The Effect of Medicaid Expansion on Part-Time Jobs and Self-Employment

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November 6, 2023

Abstract

We measure the effect of Medicaid Expansion on the share of low-income workers in part-time jobs and self-employment. Workers in these jobs commonly lack access to subsidized health plans through their employers. However, Medicaid expansion provided many low-income workers in these jobs access to publicly subsidized health plans, potentially making these positions more desirable. Our identification strategy is the difference-in-difference design from Callaway and Sant'Anna (2021), which compares labor market outcomes for workers in states that expanded Medicaid against those that did not. We focus on a sample of low-income workers who were not eligible for Medicaid before the expansion: childless, non-disabled adults in states without confounding state-level policies. Using American Community Survey data, we find that Medicaid expansion had a statistically insignificant effect on the share of our sample in part-time jobs or self-employment in both the short and long term. We conclude that Medicaid Expansion had a negligible impact on both types of work arrangements for low-income workers.

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1 Introduction

Medicaid is a government program that provides subsidized health insurance to people in need. Historically, it was primarily only available to low-income families with children and individuals with disabilities (Gruber, 2003). This changed with the passage of the Affordable Care Act (ACA) in 2010, as states were given the option to expand their Medicaid programs to provide greater access. After this legislation was passed, many states expanded Medicaid eligibility to all individuals with incomes below 138% of the Federal Poverty Line, regardless of whether they had children or were disabled. This significantly increased the number of people eligible for Medicaid, and many researchers have studied the effect of the expansion on labor market outcomes for these newly eligible low-income workers.

In theory, Medicaid expansion could increase the number of low-income workers in part-time jobs and self-employment. In the US, health plans available directly from insurers on the private market are expensive (Currie and Madrian, 1999). As a result, most people covered by health insurance depend on subsidized plans from employers or the government. In 2021, only 6% of people were covered by plans purchased directly from the private market, while 85% were covered through an employer or a government program (Kaiser Family Foundation, 2021). While many employees have access to employer-subsidized health plans, part-time and self-employed workers typically do not. According to the 2017 Contingent Worker Survey, only 9% of self-employed workers and 11% of part-time workers were covered by health insurance from their work arrangements. These work arrangements may be considered unfavorable because of the lack of employer-subsidized health plans and the high costs on the private market. However, Medicaid expansion could give low-income workers in these positions access to subsidized public health insurance, increasing employment in these arrangements.

Using a difference-in-difference method, we identify Medicaid expansion's effect on part-time status and self-employment for low-income workers. We use the method described in Callaway and Sant'Anna (2021) to account for variation in the timing of the expansion across states and the doubly robust estimator from Sant'Anna and Zhao (2020) to control for heterogeneity in pre-treatment covariates. We focus on a sample of low-income workers who did not have access to Medicaid before the expansion: childless, non-disabled adults in states without public healthcare programs that included these workers. To construct our sample, we draw on data from the 2010-2019 American Community Survey. We find that Medicaid expansion had a statistically insignificant effect on part-time work and self-employment for low-income, childless, non-disabled adults. We further decompose the impact of the expansion into short-term and long-run effects and find that both are insignificant.

The effects of the Medicaid expansion on labor market outcomes for low-income workers have been studied extensively.[1] We make three main contributions to the literature. First, we use the difference in difference technique from Callaway and Sant'Anna (2021). This method addresses the well-known issues of using the typical two-way fixed effect DiD method to identify average treatment effects (e.g., Goodman-Bacon (2021)). Second, we use data spanning the early 2010s to 2019, allowing us to measure both short-term and long-term effects of the expansion. Third, we measure the effect of Medicaid expansion on multiple labor market outcomes of low-skill workers — full-time employment, part-time employment, self-employment, unemployment, and not in the labor force — granting a holistic picture of how Medicaid expansion impacted workers.

This paper is organized as follows. Section 2 details a simple theory that illustrates how Medicaid expansion could increase the share of low-income workers in part-time jobs and self-employment. Section 3 outlines background information on Medicaid. Section 4 describes the data we use to build our sample of low-income workers. Section 5 describes the difference-in-difference strategy used to measure Medicaid expansion's impact on work arrangements, and Section 6 summarizes our main results. Finally, Section 7 concludes.

2 A Theory of Labor Supply and Health Plans

We use a static, partial equilibrium theory of labor supply to illustrate how Medicaid expansion could increase part-time and self-employment. The key idea is that Medicaid expansion increases the utility of workers in part-time and self-employment because these positions do not have access to health insurance through their employers. However, it does not change the utility level of workers in typical, full-time arrangements because they have access to

[1] Baicker et al. (2014) finds that Medicaid had little effect on employment for low-income, uninsured adults in Oregon. Kaestner et al. (2017) and Leung and Mas (2018) also find little employment effects for low-income adults. Gooptu et al. (2016) finds that the expansion did not cause significant changes in employment, job switching, or part-time employment among adults below 138% of the federal poverty line. On the other hand, Dague et al. (2017) finds a significant reduction in employment following expansion among childless adults in Wisconsin. Peng et al. (2020) finds a small, negative effect on employment.

employer-provided health insurance. This increase in relative utility, in turn, increases the number of workers in part-time jobs and self-employment.

