DOES MEDICAID EXPANSION AFFECT EMPLOYMENT TRANSITIONS?

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Abstract

This paper investigates the pre/post labor market implications of the Affordable Care Act's (ACA) Medicaid expansion for a population near the eligibility cutoff. Using an arguably exogenous variation at the eligibility cutoff, I find that Medicaid enrollment increases for adults without dependent children. This leads to an employment transition from full-time ($\geq$35 Hrs) to part-time employment ($<$35 Hrs) after the expansion. The employment transition is mainly driven by the increase in employment for working less than 20 hours. Falsicification checks show no effect on employment for non-expansion states and Medicare-eligible adult groups. The estimates are robust to the inclusion of early expansion states, increasing bandwidths, and various functional forms of the running variable. These findings imply that individuals primarily work to secure private health insurance ("employment lock") prior to the expansion. When replicating the existing studies that use a difference-in-differences (DD) model with expansion states as the treatment group, I find no employment effects. The main limitation of this DD model is the large and heterogeneous treatment group that includes adults who are less likely to be eligible for Medicaid.

Keywords: ACA's Medicaid expansion; labor market outcomes; employment-lock; difference-in-discontinuities

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1. Introduction

The Affordable Care Act (ACA), also known as Obamacare, is enacted on March 23, 2010 by President Barack Obama. The reform targets multiple dimensions of the health care status quo in the United States. One of the most debated components of the reform is the Medicaid expansion in 2014, which proposed a nationwide expansion of the eligibility limits to 138% of the federal poverty level (FPL). Although the Supreme Court decision in 2012 allowed states to opt-out of expansion, most of the coverage gains for uninsured adults in the post-reform are due to the ACA's Medicaid expansion (Frean, Gruber, and Sommers, 2017).

The literature has provided an extensive set of studies that investigate the impact of Medicaid expansions prior to 2014 on health outcomes[1] and fiscal measures[2]. An important issue that gained more attention in recent years is the labor market implications of Medicaid expansions. The "employment lock" phenomena implies that individuals primarly work to secure private health insurance.[3] A Medicaid-induced income effect or "windfall" could affect labor market behavior of individuals by allowing flexibility in employment choices. The income effect could make the job search and/or reduction in working hours less costly.[4] In fact, the Congressional Budget Office estimates a reduction in the net total of hours worked by around 1.5% to 2% from 2017 to 2024 due to the ACA's Medicaid expansion (CBO, 2014).

This paper provides a novel contribution to the literature by investigating all possible employment transitions resulting from the ACA's Medicaid expansion for a population

[1]Piper, Ray, and Griffin (1990) found that Medicaid coverage in Tennessee did not improve the use of prenatal care and hence there was no significant effect on birth outcomes including birth weight and neonatal mortality. Sommers, Baicker, and Epstein (2012) found a strong evidence of a reduction in mortality, improved self-assessed health, and access to care in three expansion states (see, also, Sommers, Long, and Baicker, 2014). Baicker et al. (2013), using a randomized experiment in Oregon, found that both health care utilization and self-assessed health improved after expansion but the effect was not prevalent for physical health in the short-run.

[2]It is argued that Medicaid programs worsen fiscal outcomes of states and the budgetary pressure is highest during recessions. Under the presence of fiscal pressures, deep cuts in eligibility are avoided at the expense of trimming some benefits (see, for example, Coughlin et al., 1994 and Hoadley, Cunningham, and McHugh, 2004).

[3]Using the loss of public coverage in Tennessee, Garthwaite, Gross, and Notowidigdo (2014) found an increase in employment that suggests a strong employment lock. Gooptu et al. (2016), however, found no employment lock under the ACA's Medicaid expansion.

[4]This outcome has been predicted by the economic theory of the allocation of time. A simple model of leisure, home production, and work shows that an increase in income increases leisure, reduces work in the market, and has no effect on home production (Gronau, 1977).

near the eligibility cutoff. The impact of the expansion on employment transitions, observed as a discontinuity at the cutoff, is captured by exploiting the changes in simulated eligibility vis-á-vis the FPL. The main group of interest is the non-elderly adults without dependent children ("childless adults"), a group that gained access to Medicaid coverage after the ACA.[5] Parents and children, however, have prior eligibility that could confound the estimates on enrollment due to increased outreach.[6]

There are a few studies in the literature that focus on the employment effects of the ACA's Medicaid expansion. Most of these studies analyze the effect of Medicaid expansion on childless adults by using multiple expansion states. These studies find little to no effect on employment (see, for example, Gooptu et al., 2016, Leung and Mas, 2016, Kaestner et al., 2017), while contradicting to the findings for Wisconsin (WI), Tennessee (TN), and Connecticut (CT) (see, Dague, DeLeire, and Leininger, 2017, Garthwaite, Gross, and Notowidigdo, 2014, Kim, 2016, respectively).[7] The estimates for WI and CT suggest a reduction in employment by 12 percent after Medicaid expansion and an increase in employment by 6 percent in TN when childless adults lose Medicaid coverage, which is considered as an evidence of employment lock.[8] Table 1 provides a comprehensive list of the recent studies and compares the findings with respect to earlier Medicaid expansions on different adult groups.[9] Although couple of studies investigate the expansions in 1970s, I restrict the list of studies to post-2010 to understand the impact of recent Medicaid expansions on employment.[10] Table 1 shows that employment effects of Medicaid expansion are mixed among adult groups with different signs and magnitudes. In particular, studies that use a differences-in-differences (DD) model with expansion states as the treatment group show no employment effects (or limited effects) after the ACA's Medicaid expansion.

[5]Nine states expanded eligibility for childless adults in 2013. These states are: Arizona (AZ), Colorado (CO), Connecticut (CT), Delaware (DE), District of Columbia (DC), Hawaii (HI), Minnesota (MN), New York (NY), and Vermont (VT).

[6]The ACA's Medicaid expansion is unique in terms of its outreach efforts that involve mass marketing campaings. If previously eligible adults are coming out of the woodwork due to increased outreach, then the enrollment is likely to be driven from the "woodwork" effect, also referred as the "welcome-mat" effect (Sommers and Epstein, 2011, Frean, Gruber, and Sommers, 2017, Aslim, 2017).

[7]Gooptu et al. (2016) also find no transition between part-time and full-time employment.

[8]Tuzemen and Nakajima (2014) support the findings on employment lock using a general equilibrium model that accounts for worker and firm heterogeneity in labor markets.

[9]I only select empirical studies that investigate the impact of Medicaid expansions on adult groups. Studies on the Children's Health Insurance Program (CHIP) are not in the scope of this paper.

[10]Some of the earlier studies focus on potential changes in work incentives when there is an increase in Medicaid income thresholds (Yelowitz, 1995 and Meyer and Rosenbaum, 2001).

This paper distinguishes from prior studies on multiple grounds. First of all, I introduce an alternative quasi-experimental design by using an arguably exogenous variation at the eligibility cutoff. I use a regression discontinuity (RD) model that incorporates the dichotomous treatment (i.e., Medicaid eligibility) as a deterministic function of the relative distance to the eligibility cutoff, which is centered around 138% FPL.[11] It has important gains with respect to internal validity by comparing adults with similar observable characteristics around the eligibility cutoff. This procedure is shown to yield credible results as it is in a randomized experiment (see, for example, Battistin and Rettore, 2008, Lee, 2008, Lee and Lemieux, 2010). Estimating the difference in discontinuities between pre- and post-2014, mainly to eliminate pre-existing trends, yields the policy effect. This model is coined as "difference-in-discontinuities" in the paper.[12] This is the first study to use this approach to investigate the employment effects of the ACA's Medicaid expansion.

Secondly, the data set used in this study is the Current Population Survey (CPS) from January 2010 to July 2016 with more years of data in the post-period than the existing studies. Leung and Mas (2016) use the CPS data between January 2010 to July 2015. Gooptu et al. (2016) use the same data up to March 2015. The largest years of data used among these studies are up to May 2016 by Kaestner et al. (2017). In addition, it is a common practice in the literature to construct a simulated eligibility measure using a single data source that has information on both household income and outcome variables (see, for example, Cutler and Gruber, 1996, Gross and Notowidigdo, 2011, Sabik et al., 2017). A major contribution of this study is the construction of a simulated eligibility measure using two data sets, March CPS and basic monthly CPS, where the former has information on household income and the latter on labor market outcomes for each month. This overcomes the issue of using March CPS as the sole data source, which does not capture the monthly variation in eligibility limits and outcome variables.[13]

[11] The eligibility thresholds vary for DC and WI. Eligibility in DC and WI are determined based on 215% FPL and 100% FPL threshold, respectively.

