The Effect of Medicaid Expansion on Work Arrangements

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Abstract

We measure the effect of Medicaid Expansion on the work arrangements of low-income adults. Before the expansion, many of these individuals only had access to subsidized health insurance through a traditional full-time job. After the expansion, they also had access to Medicaid, potentially allowing them to change their labor supply decisions. Using American Community Survey data, we built a sample of low-income adults who only had access to subsidized health plans through a typical full-time job or the Medicaid Expansion. Adults in the sample are childless, spouseless, non-disabled, and reside in states without confounding state-level policies. To identify the effect of newly-found Medicaid access on this sample, we use a difference-in-difference design from Callaway and Sant'Anna (2021) . We find that the expansion had a statistically insignificant effect on the share of our sample in several labor market arrangements: traditional full-time employment, part-time employment, self-employment, unemployment, and not participating in the labor force. These results are robust to including pre-treatment covariates and adjustments to our underlying sample framework. We further decompose treatment effects into short- and long-term effects and find both are statistically insignificant. We conclude that Medicaid Expansion had a negligible impact on both the work arrangements for low-income workers.

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1 Introduction

In the US, purchasing health insurance directly from an insurer is prohibitively expensive. So, most people are covered by a plan subsidized by an employer (Kaiser Family Foundation, 2021). However, employer-provided plans are largely only available to full-time employees (or spouses and children of full-time employees), and economists have extensively studied the distortionary effects of this feature. For example, some economists hypothesize that this locks workers into jobs they would rather not have (e.g. Madrian, 1994).

An alternative to employer-subsidized health insurance is publicly subsidized health insurance, like Medicaid. Medicaid is a federally funded government program that offers low-income people health insurance coverage. After employer-sponsored plans, Medicaid covers the most people in the US (Kaiser Family Foundation, 2021). Access to Medicaid could lessen the distortionary effects of employer health insurance, ultimately affecting labor supply decisions.

This paper studies the effect of Medicaid access on labor market decisions. We exploit the ACA's Medicaid expansion as a natural experiment. Before the expansion, Medicaid was largely only offered to low-income people with children or disabilities. After the expansion, Medicaid was available to everyone in participating states with income below 138 percent of the federal poverty line. The expansion allows us to study the impact of Medicaid access, by comparing the labor market decisions of those who gained access to Medicaid and their counterparts in non-participating states.

Using the American Community Survey (ACS) we build a sample of low-income adults who could only access subsidized plans through a typical full-time job or Medicaid Expansion. We carefully reconstruct family income following the government's Medicaid eligibility guidelines, restricting to those with family income less than 138 percent of the federal poverty line. We drop adults with children or disabilities, as they frequently had access to Medicaid before the expansion. We also filter by age and marital status to ensure that individuals in our sample did not have access to insurance through their parents, spouse, or Medicare. We also filter to states without confounding state-level programs.

Using our ACS sample, we identify Medicaid expansion's effect on the employment statuses of our sample using a difference-in-difference design. 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 find that Medicaid did not affect employment statuses. For example, we reject Medicaid increasing the share of our sample in part-time positions by over 1 percentage point. For self-employment and NILF status, we reject effects larger than 0.2 and 1 percentage point. These results are robust to a battery of covariates and small changes in our underlying sampling framework. We also decompose treatment effects into both short- and long-term effects, finding no effect in either. We conclude that Medicaid expansion had an economically and statistically insignificant effect on low-income worker's work arrangements.

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 outlines background information on Medicaid. Section 3 summarizes the different channels by which Medicaid expansion can effect work arrangements. 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.

[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.

2 Institutional Background: Medicaid

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]

[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

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]

3 How Medicaid Can Effect Work Arrangements

Having discussed how many low-income workers gained access to Medicaid through the expansion, this section outlines how this newly-found access can impact work arrangements.

Job Lock. Economists hypothesis that employer-health insurance causes 'job lock' (e.g. Gruber and Madrian, 1994; Garthwaite et al., 2014; Gooptu et al., 2016). This is the phenomena where workers stay in full time jobs solely for access to their employer-sponsored plans. Medicaid access could alleviate job lock, increasing the percent of workers unemployed, not participating in the labor force, or in work arrangements without employer-sponsored plans, like self employment or part time positions.