The model is static. The only agents are workers. There is a mass of N workers with preferences over jobs. Each job j is a tuple (w_j, d_j) where $w_j > 0$ is wages and $d_j \in \{0, 1\}$ is a dummy that equals one if the job provides health insurance. The exogenous discrete set of jobs is $\mathcal{J}$.

Given a job j, each worker i chooses whether to purchase health insurance at (exogenous) price p on the private market. If their job already supplies health insurance, there is no benefit to purchasing it on the private market at price p. Worker i's utility for working job j is

$$\log\left(w_j + \gamma d_j + (1 - d_j)\max\{\gamma - p, 0\}\right) + \epsilon_{ij} \tag{1}$$

where $\gamma > 0$ governs how much workers value health insurance, and ϵ_{ij} is an idiosyncratic measure of how much person i values job j. If a job offers health insurance $d_j = 1$, then the worker receives utility γ. If a job does not offer health insurance $d_j = 0$, the worker chooses whether to purchase it on the private market at exogenous price p. We assume that the benefit of health insurance is less than the price $\gamma < p$, but this assumption is strictly for brevity and not necessary to solve the model.

Given the set of jobs $\mathcal{J}$, workers choose which job to accept. Because they are free to choose any job, they simply choose the job that maximizes utility,

$$\max_{j \in \mathcal{J}} \left\{\log\left(w_j + \gamma d_j\right) + \epsilon_{ij}\right\}. \tag{2}$$

The reason we add the idiosyncratic shocks ϵ_{ij} is simply to smooth this discrete choice and prevent all workers from accepting the same job.

An equilibrium is a mass of workers in each job $\{n_j\}_{j \in \mathcal{J}}$ that follows from workers maximizing utility (2). We assume that the idiosyncratic shocks ϵ_{ij} are independently drawn from a type 1 extreme value distribution. Following this assumption, the mass of workers in job k, n_k, takes a simple form (McFadden et al., 1973):

$$n_k = N \frac{w_k + \gamma d_k}{\sum_{j \in \mathcal{J}} w_j + \gamma d_j}.$$

Consider an economy with only two jobs: a full-time job f with health insurance $d_f = 1$

and a part-time job p without health insurance $d_p = 0$. The part-time job can be interpreted as any position without access to employer-provided health insurance, including self-employment or even the choice to not be in the labor force. The share of workers that are part-time is

$$\frac{n_p}{N} = \frac{w_p}{w_f + \gamma + w_p}.$$

Suppose that the government expands Medicaid, offering all workers health insurance. This policy does not change the utility level of full-time workers, as they already were offered health insurance through their work arrangements, but it does increase the utility level of being a part-time worker by γ. This increases the number of workers in part-time positions by

$$\Delta \frac{n_p}{N} = \frac{w_p + \gamma}{w_f + \gamma + w_p + \gamma} - \frac{w_p}{w_f + \gamma + w_p} = \frac{\gamma(w_f + \gamma)}{(w_f + w_p + 2\gamma)(w_f + w_p + \gamma)} > 0.$$

Thus, Medicaid expansion can increase the number of workers in labor market arrangements who do not have access to employer-provided health insurance, which includes part-time jobs, self-employment, or not being in the labor force entirely. In the next section, we discuss the Medicaid expansion in detail, and in Section 5 we measure the effect of Medicaid expansion on the labor market outcome of low-income workers.

3 Institutional Background: Medicaid

Having shown theoretically how Medicaid expansion can impact the labor market decisions of workers, we turn to discuss Medicaid in detail. Medicaid is a government program enacted in 1965 that offers subsidized health insurance to people in need (Gruber, 2003). The program allowed the federal government to provide matching funds to states for providing health care to low-income or disabled people. Under broad federal guidelines, each state and the District of Columbia was tasked with administering their own state-level programs — establishing eligibility standards, determining what services to offer and for how long, and setting the payment structure (Social Security Administration, 2015). All states plus the District of Colombia were participating by 1982 when Arizona established its Medicaid program (AHCCCS, n.d.).

While Medicaid is designed to assist low-income people, the variation in state programs created vast differences in eligibility requirements across states. Income cut-offs that determine Medicaid eligibility vary across states by whether an individual is working, is disabled, or has children. For example, in January 2013, the income cut-offs for working parents of dependent children in a family of three ranged from 16% of the Federal Poverty Line (FPL) in Arkansas to 215% in Minnesota. Across states, the median income cut-off for such individuals was 58% of the FPL (Kaiser Family Foundation, 2014).