[12] Grembi, Nannicini, and Troiano (2016) use a similar empirical strategy to examine the impact of fiscal rules on taxes and budget deficits. The difference-in-discontinuities model is also used in the health economics literature (see, for example, Chay, Kim, and Swaminathan, 2010; Hu, Decker, and Chou, 2017).

[13] For example, Indiana and Louisiana increased the eligibility limit on February 2015 and July 2016, respectively. In March CPS, all of the changes in eligibility limits are assumed to happen in March, which could lead to an underestimation of the effect if people change their employment decisions after the expansion.

Using a difference-in-discontinuities model, I find a statistically significant jump for Medicaid enrollment at the eligibility cutoff. This leads to an employment transition from full-time (≥35 Hrs) to part-time employment (<35 Hrs) after the ACA's Medicaid expansion. The employment transition is mainly driven by the increase in employment for working less than 20 hours. There is also heterogeneity across subgroups with respect to employment transitions. The estimates on employment transitions are robust to the inclusion of early expansion states, increasing bandwidths, and varying functional forms of the running variable. Falsification checks show no employment effects on non-expansion states and Medicare-eligible adult groups. All of these findings imply a strong presence of employment lock prior to the expansion.

I replicate existing studies that use a difference-in-differences (DD) model with expansion states as the treatment group. I use various samples that are comparable to this study and existing studies in the literature. The estimates of DD model suggest no employment effects after the ACA's Medicaid expansion. This study shows that one possible reason why no employment effects are found in existing studies is that the treatment group, which is expansion states, is large and heterogeneous. Simulated eligibility measure, however, alleviates these concerns by including a population that benefits from the expansion.

In what follows, Section 2 provides a brief background information about the Medicaid program. Section 3 introduces the data, sample, and variables. The empirical strategy is discussed in Section 4. Section 5 presents the results. Section 6 concludes with a discussion.

2. Background Information on the Medicaid Expansion

2.1. Information on Expansion States and Eligibility

Prior to the ACA, access to Medicaid coverage was limited to children, pregnant women and parents who are below a specific income threshold.[14] Elderly and disabled adults on supplemental security income (SSI), mainly those below 75 - 83% FPL, were also eligible for Medicaid. A group that did not meet any of the eligibility categories was non-elderly

[14] Medicaid eligibility thresholds for children and pregnant women, excluding CHIP, have varied between 100 - 133% FPL whereas this cutoff was much lower for parents in non-expansion states (see Table 2 for updated thresholds).

adults without dependent children - so called "childless adults". The ACA, however, was successful in eliminating categorical eligibility (e.g., disability, pregnancy etc.) and allowing childless adults to access to care via Medicaid.[15]

In the post-ACA period, states had the option to fully subsidize low-cost health insurance plans to adults with incomes below 138% FPL and partially subsidize those between 138 - 400% FPL.[16] The Supreme Court decision, however, ruled out the reform to be an obligation for states (Supreme Court of the United States, 2012). Figure 1 depicts the expansion profile of states. As of July 2016, there are 32 expansion states and 19 non-expansion states. It is important to emphasize that Wisconsin (WI) has a unique case among non-expansion states, where health coverage is fully subsidized to adults below 100% FPL under BadgerCare. In the following analysis, WI is treated as an expansion state due to its high income threshold. There are also major differences in state characteristics between expansion states and non-expansion states, which can be seen from the distribution of states on Figure 1. It is cruical to account for these differences in order to disentangle the effect of Medicaid expansion. This important issue is further discussed in Section 3.

Table 2 summarizes the effective expansion date for each state and the corresponding eligibility levels for both childless adults and parents. As evident from the effective dates, not all expansion states have expanded at the same time. In fact, seven states expanded Medicaid after the main expansion on January 2014.[17] There are also nine early expansion states that provided health coverage to low-income childless adults in 2013.[18] I exclude these nine states in the benchmark analysis because the change in labor supply could be driven from either by the change in income limits or the "woodwork" effects.[19] The adults who are eligible but did not enroll for Medicaid might take-up after the outreach efforts of the ACA's Medicaid expansion (Sommers and Epstein, 2011; Sonier, Boudreaux, and

[15]Several states have expanded Medicaid to childless adults before the ACA. Sommers, Baicker, and Epstein (2012) use the expansions for Arizona (November 2001), Maine (October 2002), and New York (September 2001) and show that the expansions increase access to care and reduce mortality for childless adults between 35 to 64 years of age. The authors also caution the readers about the external validity of their estimates because of limiting the sample to three expansion states.

[16]The subsidies above the eligibility threshold are not uniform. Low cost-sharing plans are available for those between 138 - 250% FPL.

[17]Three recently adopting states are Alaska (AK), Montana (MT), and Louisiana (LA). The effective implementation of the policy by AK is on September 1, 2015. MT's effective implementation date is January 1, 2016. Finally, the expansion date for LA is July 1, 2016.

[18]The list of these states are: AZ, CO, CT, DE, DC, HI, MN, NY, and VT.

[19]Leung and Mas (2016) also exclude 13 states that had limited benefits in 2013 and their DD estimates are robust to the exclusion.

Blewett, 2013).[20] However, I probe the robustness of the estimates to the inclusion of early expansion states.

Overall, the sample in this paper is composed of 23 expansion states with 138% FPL eligibility for childless adults, 1 (expansion) state with 100% FPL eligibility for childless adults, and 18 non-expansion states. An important issue on adults who are eligible for Medicaid is whether they actually take-up the coverage. In the next section, this issue is discussed thoroughly using an administrative data.

2.2. Medicaid Enrollment

Medicaid take-up rate is cruical in understanding the effect of the reform on labor market outcomes. If eligible adults do not enroll for Medicaid, then the changes in labor supply cannot be attributed to the ACA's Medicaid expansion. The CBO estimates that 13 million newly eligible individuals will take-up Medicaid and CHIP in 2016 with an increase to 16 million individuals after 2019 (CBO, 2015).[21] The predictions signal a relatively high marginal take-up rate after the Medicaid expansion in 2014.[22] Studies that simulate the effect of Medicaid expansion show a reduction in the number of underinsured people by 70 percent and the number of uninsured by 20 million via the provision of low cost-sharing plans (Schoen et al., 2011, Parente and Feldman, 2013).

The updated total enrollment in July 2016 for both Medicaid and Children's Health Insurance Program (CHIP) is more than 73 million with an enrollment growth rate of 28.72% between the average of July - September 2013 and July 2016.[23] There is an upward trend in the take-up rate of Medicaid especially with the increase in outreach after 2014. The earlier studies, however, show modest take-up rates for Medicaid.[24]

[20] These concerns could be addressed if the researcher have access to individual-level information on health insurance prior to 2014. The current data set has limitations in observing enrollment and the woodwork effects are not in the scope of this paper.

[21] Figure A1 shows the total enrollment growth rate of Medicaid and CHIP. It is observed that enrollment is higher in expansion states relative to non-expansion states. The recent bending of the curve might be due to a smaller pool of uninsured people and a possible convergence to a steady-state.

[22] It is important to distinguish between marginal take-up and average take-up after the expansion. Marginal take-up includes those who are newly eligible whereas average take-up includes all eligible individuals.

[23] The numbers of enrolled are 51,557,834 and 21,909,593 in expansion states and non-expansion states, respectively. For the growth rate, the average enrollment in July - September 2013 and the enrollment in July 2015 exclude Connecticut and Maine. Data are publicly available by Centers for Medicare & Medicaid Services (CMS) and it is accessible from http://www.medicaid.gov.

[24] The estimates of average Medicaid take-up among adults vary between 52% to 81.3% (Sommers et al., 2012).

Using the CPS data from 2007 to 2009, for example, Sommers and Epstein (2010) found an average Medicaid take-up rate of 61.7% in the U.S. with Massachusetts having 80% average take-up. Kenney et al. (2012), using the 2009 American Community Survey (ACS), found the average Medicaid take-up rate as 67% for adults. The outreach efforts have an important role in increasing enrollment under the ACA's Medicaid expansion (Frean, Gruber, and Sommers, 2017, Aslim, 2017).

I use administrative data from the Centers for Medicare & Medicaid Services (CMS) through the Medicaid Budget and Expenditure System (MBES) to analyze the average and marginal take-up rate of Medicaid after the expansion. Figure 2 shows that the total enrollment growth rate (average take-up rate) is smoother than the enrollment growth rate for those who are newly eligible (marginal take-up rate), where both enrollment growth rates are defined as a percent change from January 2014. The upward trend in the marginal take-up rate captures the enrollment trend for childless adults since they do not have eligibility prior to the expansion.[25] There is also a consensus in the literature that more than 10 million newly eligible adults will have access to health insurance with the ACA's Medicaid expansion (Sommers et al., 2012). I support this analysis by using a national survey, which is the Annual Social and Economic Supplement (ASEC) of the CPS, to test whether there is a discontinuity in Medicaid enrollment at the eligibility cutoff. These findings are presented in Section 5.