Improved Health. Health impacts the amount of hours employees work. Currie and Madrian (1999) reviews the literature, and finds that negative health limits labor force participation. Medicaid expansion could improve worker's health, thus increase their labor supply, decreasing the share of adults not in the labor force.

Internalizing the Eligibility Cut-Off. Medicaid is largely only available to those with family income below 138 percent of the Federal Poverty Line. Workers could internalize this hard cut-off, decreasing their labor supply so that their family income lies below 138 percent of the Federal Poverty Line. This channel could decrease labor supply on the extensive and intensive margin.

In Kind Transfer. Medicaid acts like a monetary transfer, ultimately expanding low-income worker's budgets. With increased income, workers may substitute away from labor

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).

to leisure. This channel could then shift workers from full time arrangements to part time, or employment to out of the labor force.

More Time Searching for Jobs. Job search is a two-sided game where both workers and firms try to find a good match. Given a job offer, a worker's outside option is unemployment. Without health insurance, workers may feel compelled to accept a job offer even if it is a poor match. With Medicaid, a worker's outside option of unemployment is improved, allowing workers to be more choosy when picking a job. This channel could ultimately increase unemployment.

Altogether, the effect of Medicaid, in theory, is unclear. Different channels have different effects, so even the direction of the effect of Medicaid expansion is difficult to predict without an empirical analysis.

4 Data: Building a Sample of Low-Income Workers

We use worker level micro data from the 2010 to 2019 American Community Survey (ACS) to study the effects of Medicaid expansion. 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 percent 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]

[4] The ACA permitted dependents to remain on their parent's 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

The resulting sample of low-income adults has a total of around 370,000 observations, averaging around 37,000 each year. Before the expansion, people in our sample had access to subsidized health plans only through employment. After, they had access to such plans through either employment or Medicaid. 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 workers 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 states never 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 gained access to Medicaid through the expansion, we estimate the expansion's effect 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,

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

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	6300	6800	6300
Rural	29	30	31
Age $\geq$ 50	23	26	26
College	16	16	17
Male	34	36	38
White, non hispanic	54	52	51
Black, non hispanic	27	28	28
Hispanic	13	14	14
Other Race, non hispanic	2	3	3
Construction	9	8	8
Manufacturing	7	7	6
Natural resources and mining	2	2	2
Service-producing	81	83	85
Full time	20	24	23
Part time	10	11	12
Self employed	5	5	5
Employed	35	40	40
Unemployed	24	15	12
NILF	40	44	48
Observations	35022	38254	35954

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.

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 (two time periods, one before and one after treatment, and two 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

[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.

we take the average of all the $ATT(e)$s to get a single average treatment effect for Medicaid expansion, ATT:

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

$$ATT(e) = \sum_{g\in\mathcal{G}} \mathbf{1}\{g+e \leq T\} P(G=g|G+e \leq T) ATT(g, g+e) \tag{2}$$

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 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).

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

	Medicaid Expansion Group		
	Non-expanders	2014	Late
Wage	6500	6100	6300
Rural	32	25	33
Age $\geq$ 50	21	23	26
College	15	17	16
Male	33	34	35
White, non hispanic	48	60	59
Black, non hispanic	31	22	29
Hispanic	17	11	7
Other Race, non hispanic	5	6	5
Construction	11	8	9
Manufacturing	6	7	7
Natural resources and mining	2	2	2
Service-producing	80	83	82
Full time	22	18	20
Part time	9	11	10
Self employed	6	5	4
Employed	37	34	34
Unemployed	24	26	22
NILF	40	40	44
Observations	15801	13958	5263

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	0.737	0.102	–0.287	0.253	–0.806
	(0.834)	(0.421)	(0.285)	(0.760)	(0.980)

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.

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 percentage of our sample in part-time positions by 0.102 pp, with standard errors of 0.4. We can reject a positive effect on part-time status larger than one percentage point. For self-employment, we find an effect of -0.287 pp, with standard errors of roughly the same magnitude as the treatment effect. We can reject a positive effect on self-employed status larger than roughly 0.3 percentage points.