While income cut-offs varied across states, low-income adults without children or disabilities did not have any access to Medicaid in a majority of states. In January 2013, childless adults were not eligible for Medicaid in 42 states regardless of how low their incomes were. In the remaining eight states plus Washington DC, the income cut-offs for working, childless adults ranged from 20% in Colorado to 211% of the FPL in Washington DC (Kaiser Family Foundation, 2014).

The lack of Medicaid access for low-income people without children or disabilities changed with the passage of the Affordable Care Act. A major provision of the new law was Medicaid expansion, which gave anyone with incomes below 138% of the Federal Poverty Line (FPL) access to Medicaid in participating states. This change affected everyone, regardless of whether they were disabled or had children. The number of people eligible for Medicaid greatly increased as a result. For context, a single, full-time worker making the Federal minimum wage in 2014 made below 138% of the FPL and was eligible for Medicaid if they lived in a participating state.[2]

While the ACA was passed in 2010, states implemented the Medicaid expansion in different years. Seventeen states and Washington DC adopted and implemented the expansion in 2014. Nine states expanded early before 2014, while twelve expanded after. In May 2023, 38 out of 50 states had adopted and implemented the Medicaid expansion.[3]

[2]The Federal minimum wage in 2014 was $7.25, or roughly $14,500 in annual income for a full-time worker. The Federal Poverty Line for a worker in a single-person household was $11,670, placing the Medicaid eligibility cut-off at just above $16,100.

[3]Two states adopted but had not implemented the expansion, leaving only ten states having not adopted the expansion (Kaiser Family Foundation, 2023).

4 Data: Building a Sample of Low-Income Workers

Because Medicaid access varied across low-income workers before the expansion, we build a sample of this population that we can say with certainty gained access to Medicaid due to the expansion. This sample allows us to measure how newly found Medicaid access affects labor market outcomes. Data is drawn from the 2010 to 2019 American Community Survey (ACS). The advantages of the ACS are that it is a large sample, representative at the state level, and it has all the necessary variables to determine whether an adult is eligible for Medicaid. We consider an adult to have low income if they had family-level incomes less than 138% of the FPL, as the expansion gave everyone below this cut-off access to Medicaid. We calculate each person's family income following the federal government's Medicaid eligibility criteria, as described in the Appendix A. We restrict to people between the ages of 27 and 64 so that each individual is not eligible for their parent's employer health plans or Medicare.[4] We further restrict to childless, non-disabled adults, as adults with children or disabilities had varying access to Medicaid across states before Medicaid expansion. We drop DC and the ten states that gave low-income childless adults access to Medicaid or comparable subsidized health insurance before they expanded Medicaid, as detailed in Simon et al. (2017).[5]

The resulting sample of low-income adults has a total of almost 400,000 observations, averaging just under 40,000 each year. Table 1 shows descriptive statistics for our 2010, 2015, and 2019 samples. Demographics and outcomes for the sample stay fairly constant across time.

Our outcomes of interest are broad employment classifications for each worker. These are employment, unemployed, and not in the labor force. We further decompose employment into self-employment, traditional full-time employment, and traditional part-time employment. We consider a worker part-time if they usually work less than 30 hours a week.

We collapse observations to state-year averages. Our outcome variables of interest are the share of our sample self-employed, in part-time jobs, in full-time jobs, unemployed, and not in the labor force. The collapsed data covers 40 states between 2010 and 2019. Sixteen

[4] The ACA permitted dependents to remain on their parents' insurance plans until their 26th birthday.

[5] See table A1 in Simon et al. (2017). We drop Arizona, Colorado, Connecticut, Delaware, Washington DC, Hawaii, Minnesota, New Jersey, New York, Vermont, and Washington. These are all states that had substantial or mild expansion according to Simon et al. (2017), with the exception of Arizona. Arizona began covering childless adults in 2000. In 2011, it stopped admitting new childless adults into the program, but previously enrolled childless adults were allowed to stay in the program. In July 2010, enrollment was still substantial: over 200,000 childless adults were enrolled in the program (Roy, 2013).