3. Data, Sample, and Variables

3.1. Data and Sample

The main data set used in the analysis is the basic monthly Current Population Survey (CPS). Supplemental data sets on Medicaid enrollment and eligibility criteria that vary by state and year are obtained from both the Henry J. Kaiser Family Foundation and the Centers for Medicare & Medicaid Services. The CPS monthly data contain all of the relevant information on household demographics and labor market outcomes using a nationally representative sample. There is a multistage stratification for the sample households where a household is interviewed by 4 months consecutively, then followed

[25] Note that newly eligible enrollees are not only childless adults but also those who are not eligible with the previous income thresholds. In MBES data, it is not possible to distinguish between different adult groups (i.e., parents vs. childless adults).

by a 8 months break, and finally they are interviewed for another 4 months. Most importantly, quick release of the data allows researchers to analyze immediate impacts of a policy change.[26]

The sample period used in the analysis is from January 2010 to July 2016 with more years of data after the expansion in January 2014 compared to the studies given in Table 1. As discussed earlier, the sample includes 24 expansion states and 18 non-expansion states. The remaining nine early expansion states are dropped because of its confounding effects on Medicaid enrollment. Individuals who are below 26 years of age could remain on parent's coverage via ACA's dependent coverage mandate[27] and those who are above 64 years of age are qualified for Medicare. Moreover, those who are in the armed forces are eligibile for HMO-type military health-care plans, which is known as TRICARE. In order to mitigate the potential bias resulting from dependent's coverage, Medicare, and TRICARE, the sample is restricted to non-institutionalized civilized adults who are between 27 to 64 years of age.[28]

When applying for Medicaid, the tax filers rules include step child, adopted child, foster child, brother, sister, niece, nephew, or grandchild for the household counting.[29] Since the group of interest is childless adults, I restrict the sample to those who do not have an own (and/or related) children under the age of 18 living in the household. The main reason for restricting the sample to childless adults is because parents had access to Medicaid prior to the ACA, which could make employment decisions dependent on factors that are unobservable in the data (e.g., woodwork effects). Finally, the household size is restricted to less than seven in order to prevent issues regarding multiple families. The sample restrictions defined above are also applied to March CPS when used for eligibility simulation.

The employment measures are constructed using the information on working hours. It is important to note that 5 percent of the overall sample have varying working hours and hence a specific working hour is not observed. For adults who are working part-time

[26] An alternative data set is the American Community Survey (ACS) but the main limitation is the lagged release of the data. As of now, the ACS only have one year of observation for the post-expansion period.

[27] Antwi, Moriya, and Simon (2013) found a high take-up rate of parental coverage with an evidence supporting the ease of employment lock by reducing work hours. Bailey and Chorniy (2016), however, found no evidence of job lock, measured by job mobility, for young adults.

[28] Since an individual can remain on parent's insurance plan until December 31 of the year he/she turns 26, it is more accurate to have a sample starting from 27 years of age.

[29] Moreover, non-relatives who live for an entire year in the tax filer's house can be included as a household member.

and have varying working hours, I imputed the weighted average of those who work less than 20 hours and 20-34 hours. This weighted average is calculated to be 22.76 hours for adults who work part-time.

3.2. Eligibility Simulation

The most important component of simulated eligibility is household income given that eligibility is a function of income.[30] In order to simulate eligibility, I exploit the information on household income given in March CPS. I use the sample between 2011 to 2013 in the March CPS, excluding nine months before the ACA's Medicaid expansion, to avoid any anticipated changes in household income.[31] The increase in income threshold to 138% FPL could give an incentive to adults to manipulate their household income ex-ante to become eligible for Medicaid. In addition, the motivation behind using a sample after 2010 is to avoid any confounding effects resulting from the Great Recession.[32] The specification used for the data generating process is defined as follows:

$$y_{it_ms} = \gamma_0 + X_i^{'}\gamma_1 + \tau_{t_m} + \tau_{t_m}^2 + \xi_s + \tau_{t_m} * \xi_s + \epsilon_{it_ms} \tag{1}$$

where y is household income for individual i at time t_m (year and month) in state s.[33] X includes cell blocks on age, race, gender, marital status, educational attainment, and household size.[34] Linear time trend is captured by τ_{t_m} and $\tau_{t_m}^2$ is trend-squared.[35] State fixed effects are ξ_s, and $\tau_{t_m} * \xi_s$ is an interaction that captures state-specific linear trends. The error term is ϵ. The coefficients obtained from March CPS is used in basic monthly CPS to get $\hat{y}_{it_ms}$, which is denoted as the simulated household income ($SHHI_{it_ms}$).

In order to determine eligibility for Medicaid, poverty thresholds provided in Table A1 are used.[36] Thus, the formula used to calculate simulated eligibility has the following

[30] Tax data from IRS could be matched using states but it would not serve the purpose for determining eligibility through adjusted gross income.

[31] The remaining sample restrictions are the same as basic monthly CPS (see Section 3.1).

[32] Based on the NBER Recession Indicators for the United States, the Great Recession spans the period between December 2007 and June 2009 (see `https://fred.stlouisfed.org/series/USREC`). Due to slow recovery and high unemployment rates in 2010, I start the sample period as early as 2011.

[33] Note that household income could be negative due to accumulated debt.

[34] When simulating Medicaid eligibility, Golberstein and Gonzales (2015) use cells on age, sex, marital status, number of children, race, and educational attainment.

[35] Note that linear time trend is defined for year-month pairs: $\tau_{t_m} = \{1, \ldots, 79\}$.

[36] For example, 100% FPL in 2015 for a single household is \$11,770 and 138% of FPL is \$16,242 (see Table A1).

first step:

$$P_{it_m s} = \frac{SHHI_{it_m s}}{FPL_{ts}} \times 100 \tag{2}$$

where P_{ihs} is the percentage poverty level of individual i at time t_m (year and month) in state s. FPL_{ts} is the 100% federal poverty level (FPL) that varies by year t and state s. The variables in Equation (2) also vary by household size (h). For simplicity in notation, h is suppressed hereinafter. Then, the second step is constructed as follows:

$$E_{it_m s} = I\{P_{it_m s} \leq 138\} \tag{3}$$

where $E_{it_m s}$ is eligibility and $I\{.\}$ is an indicator variable taking the value 1 if $P_{it_m s} \leq 138$ and 0 otherwise.[37] This simulated eligibility measure accounts for both individual- and state-level differences in household income by using state-specific rules for eligibility. A similar approach is used by Dave et al. (2015) to capture the heterogeneity in the distribution of income using a state-specific sample. Cutler and Gruber (1996) construct simulated eligibility using each cell of observable characteristics for a nationally drawn sample and use it as an instrument for actual eligibility.[38] Pohl (2014) uses a similar simulated eligibility measure as a proxy for actual eligibility rather than using the IV method due to concerns on inconsistent estimates. A major contribution of this study is the use of two different data sets, March CPS and basic Monthly CPS, to construct simulated eligibility. This overcomes the issue of using March CPS as the sole data source, which does not capture montly variation in the changes in income thresholds and the outcome variables.

The running variable, $d_{it_m s}$, is constructed by centering $P_{it_m s}$ around zero. This is defined as follows:

$$d_{it_m s} = P_{it_m s} - R_s, \tag{4}$$

where R_s is the state eligibility rule, which is 100% FPL for WI and 138% FPL for the remaining expansion states. Although the sample used for the simulations reduces the

[37] The indicator function is $I\{P_{it_m s} \leq 100\}$ for WI.

[38] There are many studies following the approach suggested by this study. Gross and Notowidigdo (2011) use information on state, year, household income, number of children, and gender to construct Medicaid eligibility. Sabik et al. (2017) use state, year, household income, and family size to construct Medicaid eligibiliy.

possibility of systematic manipulation, I probe the continuity of the running variable using the density test proposed by McCrary (2008). Any non-random sorting around the cutoff biases the estimates. Figure 3 clearly shows no evidence of systematic manipulation around the cutoff prior to the policy.[39]

3.3. Descriptive Statistics

Table 3 provides descriptive statistics on outcome and control variables in expansion states for both eligible and non-eligible adults defined by Equation (3). The sample is stratified by pre- and post-expansion period to observe possible trends in outcomes. The preferred bandwidth is ±4% FPL, which is the largest bandwidth that has smooth covariates around the cutoff. There is a tradeoff between sample size and covariate smoothness: as bandwidth increases covariates are less smooth around the eligibility cutoff. The preferred bandwidth in this paper is selected based on covariate smoothness and the largest sample that is possible. I probe the robustness of the estimates to bandwidth selection.

