16	-0.14	-174.50	-0.09
	[-144.39, -75.26]	[-0.06, -0.03]	[-370.14,-174.17]	[-0.19,-0.09]	[-288.70,-60.31]	[-0.16,-0.02]
b. Total						
mean	-38.25	-0.02	-212.03	-0.08	-90.66	-0.06
	[-69.81,-6.70]	[-0.03,-0.01]	[-334.08,-89.97]	[-0.14,-0.03]	[-206.91,25.60]	[-0.11,-0.01]
p5	-28.41	-0.04	-2.56	-0.00	-5.79	-0.01
	[-49.40,-7.42]	[-0.06,-0.01]	[-73.06,67.95]	[-0.10,0.10]	[-71.39,59.81]	[-0.13,0.12]
p10	-24.34	-0.02	0.77	0.00	-40.50	-0.05
	[-47.65,-1.03]	[-0.04,-0.00]	[-86.09,87.62]	[-0.10,0.10]	[-110.14,29.14]	[-0.12,0.02]
p25	-36.46	-0.02	-55.89	-0.04	-99.29	-0.08
	[-62.33,-10.59]	[-0.05,-0.00]	[-144.19,32.41]	[-0.12,0.03]	[-204.10,5.52]	[-0.15,-0.01]
p50	-51.67	-0.02	-197.56	-0.10	-98.83	-0.05
	[-82.27,-21.08]	[-0.04,-0.01]	[-308.98,-86.14]	[-0.16,-0.05]	[-217.17,19.50]	[-0.11,0.01]
p75	-64.26	-0.02	-398.33	-0.13	-75.66	-0.03
	[-120.47,-8.05]	[-0.04,-0.00]	[-523.84,-272.81]	[-0.18,-0.09]	[-253.72,102.40]	[-0.09,0.03]

Notes: State-clustered standard error (95 percent) in parentheses; these are only provided for the DID model. Bootstrapped and state-clustered confidence intervals (95 percent) in brackets are provided for the CIC models.

where u is the von Neuman-Morgenstern utility function.

As in Finkelstein et al. (2019), define the certainty equivalent γ of the Medicaid expansion as the amount of consumption a person would have to give up in the expansion state of the world to be indifferent between expansion and non-expansion. γ is implicitly defined by

$$\sum_k p_k u(c_k^1 - \gamma) = \sum_k p_k u(c_k^0). \tag{5}$$

Finally, define the risk premium π as the difference between the certainty equivalent and the expected value (in consumption) of expansion:

$$\pi \equiv \gamma - E[C_1 - C_0]. \tag{6}$$

Estimation In the data we observe consumption under expansion for the expansion states in the post period. We don't know the distribution of consumption had these states not expanded. Let $\hat{c}_1^1, \ldots, \hat{c}_K^1$ be the empirical percentiles of the consumption distribution, and percentiles $P_1, \ldots, P_k$. We assume that the CIC method yields estimates of percentiles of the counterfactual distribution, i.e., $\hat{c}_1^0, \ldots, \hat{c}_K^0$.

Given these estimates, estimate $E[C_j]$ in a straightforward manner:

$$E[\hat{C_j}] = \sum_{k=1}^{K} (P_k - P_{k-1}) c_k^j, \tag{7}$$

with $p_0 = 0$.

To find γ, we need to assume a utility function. For this report, we follow Finkelstein et al. (2019) and use constant relative risk aversion utility with coefficient of relative risk aversion = 3.

Given $u(\cdot)$ and the estimated distributions, the only challenge is recovering γ. Estimating γ requires solving one equation in one unknown (i.e., equation 5), which is straightforward.

So the approach is:

1. Approximate the factual consumption distribution with a, say, 19 point distribution, evenly spaced from 5th to 95th percentile.
2. Use CIC to recover counterfactual consumption percentiles.
3. Solve for $\hat{\gamma}$ by implementing the sample analog of equation 5.
4. Solve for $\hat{\pi}$ by subtracting off $E[\hat{C_1}] - E[\hat{C_0}]$.

Inference Steps 1–4 yield a single estimate of π. We obtain confidence intervals via the bootstrap, re-estimating π in each bootstrap iteration.

5.1 Results

y We estimate the risk premium to be $3.43; the 95 percent confidence interval is [-$119.50,$48.66]. To obtain this estimate, we estimate a risk aversion parameter of 3. The risk premium we estimate is below the lower end of the range of estimated consumption welfare benefit from Medicaid as estimated in Finkelstein et al. (2019). That paper uses the 2008 Oregon Health Insurance Experiment to estimate an insurance value ranging from $112 to $883 per recipient-year (Table 2 in that paper). The $3.43 benefit is also small relative to the per-capita cost of Medicaid, which is several thousand dollars for most states.[4]

6 Discussion

Many SSA beneficiaries are low income with little savings, generating vulnerability to shocks such as uninsured health needs. Expanding health insurance seems a natural way to insure against such shocks, and indeed it has been shown to increase health care utilization, reduce mortality, and improve financial outcomes such as credit scores, medical debt, and bankruptcy. There has been a gap, however, in terms of how much these financial shocks translate to consumption shocks.

[4]Source: https://www.medicaid.gov/state-overviews/scorecard/how-much-states-spend-per-medicaid-enrollee/index.html.

In this report, we find that health insurance expansion does not exert a protective consumption effect for individuals even at the left tail of the consumption distribution. This finding is supported using data on household grocery expenditures as well as total well-measured consumption from the Consumer Expenditure Interview Surveys as studied in Meyer and Sullivan (2023). Our estimate of the risk premium implies a low *consumption insurance* value to Medicaid, though certainly the program offers large insurance benefits on health, financial shocks, and other dimensions of wellness. Strength in social insurance in other forms, such as food stamps or payment assistance plans that can be activated on hardship, could be other reasons that we do not observe strong consumption insurance benefits to Medicaid.

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