Table 1: Descriptive Statistics for ACS Sample

	Year		
	2010	2015	2019
Wage	6800	7100	6700
Rural	38	38	38
Age $\geq$ 50	49	51	52
College	13	14	16
Male	48	49	51
White, non hispanic	64	61	60
Black, non hispanic	20	21	21
Hispanic	12	13	13
Other Race, non hispanic	2	3	3
Construction	10	8	8
Manufacturing	7	7	6
Natural resources and mining	2	2	2
Service-producing	80	83	84
Full time	18	21	20
Part time	9	10	10
Self employed	6	6	5
Employed	33	36	36
Unemployed	20	11	9
NILF	48	53	55
Observations	107269	106139	96610

Notes: The table displays descriptive statistics for our 2010, 2015, and 2019 ACS samples. All rows are in percentages except wage, which is a weighted average, and observations, which is a count. The wage and industry rows are calculated over all employed people. The sample is restricted to adults aged 27-64 who are childless, do not live in group quarters, and are at or below 138 percent of the Federal Poverty Line. Individuals in states with confounding state-level programs are dropped from the sample. Wages are in real 1999 dollars.

states never expanded or had not expanded before 2020, 17 states expanded in 2014, and seven states expanded after 2014.

5 Empirical Strategy: A Difference-in-Difference Design

Having built a sample of low-income workers, who we can say with almost certainty did not have access to Medicaid before the expansion, we turn to estimating the effect of the Medicaid expansion on their labor market arrangements. We use the difference-in-difference (DiD) strategy from Callaway and Sant'Anna (2021) to estimate the effect of Medicaid expansion on the labor market outcomes of low-income workers. Let Y denote the share of our sample with a particular labor market outcome. Let $Y_{it}(0)$ denote state i's untreated outcome at time t, and let $Y_{it}(g)$ denote state i's outcome at time t if they were first treated at time g. Let G_{ig} be a dummy that equals one if state i was first treated in time period g. The Average Treatment Effect on the Treated (ATT) in year t for the group first treated in year g is the expected difference between the outcome variable with and without treatment,

$$ATT(g,t) = \mathbb{E}[Y_{it}(g) - Y_{it}(0)|G_{ig} = 1].$$

The ATT is typically estimated using a two-way fixed effect difference-in-difference (DiD) approach:

$$Y_{it} = \alpha_i + \phi_t + \beta D_{it} + \epsilon_{it}$$

where Y_{it} is the outcome variable (employment share in part-time work or self-employment), α_i is a fixed effect for state i, ϕ_t is a fixed effect for year t, and D_{it} is a dummy equal to 1 if state i expanded Medicaid in year t or before. In a 2x2 DiD (2 time periods, one before and one after treatment, and 2 groups, a treated and a control), the coefficient β can be interpreted as the casual parameter $ATT(g,t)$.

However, as discussed extensively in Goodman-Bacon (2021), when treatment timing is staggered across units, the casual interpretation of β from this two-way fixed effect approach becomes less clear. The two-way fixed effect approach uses every possible 2x2 design, including one in which the early-treated group is the control group and the late-treated group is the treated group. This biases the ATT if treatment effects change over time. Further, this approach aggregates the ATTs from each 2x2 together using an un-intuitive weighting scheme that puts relatively high weights on units treated in the middle of the sample period. In all, the two-way fixed effect difference-in-difference approach is not guaranteed to recover an interpretable causal parameter.

Callaway and Sant'Anna (2021) addresses these issues with a two-step approach. First, every feasible 2x2 DiD design possible is computed. In our setting, consider the states that expanded Medicaid in 2014. For this group, six 2x2 DiDs are computed, one for each year between 2014 and 2019 (as our data ends in 2019). Each 2x2 DiD compares the 2014 expanders to the states that have not yet received treatment, using the year before treatment, 2013, and one of the years between 2014 and 2019.[6] This step is repeated for the states that expanded in 2015, 2016, and 2019. Each 2x2 DiD yields an average treatment effect $ATT(g, t)$.

Second, the $ATT(g, t)$s are aggregated together. Let e be event time – the time elapsed since treatment was first adopted, $e = t - g$. For all possible event times, we average the $ATT(g, t)$s to estimate the average treatment effect e periods after treatment, $ATT(e)$. Then we take the average of all the $ATT(e)$s to get a single average treatment effect for Medicaid expansion, ATT:

$$ATT = \frac{1}{T-1} \sum_{e=0}^{T-2} ATT(e) \tag{3}$$

$$ATT(e) = \sum_{g \in \mathcal{G}} \mathbf{1}\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g + e) \tag{4}$$

where T is the last year in our sample, G denotes the year when a unit first becomes treated, and $\mathcal{G}$ is the support of G. Turning to the components of $ATT(e)$, the indicator function equals one if the data covers state g at least e periods after treatment. The second term is the probability a state is in group g, given that the data covers state g at least e periods after treatment. Hence, these two terms together act as weight; groups are weighted by the number of states that are in them. We interpret $ATT(e)$ as the effect of Medicaid on our outcome e periods after treatment. We interpret the parameter ATT as the expected effect

[6]For our control group, we could use either not-yet-treated states or never-treated states. We use the not-yet-treated states because doing so allows additional states, the 2020 and 2021 expanders, to be included in the control group. This increases our number of observations.

of Medicaid expansion on our outcome variable.