Panel A shows the mean of the outcome variables including the employment measures. The total number of observations used in the study can be calculated by adding the observations in each column. The analysis sample given the bandwidth is captured by labor force participation (N=4,140) and the remaining outcome variables are subsamples of those who are in the labor force. Note that the base group for labor force participation is those who are not in the labor force. The variable on employed captures the share of employed relative to unemployed (N=3,111). Part-time employment categories (e.g., <20 Hrs, 20-34 Hrs, and <35 Hrs) are relative to full-time employment (≥35 Hrs) and capture the working population around the cutoff (N=2,796). Note that the Bureau of Labor Statistics (BLS) defines part-time employment as working less than 34 hours per week.

Before the policy change, part-time employment (<35 Hrs) is relative higher for non-eligible adults. With the ACA's Medicaid expansion, there is a significant change in employment, where eligible adults reduce working hours by transitioning into part-time employment (<35 Hrs) and non-eligible adults increase full-time employment (≥ 35 Hrs) relative to part-time employment (<35 Hrs). After all the employment transitions, part-time employment (<35 Hrs) increases by 1 percentage point at the cutoff for eligible

[39]There is also no evidence of discontinuity when the sample is not restricted to pre- and post-period.

adults. The change in part-time employment (<35 Hrs) is driven from the increase in employment of 20 working hours for eligible adults that leads to a 2.9 percentage points difference relative to non-eligible adults. The decline in the employment category for 20-34 hours of work also suggests that the dominating effect is the increase in employmet for the bottom portion of working hours, which is less than 20 hours of work. Both labor force participation and the share of employed increase for eligible and non-eligible adults with the latter being greater in magnitude. Overall, eligible adults have higher part-time employment (both <35 Hrs and <20 Hrs), and lower labor force participation and share of employed relative to non-eligible adults. All of these changes support the presence of employment lock before the expansion.

Panel B introduces the control variables used in the benchmark model which include both individual- and state-level characterictics. Prior to the expansion, eligible adults relative to non-eligible adults are more likely to be females, divorced, or Asian. In terms of educational attaintment prior to the expansion, eligible adults have a higher average of having less than high school education or at most a high school diploma. All of the composition changes are consistent for eligible and non-eligible adults in the post-period. When the average of a control variable increases (or decreases) after the expansion for eligible adults, it also increases (or decreases) for ineligible adults excluding separated adults.

Once the changes in control variables are differenced out for eligible and non-eligible adults before and after the expansion, there are no significant jumps observed. This is analyzed in detail when the test for covariate smoothness is conducted. In addition, the changes in state unemployment rate between pre- and post-2014 capture the spillover effects of the Great Recession. State unemployment rate is seasonally adjusted and obtained by the U.S. Bureau of Labor Statistics. State GDP is a percent change from preceding quarters and measured in chained dollars. The dataset on state GDP is publicly available through the U.S. Bureau of Economic Analysis. Note that state time-varying charateristics are cruical in terms of capturing differences between expansion and non-expansion states.

The visual representation of discontintuities resulting from the policy change is illustrated in Figure 4.[40] The discontinuity plots are centered around zero and the running

[40] Discontinuity plots are commonly used to support RD models to visually identify the policy effect (see, for example, Carpenter and Dobkin, 2009; Card, Dobkin, and Maestas, 2009).

variable represents the percent FPL relative to the cutoff. The scatter plot represents the mean of the outcome variable within a bin and the fitted lines are local linear regressions on both sides of the cutoff. The comparision of discontinuities is made for expansion states in pre- and post-period of the policy. The test on discontinuities for non-expansion states is conducted later as a falsification test. For the discontinuity plots, I focus on the transition between part-time employment (<35 Hrs) and full-time employment (≥35 Hrs).

The findings of discontinuity plots are similar to those shown in Table 3. Relative comparison of the discontinuities suggests that part-time employment (<35 Hrs) increases relative to full-time employment (≥35 Hrs) for those who are eligible for Medicaid. Moreover, this increase is mainly driven from the increase in the bottom portion of working hours, which is less than 20 hours of work.[41]

In the next section, I introduce the benchmark model that incorporates both simulated eligibility and the variables introduced in Panel A and B of Table 3.

4. Empirical Strategy

In this section, I present an RD model that takes the treatment as a deterministic function of the covariate given the upward trend in the Medicaid take-up rate, which is further tested using Medicaid enrollment in March CPS.[42] The ignorability or unconfoundedness assumption holds by design. This specification is preferred due to its strong foundation on internal validity by comparing similar populations near the cutoff.[43] A standard RD model is defined as follows:

$$y_{it_ms} = \beta_0 + \beta_1 E_{it_ms} + g(d) + \beta_2 E_{it_ms} * g(d) + X'_{it_m}\beta_3 + \delta_m + \gamma_t + \xi_s + [\psi_{t_ms}] + v_{it_ms} \quad (5)$$

where y is labor market outcomes (and Medicaid enrollment) for individual i at year

[41] The discontiuity plot for 20-34 working hours does not show any significant increase for those below the cutoff. This plot is available upon request.

[42] This paper does not use March CPS as the sole data source due to its limitations on constructing simulated eligilibity (see Section 3.2). Note also that the questions on health insurance in March CPS are redesigned at the time of the ACA's Medicaid expansion and hence could bias the estimates on enrollment when used in a fuzzy RD design.

[43] See Imbens and Lemieux (2008) for a detailed discussion on the use of RD models in economics.

and survey month t_m in state s. E_{it_ms} is the simulated eligibility defined by Equation (3). The running variable, denoted as d, is obtained through Equation (4). The center of d corresponds to 138% FPL, which is normalized to zero. The functional form of d is captured by $g(d)$ - linear, quadratic and cubic functions. The robustness of the estimates with respect to the functional form of d is tested in the results section. X is composed of control variables including age, age-squared, race, gender, marital status, and educational attainment. The period effects, defined as month and year effects, are δ_m and γ_t, respectively. State fixed effects are defined as ξ_s, and ψ_{t_ms} is state timing-varying effects including state unemployment rate and GDP growth rate.[44] The error term is v_{it_ms}.

A standard RD model can show the discontinuity in expansion states after the policy. The discontinuity in both non-expansion states and expansion states before 2014 could be solely treated as falsification checks. The visual representation of discontinuities, however, in the expansion states shows significant jumps in the pre-period for some of the outcome variables (see Figure 4).[45] Thus, taking the difference in discontinuities accounts for the pre-existing trends that vary by household income. Thus, Equation (5) is modified by including "*Post*" interactions to difference out trends. This model can be written as follows:

$$\begin{aligned} y_{it_ms} =& \alpha_0 + \alpha_1 E_{it_ms} + g(d) + \alpha_2 E_{it_ms} * Post_{t_ms} + \alpha_3 g(d) * Post_{t_ms} \\ &+ \alpha_4 E_{it_ms} * g(d) * Post_{t_ms} + X_i^{'} \alpha_5 + \delta_m + \gamma_t + \xi_s + [\psi_{t_ms}] + v_{it_ms} \end{aligned} \tag{6}$$

where $Post$ varies by state (s), year and month (t_m) and takes the value 1 after the expansion date and 0 otherwise (see Table 2). The rest of the variables are the same as those discussed in Equation (5). This is the benchmark model of the paper with β_2, denoted as *Eligibility* $*$ *Post* in the tables, being the coefficient of interest. This coefficient captures the change in labor market outcomes at the eligibility cutoff before and after 2014. Since differencing out eliminates pre-existing trends, any change at the cutoff is attributed to the ACA's Medicaid expansion. This discontinuity is expected to be statistically insignificant for non-expansion states since they are not (directly) affected

[44]Note that the time dimension for ψ_{t_ms} captures monthly variation in the unemployment rate and quarterly variation for the GDP growth rate.

[45]These jumps are not due to any selection around the cutoff as this is checked in the paper via manipulation test and covariate smoothness test.

from the reform. For the benchmark model, the preferred bandwidth is the largest that passes the covariate smoothness test, which is ±4% FPL. The relationship between the potential outcomes and the running variable has to be smooth to interpret any resulting discontinuity as the average treatment effect. The standard errors are bootstrapped with 400 replications and clustered by state.[46]

In this paper, the validity of model assumptions and the robustness of the estimates are tested using the following approaches: i) density test for the running variable d (discussed in Section 3.2); ii) covariate smoothness test around the eligibility cutoff; iii) testing the robustness of the estimates to different bandwidths; iv) changing the functional form of the running variable; and v) including early expansion states in the analysis.