These results are robust to alternative specifications with varying controls, as shown in Table 4. We control for the pre-treatment characteristics that were the most imbalanced between the non-expanders and the 2014 expanders: age, sex, race, and college completion. As with the specifications without controls, the average treatment effect for each specification with controls is statistically insignificant. For instance, with controls, the treatment effect of Medicaid expansion on part-time status is roughly -0.64pp, with standard errors double the magnitude of the treatment effect.

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, 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. We also modify the original sample by including married individuals, not just singles. This increases the number of observations, while introducing people who may have access to spousal coverage. The results, omitted for brevity, are similar to the original sample's. 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 (2), 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 and long run.

7 Conclusion

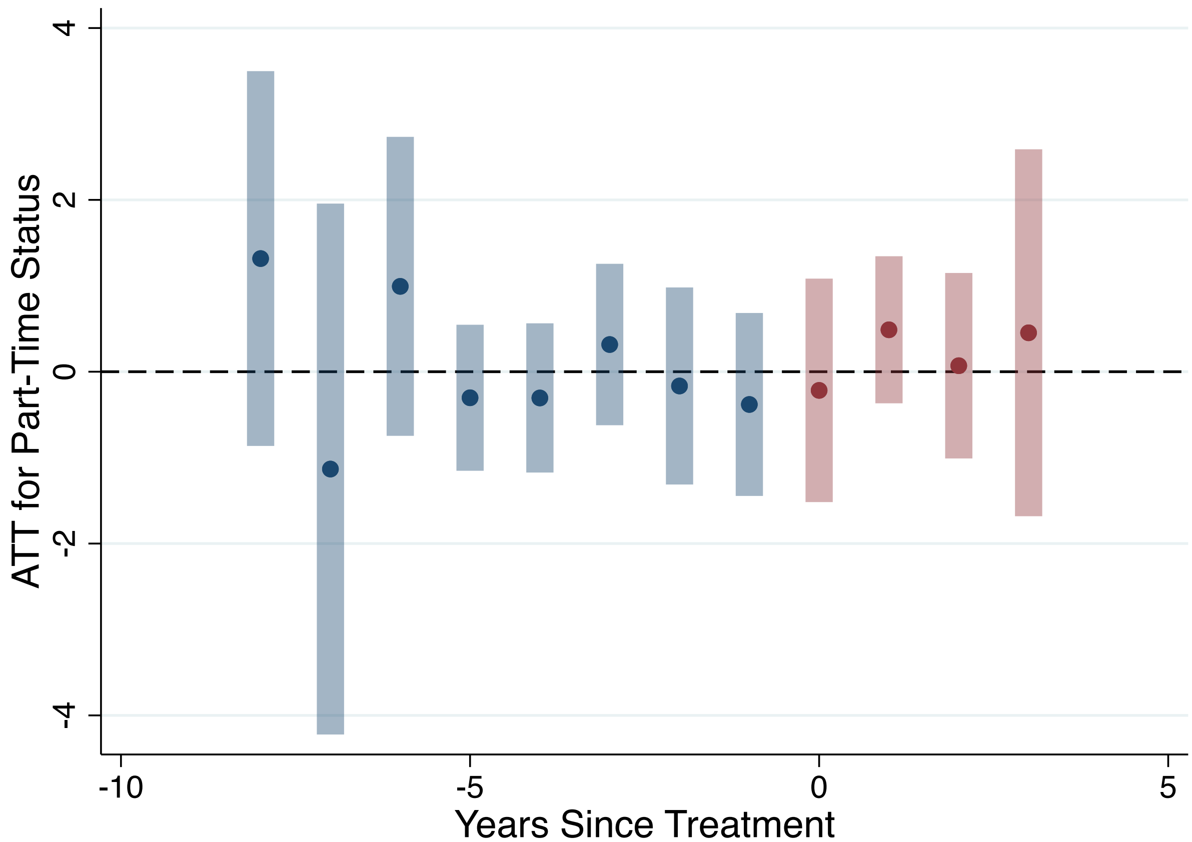
Using a difference-in-difference design, we test whether Medicaid Expansion affected the labor supply decisions of low-income, spouseless, childless, non-disabled adults. We build a sample of these individuals using ACS data. We find no discernible impact of the policy on work arrangements in the short 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