Identification of each $ATT(g, t)$, and thus the aggregate ATT, requires the parallel trends assumption to hold. This assumption requires that expected changes in the untreated outcomes across time are identical between the states that expanded Medicaid and those that never expanded. The parallel trend assumption is un-testable, but researchers typically look at pre-treatment characteristics to determine if it is plausible. If characteristics that are expected to affect how Medicaid expansion and work arrangements interact across time are balanced across treatment groups, then the assumption is expected to hold (Sant'Anna and Zhao, 2020). If these characteristics are not balanced, then researchers typically control for them. Table 2 shows observable characteristics by treatment group in the pre-treatment period; the characteristics are fairly balanced across treatment groups. We do not find strong evidence against the plausibility of the parallel trend assumption. Nevertheless, we include time-invariant controls in our analysis for robustness. To estimate each $ATT(g, t)$ with controls, we use the doubly robust estimator from Sant'Anna and Zhao (2020), as recommended by Callaway and Sant'Anna (2021).

6 Results

We use our difference-in-difference strategy to measure the effect of Medicaid expansion on the labor market outcomes of low-income workers. Table 3 presents our main results. We find that Medicaid expansion had a small, statistically insignificant effect on the share of the sample of low-income adults in every labor market outcome, with effects indistinguishable from zero. For instance, we find that Medicaid expansion increased the percent of our sample in part time positions by 0.074 pp, with standard errors of 0.367. For self employment, we find an effect of -0.241 pp, with standard errors of roughly the same magnitude as the treatment effect.

These results are robust to alternative specifications with varying controls. Table 4 shows the average treatment effect for self employment, part-time status, and NILF using various controls. (The other outcomes, unemployment and full-time, are omitted for brevity.) We control for the pre-treatment characteristics that were the most imbalanced between the non-expanders and the 2014 expanders: age, sex, race, college completion, and share of workers in the construction industry. As with the specifications without controls, the average

Table 2: Pre-treatment Characteristics and Outcomes by Medicaid Expansion Year

	Medicaid Expansion Group		
	Non-expanders	2014	Late
Wage	6900	6700	6800
Rural	40	34	42
Age $\geq$ 50	48	49	51
College	13	14	13
Male	48	48	49
White, non hispanic	58	69	69
Black, non hispanic	23	16	21
Hispanic	15	10	6
Other Race, non hispanic	4	6	5
Construction	11	8	9
Manufacturing	7	8	8
Natural resources and mining	3	2	2
Service-producing	79	82	81
Full time	19	17	17
Part time	8	10	9
Self employed	6	5	5
Employed	34	32	32
Unemployed	19	21	18
NILF	48	47	50
Observations	51872	39784	15613

Notes: The table displays descriptive statistics for our 2010 ACS sample, grouping observations by the year their state of residence expanded Medicaid. All rows are in percentages except wage, which is a weighted average, and observations, which is a count. The wage and industry rows are calculated over all employed people. The sample is restricted to adults aged 27-64 who are childless, do not live in group quarters, and are at or below 138 percent of the Federal Poverty Line. States with confounding state-level programs, which include all early expanders, are excluded from the table. The states that expanded after 2019 are included in the non-expanders group, as they are in the control group in our analysis. Wages are in real 1999 dollars.

Table 3: ATTs of Medicaid Expansion on Childless, Low-Income Adults

	Full Time	Part Time	Self Emp.	Unemployed	NILF
ATT	0.221	0.074	–0.241	–0.091	0.038
	(0.442)	(0.367)	(0.226)	(0.666)	(0.629)

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The table shows the average treatment effects of Medicaid expansion on the share of our low-income sample in part-time jobs and self-employment. Data is drawn from the 2010 to 2019 American Community Survey, as discussed in Section 4.

treatment effect for each specification with controls is statistically insignificant. For instance, with controls the treatment effect of medicaid expansion on part time status ranges from -0.232pp to 0.640pp, and each specification's standard errors are larger than its the standard errors are larger in magnitude than its treatment effects.

These results are also robust to changes to the underlying sample of low-income workers. We modify the original sample by 1) increasing the income cut-off to 200% of the FPL and 2) removing the income cut-off and instead filtering to people with less than a college education. We make these changes to mitigate concerns that the Medicaid expansion and its effect on labor supply impacted our sampling processes, changing the underlying sample of workers across time. The results, which are omitted for brevity, are similar to that of the original sample. The treatment effects are small and statistically insignificant.