5. Results

This section provides the findings from the benchmark and subgroup analysis, covariate smoothness test, robustness and falsification checks, and the DD model to replicate existing studies.

5.1. Benchmark Analysis in Expansion States

In this section, I focus on the estimates from Equation (6) for expansion states using Tables 4 and 5. First, I check the discontiuinity in Medicaid enrollment to support the findings on labor market outcomes. The estimates on Medicaid enrollment show a positive and statistically significant jump at the eligibility cutoff. When preferred bandwidth is used in column (1) of Table 4, the increase in Medicaid enrollment is by 27.5 percentage points. The findings are robust to increasing bandwidths. A detailed discussion on bandwidth selection is provided under robustness checks.

In Table 5, each panel denotes a separate regression for the given outcome variable.[47] The estimates show no effect of the ACA's Medicaid expansion on labor force participation, the probability of being employed, and employment for 20-34 working hours. The main effect, however, is observed as an employment transition from full-time

[46]The findings are robust to increasing bootstrap replications. In addition, I exclude significance at 10 percent to avoid any issues on sensitivity.

[47]As discussed earlier, part-time employment is a subgroup of adults who are employed, and those who are employed are a subgroup of adults who are in the labor force. The total number of observations for each outcome are denoted in Section 3.3.

($\geq$35 Hrs) to part-time employment (<35 Hrs). In column (3), there is an increase in part-time employment (<35 Hrs) by 13.7 percentage points relative to full-time employment. It is also evident that employment (<20 Hrs) increases (9.4 percentage points) after the ACA's Medicaid expansion.

The findings imply that the increase in part-time employment is mainly driven from the transition between full-time emploment and employment with less than 20 working hours. This is consistent with the priori that adults who are experiencing employment lock will respond to incentives created by the ACA's Medicaid expansion. The main incentive is the Medicaid-induced income effect that makes both the job search and/or employment transitions less costly.[48] For the remainder of the paper, I only focus on the most inclusive regression that has control variables, year and month effects, state fixed effects, and state-time varying effects.

5.2. Subgroup Analysis in Expansion States

In this section, I explore the heterogeneity of employment effects across subgroups in expansion states. Female and low-educated (HS or less) adults increase their employment (<20 Hrs) by 14 and 21.1 percentage points, respectively. For adults who are married once, there is a relatively stronger effect on part-time employment (<35 Hrs) with a statistically significant increase by 19.6 percentage points.[49] The increase in part-time employment ($\geq$35 Hrs) is again driven by the increase in emplPoment for working less than 20 hours (11.8 percentage points). This finding is consistent with the benchmark analysis that shows a statistically significant increase in empoyment for working less than 20 hours. This implies that subgroups respond to the ACA's Medicaid expansion by reducing working hours.

There is no evindence of a transition from employment to unemployment across subgroups. In fact, the probability of being employed increases by 10.7 percentage points relative to the probability of being unemployed for adults who are married once. There is also no evidence of a discontinuity in labor force participation and employment for 20-34 working hours across subgroups. There are no effects observed for males, high-educated adults (more than HS), and never married adults. Additionally, there is no evidence of

[48]In addition, I do not find an increase in self-employment after the expansion. The findings on self-employment are available upon request.

[49]The group on married once includes married, divorced, windowed, and separated adults.

an employment effect for different age groups (27-49 vs. 50-64). Overall, the employment effects are concentrated among females, low-educated adults (HS or less), and adults who are married once.

5.3. Covariate Smoothness Test

After selecting the bandwidth, it is cruical to test whether the population composition is similar around the eligibility cutoff. Non-random sorting of a certain group near the cutoff may bias the eligibility estimate. The main motivation here is to show that there is no selection on either side of the eligibility cutoff with respect to observable characteristics given in Table 3. If observable characteristics are smoothly distributed around the eligibility cutoff, this would mean that unobservable characteristics are also smoothly distributed around the eligibility cutoff. In this case, the concerns on internal validity with respect to omitted variables would be reduced and hence any discontinuity could be interpreted as the causal effect of Medicaid expansion.

In order to test for this formally, I run the regression model given in Equation (6) by changing the outcome variables as the control variables. Since the policy is not effective in non-expansion states, I examine the eligibility profile of demographic characteristics only in expansion states. The findings, presented in Table 7, show no evidence of a discrete jump at the eligibility cutoff. Thus, the preferred bandwidth is the largest bandwidth that passes the covariate smoothness test. It is crucial to note that the increase in bandwidth still yields statistically significant employment effects but there is a tradeoff in comparing similar individuals. This implies that sample size increases as bandwidth gets wider but at the cost of failing the smoothness test for various covariates. In cases of non-random sorting, it is not possible to claim that the sole factor causing the jump is the ACA's Medicaid expansion.

5.4. Robustness and Falsification Checks

The first robustness check is on including early expansion states in the sample. Since the analysis excludes relatively large states, I test whether the main finding prevails. The inclusion of early expansion states increases the total number of expansion states to 33 and the non-expansion states remain the same. It is observed that part-time employment ($<$34 Hrs) increases by 14.3 percentage points relative to full-time employment ($\geq$35 Hrs), where the main transition is for working less than 20 hours. These findings are consistent with the benchmark analysis. In addition, the estimates imply that the effect of ACA's Medicaid expansion on employment is not sensitive to the exclusion of early expansion states.

Another important robustness check is on the selection of bandwidths. The initial selection of bandwidth relies on covariate smoothness, where I choose the largest bandwidth possible. As discussed earlier, there is a tradeoff between sample size and covariate smoothness as the bandwidth gets wider. It is more likely to have a selection around the cutoff that would fail the test on covariate smoothness. For the studies that use RD models, it is common to double the preferred bandwidth as a robustness check (see, for example, Black, Galdo, and Smith, 2007, Schmieder, Von Wachter, and Bender, 2012). In this case, doubling the bandwidth yields $\pm 8\%$ FPL around the zero-threshold. As expected, variance gets smaller with the increased bandwidth and the results on employment (<34 Hrs and <20 Hrs) are highly significant and still have a positive sign.[50]

The final robustness check is on the functional form of the running variable, which is defined as $g(d)$ in Equation (6). I provide the estimates on employment when using quadratic or cubic running variables. In either case, the estimates suggest a transition from full-time employment to part-time employment, which is consistent with the benchmark analysis. It is important to note that the estimates get smaller as the order of the polynomial increases. Gelman and Imbens (2017) show that high-order polynomial in an RD setup could be misleading due to poor properities, especially on inference. They also add that if the researcher is confident about the functional form, which is rarely the case, then using a high-order polynomial could be a reasonable method.

The findings on non-expansion states and the elderly (age > 64) should be treated as falsification checks. I include non-expansion states both in the benchmark analysis (Table 5) and robustness checks (Table 8). For the benchmark analysis, there is no evidence of a discontinuity in Medicaid enrollment and labor market outcomes in non-expansion states. In addition, the specifications provided in Table 8 show no effect of the policy on non-expansion states. The elderly, who are above the age of 64, are also not affected from the ACA's Medicaid expansion. This finding is consistent given the fact that the

[50] I also check the robustness of the estimates by changing the preferred bandwidth by $\pm 1\%$ FPL until I have $\pm 10\%$ FPL around the eligibility cutoff. The employment effects for these different bandwidths are fairly robust but I again caution the readers about covariate smoothness. Note that the estimates are available upon request.

elderly qualify for Medicare.

5.5. Difference-in-Differences

The benchmark findings on employment transition, particularly the increase in part-time employment, contradict to the studies that use the same data source with a different identification method (see, for example, Gooptu et al., 2016, Leung and Mas, 2016, Kaestner et al., 2017). In order to replicate existing studies, I estimate the following DD model:

$$y_{imts} = \theta_0 + \theta_1 Expansion + \theta_2 Expansion * Post + X_i^{'}\theta_3 + \delta_m + \gamma_t + \xi_s + [\psi_{mts}] + \upsilon_{imts} \quad (7)$$

where *Expansion* is a dummy variable taking the value 1 if a state is an expansion state and 0 otherwise. The remaining variables are the same as those discussed for Equation (6). In this model, θ_2 is an intent-to-treat estimate that shows the changes in labor market outcomes in expansion states after 2014. For the DD model, the standard errors are clustered by state and individual-level weights are used in the regression.