	Full time		Part Time		Self Employment		Unemployment		NILF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ATT	–1.041	–1.075	–0.637	–0.650	–0.286	–0.260	3.260	3.030	–1.296	–1.044
	(2.018)	(4.307)	(1.413)	(1.416)	(0.880)	(0.898)	(2.542)	(3.105)	(1.368)	(2.308)
Age $\geq$ 50	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Male	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
White	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
College	-	✓	-	✓	-	✓	-	✓	-	✓

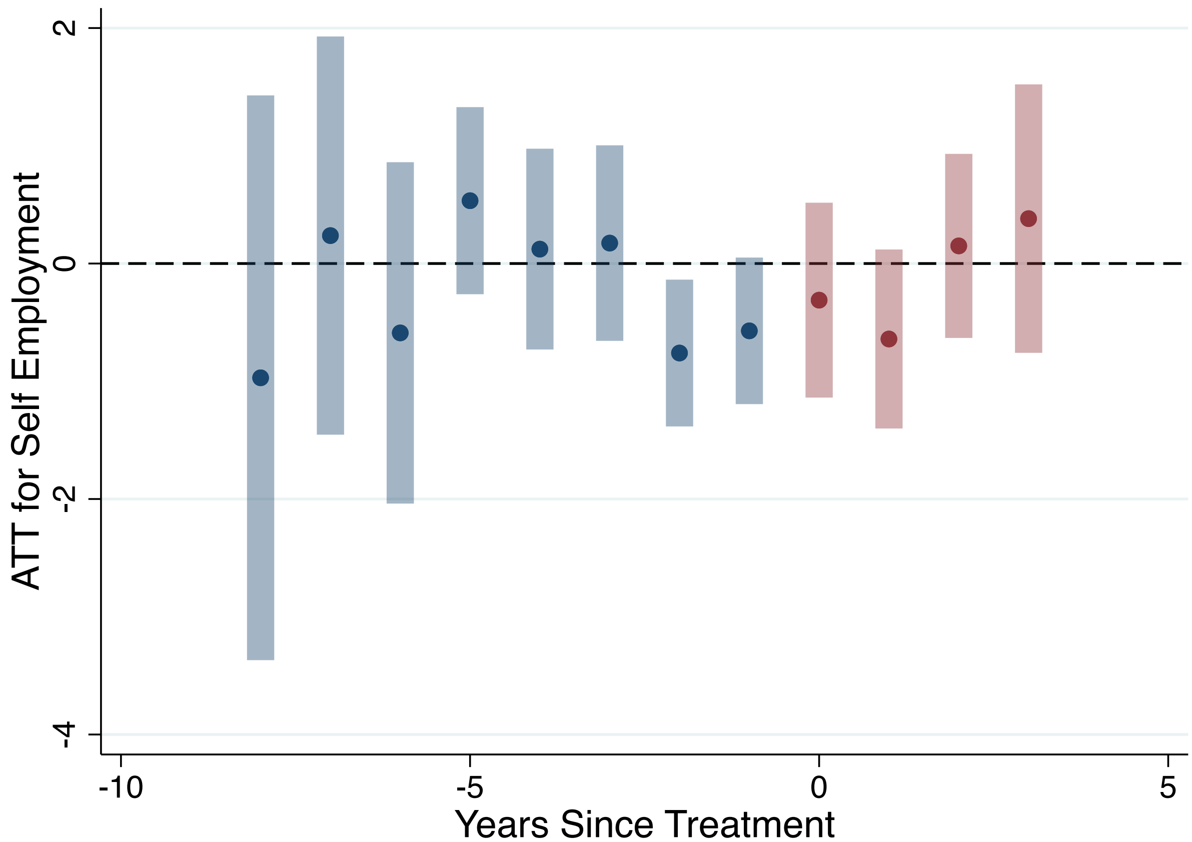
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The table shows the Average Treatment Effects of Medicaid Expansion on the share of the low-income sample in part-time jobs and self-employment, using various combinations of controls. Underlying data is discussed in Section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

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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:

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

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.