We further decompose the effect of the expansion on both short- and long-run outcomes. Figures 1 and 2 plots the average treatment effect by year since treatment, $ATT(e)$ as defined in Equation (4), for part-time status and self-employment. For the part-time outcome, each estimate in the post-treatment period is indistinguishable from 0. For self-employment, the ATT for the year immediately following treatment is negative and distinguishable from zero. However, one of the pre-treatment ATTs is also negative and distinguishable from zero, and all other post-treatment ATTs are not indistinguishable from zero. We conclude that the expansion had negligible effects on part-time and self-employment status in both the short run and long run.

These results suggest that Medicaid Expansion had a negligible effect on the share of low-income, childless, disabled adults in part-time positions or self-employment. Medicaid access did not cause a large share of these workers to switch from traditional jobs with subsidized employer health plans to more flexible jobs without such plans. Or more generally, Medicaid access did not shift workers out of the workforce.

Why do we find no economically or statistically significant effect of Medicaid Expansion on work arrangements for our low-income sample? One reason is that the sample size is small, biasing results towards zero and widening confident intervals. The second is that preference for employer provided health insurance varies across workers, and workers that want such benefits selected into traditional, full time employment before Medicaid expansion. Third, how much workers value wages, schedule flexibility, and other amenities or benefits excluding health insurance could be much larger in magnitude than preferences for health insurance. This would make the effect of changes in health insurance have a small impact on worker's preferences towards jobs.

7 Conclusion

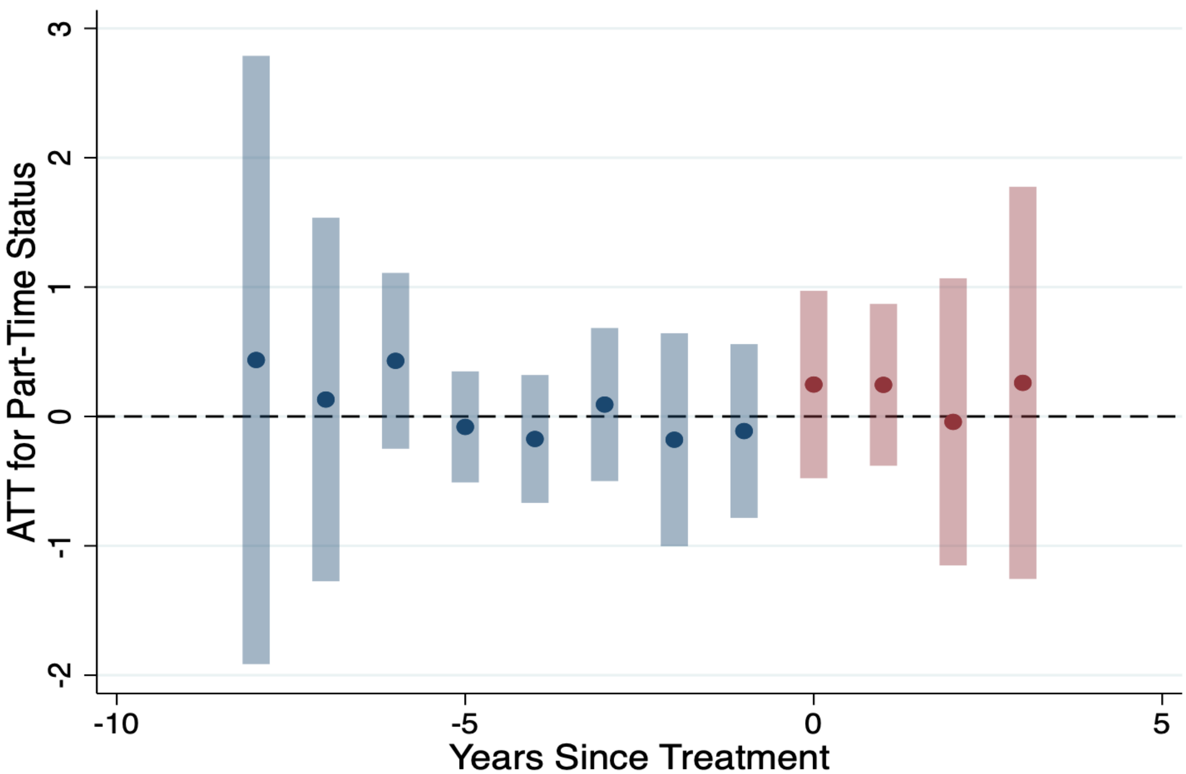
Using a difference-in-difference design, we test whether Medicaid Expansion increased employment of low-income, childless, disabled adults in part-time positions and self-employment. We build a sample of low-income workers that we can say with almost certainty did not have access to Medicaid before the expansion — childless, non-disabled, low-income adults in states without confounding state-level policies. We find no discernible impact of the policy on part-time or self-employment rates for this sample, in both the short and long term. We conclude that Medicaid eligibility has little impact on both work arrangements for low-income workers.