First, I restrict the sample to ±4% FPL and ±8% FPL to make the estimates from DD model comparable to the benchmark analysis. Second, I use the full sample to compare the estimates with those in the foregoing studies. The full sample, however, is larger than the foregoing studies because the years used are January 2010-July 2016 (see Table 1 for detailed comparison).[51]

Table 9 presents the findings from the DD model. Columns (1) to (3) show no statistically significant effect on employment measures. The first two columns show that using the same sample as the benchmark analysis does not yield similar estimates. The only statistically significant estimate is for labor force participation that has a positive sign. Although the benchmark analysis show a positive sign for labor force participation, the estimates are statistically insignificant. It is likely that the significance in the DD model is driven from the large and heterogeneous treatment group, where many of the ineligible adults are treated as eligible.

For the full sample, the estimates on employment are similar to the studies in the

[51]There are also minor differences in the sample with respect to the exclusion of states, especially compared to Kaestner et al. (2017).

literature. The probability of being employed in Column (3) increases by 0.2 percentage points and Leung and Mas (2016) found this increase to be 0.5 percentage points. Again in Column (3), part-time employment (<35 Hrs) decreases by 0.4 percentage points relative to full-time employment (≥35 Hrs). Kaestner et al. (2017) found an increase in full-time employment, defined as working more than 30 hours, by 1 percentage point for low-educated childless adults. Using CPS up to March 2015, Gooptu et al. (2016) show no transition between part-time and full-time employment.[52]

The findings imply that, using a similar DD model, increasing the sample size is not an improvement upon the previous findings. The main limitation of the DD model, however, is not incorporating eligibility and including a population that do not benefit from Medicaid. The benchmark findings improve upon this regard by using an identification method that captures eligibility. It is important to note that childless adults who are really close to the eligibility cutoff share similar characteristics and any changes in the outcomes reflect the effect of Medicaid expansion.

6. Discussion

The labor market implications of Medicaid expansions have taken considerable attention in recent years. There have been studies investigating the labor market implications of Medicaid expansions, mainly the employment lock effect, prior to the Affordable Care Act (ACA). Many of these studies focused on a single state expansion (or a small cluster of states) that had limited external validity. There have been, however, a few studies that investigated the employment effects of the ACA's Medicaid expansion with a relatively large set of expansion states. Using a difference-in-differences (DD) model with expansion states as the treatment group, these studies found no employment effects after 2014 (see, for example, Gooptu et al., 2016 and Leung and Mas, 2016).

This paper provides an alternative quasi-experimental approach for a population near the eligibility cutoff to identify the pre/post employment effects of the ACA's Medicaid expansion. The data used in the study is the basic monthly Current Population Survey (CPS) from January 2010 to July 2016. This study uses more years of data in the post-period than the existing studies that investigate the employment effects of the ACA's

[52]The probability of transitioning from full-time to part-time employment increases by 0.3 percentage points. This increase, however, is not statistically different from zero.

Medicaid expansion. A common practice in the literature is to construct a simulated eligibility measure using a single data source. I construct simulated eligibility using both March CPS and basic monthly CPS. This is an improvement upon using March CPS as the sole data source that has limitations in capturing the monthly variation in eligibility limits and outcome variables. The internal validity of the model is tested with respect to contemporaneous shocks and non-random sorting around the eligibility cutoff. There is no evidence of a selection or a manipulation prior to the expansion.

Using an arguably exogenous variation at the eligibility cutoff, I find that Medicaid enrollment increases for adults without dependent children ("childless adults"). There is also a strong evidence of an employment transition, defined as moving from full-time ($\geq$35 Hrs) to part-time employment ($<$35 Hrs), after the expansion. The employment transition is found to be driven from the increase in employment for working less than 20 hours. This finding is consistent with the priori that those who are primarily employed to secure private health insurance ("employment lock") will respond to the Medicaid-induced income effect. The employment transition is found to be heterogeneous across subgroups with a main effect on females, low-educated adults (HS or less), and adults who are married once. Falsification checks show no effect on non-expansion states and Medicare-eligible adult groups. In addition, the estimates are robust to the inclusion of early expansion states, increasing bandwidths, and varying functional forms of the running variable.

When the difference-in-differences (DD) model is used to replicate existing studies, there are no employment effects after the expansion. The estimates are similar to those found in the literature. The main limitation of the DD model, however, is the large and heterogeneous treament group that includes adults who are ineligible for Medicaid.

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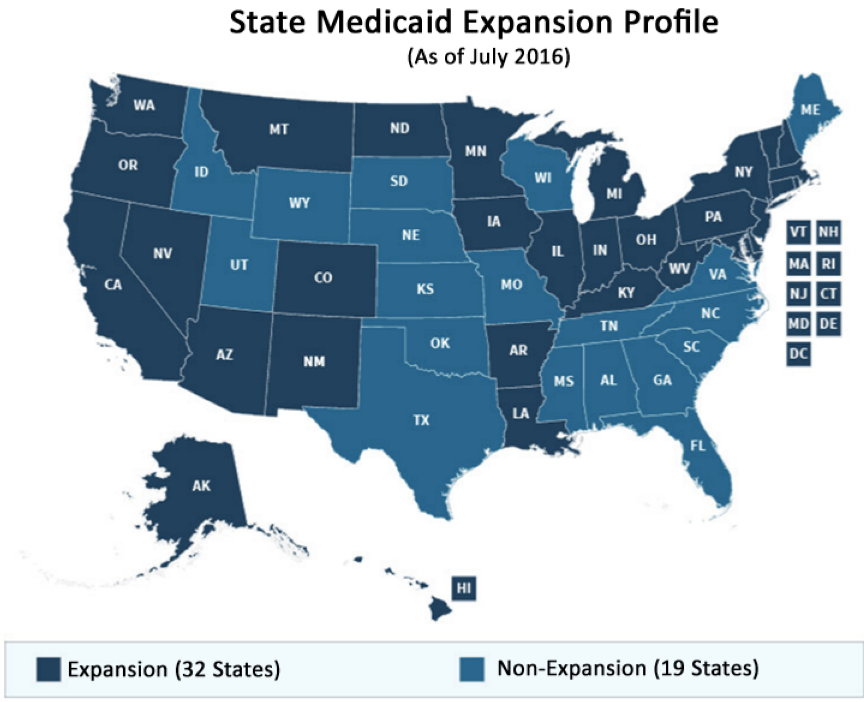

Figure 1: State Medicaid Expansion Profile

Source: Medicaid.gov

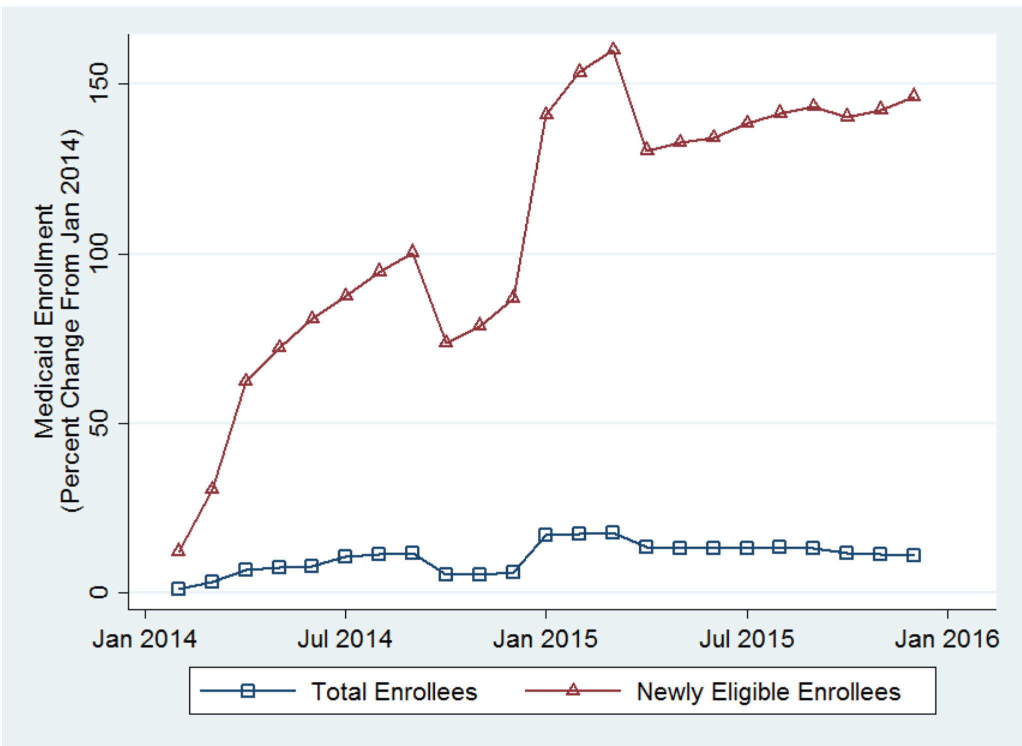

Figure 2: Medicaid Enrollment Growth Rate

Notes: The graph is constructed by the author using the Medicaid enrollment data from Centers for Medicare & Medicaid Services (CMS).