Table 4: Robustness: ATTs with Controls

	Part Time			Self Employment			NILF		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT	–0.041	–0.232	0.640	–0.724	–0.345	–0.396	0.583	0.429	–0.185
	(0.786)	(0.442)	(1.382)	(0.561)	(0.239)	(0.450)	(1.062)	(0.764)	(1.983)
Age $\geq$ 50	✓	-	-	✓	-	-	✓	-	-
Male	✓	-	-	✓	-	-	✓	-	-
White	✓	-	-	✓	-	-	✓	-	-
College	-	✓	-	-	✓	-	-	✓	-
Construction	-	-	✓	-	-	✓	-	-	✓

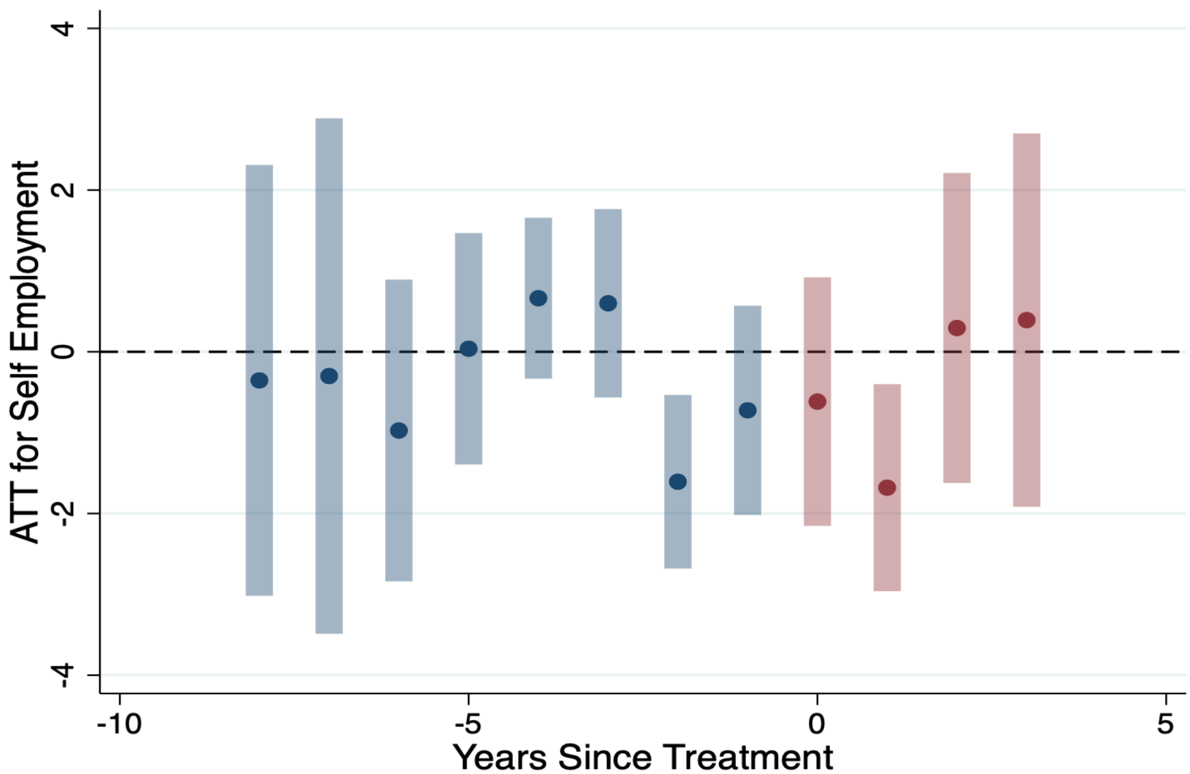
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The table shows the Average Treatment Effects of Medicaid Expansion on the share of the low-income sample in part-time jobs and self-employment, using various combinations of controls. Underlying data is discussed in Section 4.

Figure 1: Short- and Long-Term Effects of Medicaid on Part-Time Jobs



Notes: The figure shows the effect of Medicaid expansion on the share of our low-income sample in part-time jobs by years since first receiving treatment. The bands are 95% confidence intervals. Pre-treatment years are blue, while post-treatment are red. Underlying data is described in Section 4.

Figure 2: Short- and Long-Term Effects of Medicaid on Self-Employment



Notes: The figure shows the effect of Medicaid expansion on the share of our low-income sample in self-employed positions by years since first receiving treatment. The bands are 95% confidence intervals. Pre-treatment years are blue, while post-treatment are red. Underlying data is described in Section 4.

References

AHCCCS, "Difficult Choice: Expanding Adult Medicaid Coverage," n.d. .