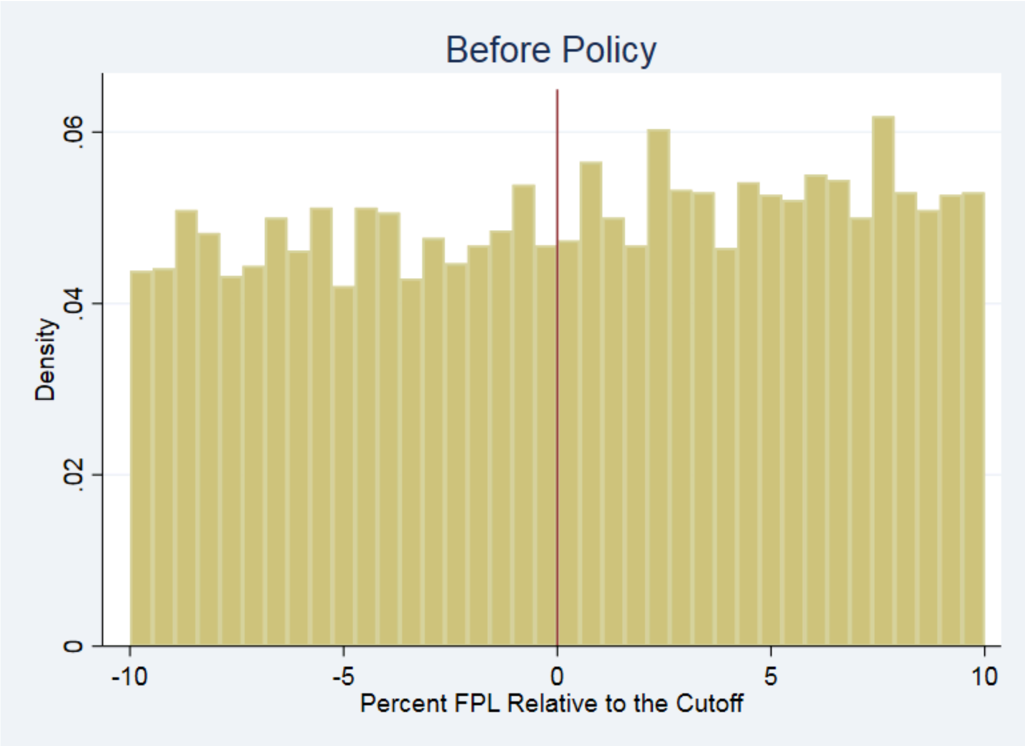

Figure 3: Density Test for Systematic Manipulation

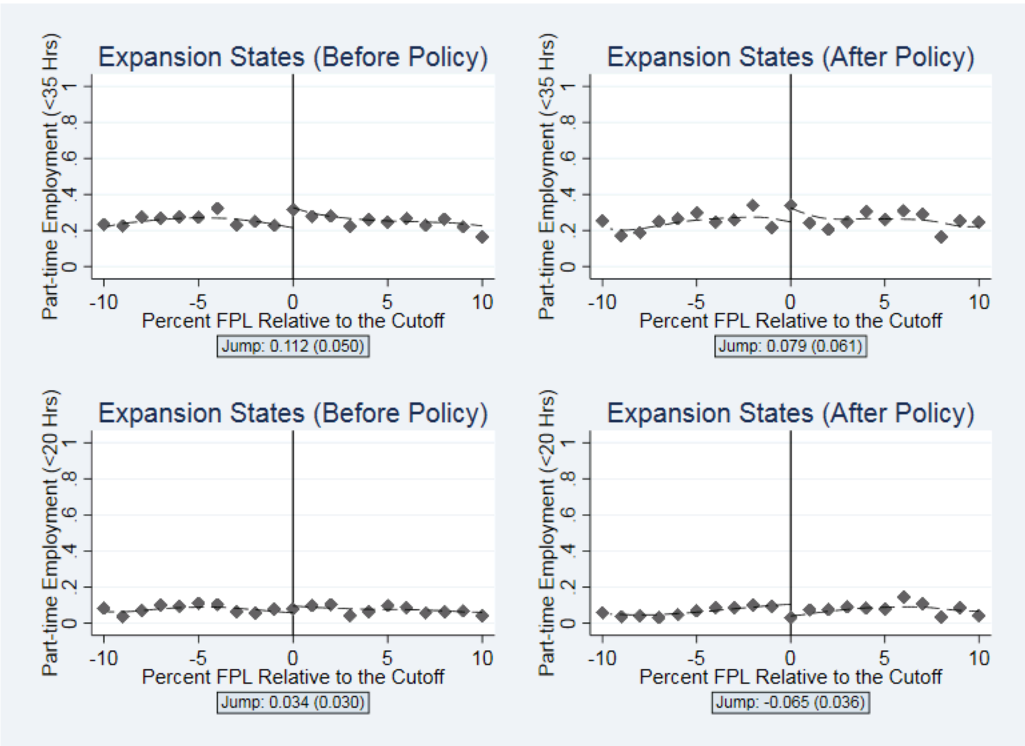

Figure 4: Discontinuity Plots

Table 1: Recent Studies on the Employment Effects of Medicaid Expansion(s)

Studies After 2010	ACA's Medicaid Expansion[†]	Adult Group[‡]	State(s) of Eligibility[††]	Data Source	Method	Employment Effect
Strumpf (2011)	No	Single women	14 states	March CPS, 1963-1975	DD, DDD models	No effect
Decker and Selck (2012)	No	Single mother	20 states	March CPS, 1966-1974	OLS	No effect
Baicker et al. (2014)	No	Low-income adults (not categorically eligible)	Oregon (limited expansion)	Oregon Health Insurance Experiment, 2008-2009	IV model	No effect
Heim and Lurie (2014)	No	Taxpayers	Massachusetts	Tax returns data (IRS), 1990-2010	DD model, synthetic control	4.7 percent (–)
Garthwaite, Gross, and Notowidigdo (2014)	No[§]	Childless adults	Tennessee[§§] (disenrollment)	March CPS, 2000-2007	DD, DDD models	6 percent (+)
Niu (2014)	No	Adults (eligible)	Massachusetts	Monthly CPS (& March CPS), 1995-2011	DD model	8.4 percent (+)
Pohl (2014)	Yes (uses simulation)	Single mothers (extension on childless adults)	All states	MEPS (restricted), 1996-2009	Multinomial logit model[*] (for employment choice)	5 - 6 percent (+)
Dave et al. (2015)	No	Unmarried pregnant women	All states	March CPS, 1985-1996	OLS, negative binomial models	13 percent (–)
Gooptu et al. (2016)	Yes	Childless adults	Expansion states[**]	Monthly CPS, 2005 - March 2015	DD model	No effect
Leung and Mas (2016)	Yes	Childless adults	21 states	Monthly CPS (& ACS), 2010 - July 2015	DD model	No effect
Kim (2016)	Yes	Childless adults	Connecticut	ACS-IPUMS, 2008 - 2013	DDD model, (using an IV approach)	12 - 14 percent (–)
Kaestner et al. (2017)	Yes	Childless adults, parents	9 or 13 states (depending on prior expansion)	Monthly CPS (& March CPS, ACS), 2010 - May 2016	DD model, synthetic control	1.8 percent[***] (+)
Dague, DeLeire, and Leininger (2017)	No	Childless adults	Wisconsin (enrollment cap)	State administrative files, 2005-2011	RD, DD models	12 percent (–)

Notes: [†]This column shows whether a study examines the ACA's Medicaid expansion or an earlier expansion. [‡]The studies on the Children's Health Insurance Program (CHIP) are excluded. [††]This column distinguishes between studies that use a single expansion state versus multiple expansion states. [§]The study includes a discussion for the ACA period by using a predicted measure. [§§]This paper focuses on the effect of losing public coverage rather than gaining access. [*]The paper includes a three-step estimation for the choice of employment, wages, and preference parameters. [**]The number of expansion states is not denoted in the paper. [***]The employment estimates are statistically insignificant when the ACS is used.