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman, "The impact of Medicaid on labor market activity and program participation: evidence from the Oregon Health Insurance Experiment," *American Economic Review*, 2014, *104* (5), 322–328.

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

Currie, J and BC Madrian, "Health insurance and the labour market," *Handbook of Labor Economics*, 1999, *3*, 3356–3363.

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

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

Gooptu, Angshuman, Asako S Moriya, Kosali I Simon, and Benjamin D Sommers, "Medicaid expansion did not result in significant employment changes or job reductions in 2014," *Health affairs*, 2016, *35* (1), 111–118.

Gruber, Jonathan, "Medicaid," in "Means-tested transfer programs in the United States," University of Chicago Press, 2003, pp. 15–78.

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

Kaiser Family Foundation, "Getting Into Gear for 2014: Shifting New Medicaid Eligibility and Enrollment Policies into Drive. Appendix.," 2014. www.kff.org.

_ , "Health Insurance Coverage of the Total Population," 2021. www.kff.org.

_ , "Status of State Medicaid Expansion Decisions: Interactive Map," 2023. www.kff.org.

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

McFadden, Daniel et al., "Conditional logit analysis of qualitative choice behavior," 1973.

Peng, Lizhong, Xiaohui Guo, and Chad D Meyerhoefer, "The effects of Medicaid expansion on labor market outcomes: evidence from border counties," *Health economics*, 2020, *29* (3), 245–260.

Roy, Akiv, "How a GOP Governor Walked Arizona into Obamacare's Medicaid Expansion Trap," 2013. www.forbes.com.

Sant'Anna, Pedro HC and Jun Zhao, "Doubly robust difference-in-differences estimators," *Journal of Econometrics*, 2020, *219* (1), 101–122.

Simon, Kosali, Aparna Soni, and John Cawley, "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*, 2017, *36* (2), 390–417.

Social Security Administration, "Medicaid Program Description and Legislative History," 2015. www.ssa.gov.

U.S. Centers for Medicare & Medicaid Services, "Count income & household size," n.d. www.healthcare.gov.

USDA, "What is Rural?," 2019. www.ers.usda.gov.

A Data Appendix

This section explains how we construct our main sample from the ACS. To construct income as a percent of the federal poverty line (FPL), we construct income and FPLs. We construct FPLs for each person as follows:

$$\text{FPL} = \text{HIUFPGBASE} + \text{HIUFPGINC} * (\text{HIUNPERS} - 1)$$

where HIUNPERS is the number of people within each "health insurance unit" (HIU), HIUFPGBASE is a base level, HIUFPGINC is how much the FPL goes up given each additional person.

We calculate each person's income at the family level using only the income sources that determine Medicaid eligibility: wage, salary, and tips; self-employment income; social security and social security disability income; retirement or pension income; alimony (but only if the divorce or separation was finalized before the start of 2019); capital gains; investment income; rental and royalty income; excluded (untaxed) foreign income; and unemployment compensation (U.S. Centers for Medicare & Medicaid Services, n.d.). All these income sources are identifiable in IPUMS except alimony and unemployment compensation.[7] These two sources are included in the "other income variable," which also includes sources not used to determine Medicaid eligibility, like child support, veteran's disability payments, worker's compensation, and proceeds from loans. In practice, family incomes constructed with and without the "other income" variable are very similar, so we do not include "other income" in our measure of family income. We drop all people with family incomes as a share of FPLs greater than 138%.

IPUMS USA provides a POVERTY variable, which is family income divided by the federal poverty line. However, using this variable to determine Medicaid eligibility is ill-advised because it includes several sources of income, like welfare income, that the government does not include when determining Medicaid eligibility.

We restrict our sample to childless adults. We consider an adult to be childless if their household has no children of their own. We also drop disabled adults, as determined by the independent living difficulty variable; we consider an adult disabled if they have any condition

[7] We assume that capital gains, rental and royalty income, and excluded (untaxed) foreign income are all included in the investment income variable, but judging by the ACS questionnaire, they may be included in the "other income" variable or omitted.

lasting more than six months that makes performing basic tasks difficult or impossible.

We restrict to employed people aged 27 to 64. We drop people living in group quarters, like prisons, and people who report 0 labor earnings. Labor earnings are wage and salary income plus self-employment income.

We use the INDNAICS variable to compute a worker's industry of work. We take the first two digits of this variable to get the worker's 2-digit NAICS code, i.e., their sector.

We use the density variable to determine if a person lives in a rural area. The density variable reports the density of a person's public use metro area, as measured by people per square mile. Following (USDA, 2019), a person lives in a rural area if there are less than 500 people per square mile in their public use metro area.

Our outcome variables of interest are part-time and self-employment status. Self employment status is taken directly from the variable CLASSWKRD. We consider a person part-time if their usual hours worked are less than 30 hours a week.