Table 2: Medicaid Profile Across States
(As of July 2016)

			Income Eligibility	
States	Status of the Medicaid Expansion	Effective Date of Expansion†	Adults with Children	Childless Adults
Alabama	Not Expanding	-	18%	0%
Alaska	Expanded	9/1/2015	138%	138%
Arizona*	Expanded	1/1/2014	138%	138%
Arkansas*	Expanded	1/1/2014	138%	138%
California	Expanded	1/1/2014	138%	138%
Colorado	Expanded	1/1/2014	138%	138%
Connecticut	Expanded	1/1/2014	201%	138%
Delaware	Expanded	1/1/2014	138%	138%
District of Columbia	Expanded	1/1/2014	221%	215%
Florida	Not Expanding	-	34%	0%
Georgia	Not Expanding	-	34%	0%
Hawaii	Expanded	1/1/2014	138%	138%
Idaho	Not Expanding	-	26%	0%
Illinois	Expanded	1/1/2014	138%	138%
Indiana*	Expended	2/1/2015	138%	138%
Iowa*	Expanded	1/1/2014	138%	138%
Kansas	Not Expanding	-	38%	0%
Kentucky	Expanded	1/1/2014	138%	138%
Louisiana	Expanded	7/1/2016	138%	138%
Maine	Not Expanding	-	105%	0%
Maryland	Expanded	1/1/2014	138%	138%
Massachusetts	Expanded	1/1/2014	138%	138%
Michigan*	Expanded	4/1/2014	138%	138%
Minnesota	Expanded	1/1/2014	138%	138%
Mississippi	Not Expanding	-	27%	0%
Missouri	Not Expanding	-	22%	0%
Montana*	Expanded	1/1/2016	138%	138%
Nebraska	Not Expanding	-	54%	0%
Nevada	Expanded	1/1/2014	138%	138%
New Hampshire*	Expanded	8/15/2014	138%	138%
New Jersey	Expanded	1/1/2014	138%	138%
New Mexico	Expanded	1/1/2014	138%	138%
New York	Expanded	1/1/2014	138%	138%
North Carolina	Not Expanding	-	44%	0%
North Dakota	Expanded	1/1/2014	138%	138%
Ohio	Expanded	1/1/2014	138%	138%
Oklahoma	Not Expanding	-	44%	0%

Table 2: Medicaid Profile Across States (Continued)

(As of July 2016)

			Income Eligibility	
States	Status of the Medicaid Expansion	Effective Date of Expansion†	Adults with Children	Childless Adults
Oregon	Expanded	1/1/2014	138%	138%
Pennsylvania*	Expanded	1/1/2015	138%	138%
Rhode Island	Expanded	1/1/2014	138%	138%
South Carolina	Not Expanding	-	67%	0%
South Dakota	Not Expanding	-	52%	0%
Tennessee	Not Expanding	-	101%	0%
Texas	Not Expanding	-	18%	0%
Utah	Not Expanding	-	45%	0%
Vermont	Expanded	1/1/2014	138%	138%
Virginia	Not Expanding	-	44%	0%
Washington	Expanded	1/1/2014	138%	138%
West Virginia	Expanded	1/1/2014	138%	138%
Wisconsin	Not Expanding	-	100%	100%
Wyoming	Not Expanding	-	57%	0%

Notes: This table is constructed by the author using the information on Medicaid expansion profile provided by the Henry J. Kaiser Family Foundation. †There are nine early expansion states: AZ, CO, CT, DE, DC, HI, MN, NY, and VT. In the analysis, WI is considered as an expansion state due to the eligibility limit of 100% FPL.

*These states have approved Section 1115 waivers for expanding coverage. This waiver allows states to be flexible in terms of federal Medicaid requirements and using federal funds.

Table 3: Descriptive Statistics

	Eligible Adults		Non-Eligible Adults	
	Before	After	Before	After
Panel A: Outcome Variables				
Labor Force Participation	53.7%	57.4%	53.4%	58.3%
N	1,223	801	1,335	781
Employed	86.2%	88.2%	86.1%	90.8%
N	669	460	752	1,230
Part-time (PT) Employment (<20 Hrs)	7.3%	8.6%	7.9%	5.7%
PT Employment (20-34 Hrs)	18.8%	17.6 %	20.7%	19.5%
PT Employment (<35 Hrs)	26.0%	26.2%	28.6%	25.2%
N	581	414	658	1,143
Panel B: Control Variables				
Female	55.0%	49.2%	51.4%	49.2%
Age	48.1	49.7	48.4	49.0
Married	3.3%	4.4%	3.4%	4.9%
Divorced	35.6%	37.8%	33.4%	37.6%
Widowed	11.4%	9.3%	12.0%	8.7%
Separated	7.5 %	8.9%	7.7%	6.6%
White	56.5%	66.0%	57.6%	64.0%
African-American	36.7%	26.5%	37.4%	28.3%
Asian	1.3%	2.4%	1.1%	3.3%
Less than High School (HS)	15.0%	17.6%	14.2%	18.4%
HS Dropout	35.8%	28.8%	38.7%	31.0%
HS Grad	48.5%	52.3%	43.1%	49.1%
State Unemployment Rate	8.44%	3.66%	8.52%	3.78%
State GDP (% change)	0.40%	0.36%	0.40%	0.39%
N	1,223	801	1,335	781

Notes: The sample is restricted to ±4% FPL around the elgibility cutoff. Nine early expansion states are excluded from the analysis. Eligible and non-eligible adults are determined using the simulated eligibility measure. Individual-level weights are used to calculate the sample means. See Section 3.3 for the base group of outcome variables.

Table 4: The Effect of Medicaid Expansion on Enrollment:
Difference-in-Discontinuities Design

	Expansion States		Non-Expansion States	
	(1)	(2)	(3)	(4)
Medicaid Enrollment				
Eligibility $*$ *Post*	0.275**	0.188**	-0.118	0.149
	(0.136)	(0.093)	(0.168)	(0.105)
Bandwidth	±4% FPL	±8% FPL	±4% FPL	±8% FPL

Notes: All of the specifications include control variables, state fixed effects, period effects (year and month dummies), and state time-varying effects. See Table 3 for a complete list of control variables. State time-varying effects include both state unemployment rate and state GDP (% change). The standard errors are bootstrapped with 400 replications and clustered by state. Significance levels are: ***0.01 and **0.05.

Table 5: Labor Market Outcomes: Difference-in-Discontinuities Design

	Expansion States			Non-Expansion States		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Labor Force Participation						
Eligibility ∗ Post	0.014	0.029	0.032	-0.046	-0.031	-0.032
	(0.050)	(0.047)	(0.047)	(0.060)	(0.058)	(0.058)
Panel B: Employed						
Eligibility ∗ Post	0.009	0.001	-0.001	0.085	0.090	0.094
	(0.046)	(0.046)	(0.046)	(0.049)	(0.048)	(0.049)
Panel C: PT Employment (<20 Hrs)						
Eligibility ∗ Post	0.087	0.098**	0.094**	0.059	0.054	0.053
	(0.041)	(0.041)	(0.041)	(0.037)	(0.038)	(0.038)
Panel D: PT Employment (20-34 Hrs)						
Eligibility ∗ Post	0.048	0.048	0.044	0.023	0.012	0.013
	(0.053)	(0.054)	(0.054)	(0.066)	(0.066)	(0.066)
Panel E: PT Employment (<35 Hrs)						
Eligibility ∗ Post	0.136**	0.146**	0.137**	0.082	0.065	0.066
	(0.063)	(0.064)	(0.064)	(0.070)	(0.070)	(0.070)
Controls	N	Y	Y	N	Y	Y
State Time-Varying Effects	N	N	Y	N	N	Y

Notes: The sample is restricted to ±4% FPL around the elgibility cutoff. All of the specifications include state fixed effects and period effects (year and month dummies). See Table 3 for a complete list of control variables. State time-varying effects include both state unemployment rate and state GDP (% change). The definition of part-time (PT) employment is taken from the U.S. Bureau of Labor Statistics. The standard errors are bootstrapped with 400 replications and clustered by state. Significance levels are: ***0.01 and **0.05.

Table 6: Subgroup Analysis in Expansion States

	Female	Male	HS or less	More than HS	Age (27-49)	Age (50-64)	Never Married	Married Once
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Labor Force Participation								
Eligibility ∗ Post	0.050	0.018	-0.008	0.068	0.002	0.028	-0.033	0.086
	(0.069)	(0.070)	(0.099)	(0.065)	(0.072)	(0.069)	(0.078)	(0.068)
	[2,139]	[2,001]	[1,948]	[2,192]	[1,806]	[2,334]	[1,652]	[2,488]
Panel B: Employed								
Eligibility ∗ Post	0.002	0.001	-0.054	-0.055	-0.058	0.073	-0.124	0.107**
	(0.061)	(0.062)	(0.078)	(0.050)	(0.066)	(0.053)	(0.070)	(0.054)
	[1,120]	[1,205]	[948]	[1,377]	[1,199]	[1,126]	[977]	[1,348]
Panel C: PT Employment (<20 Hrs)								
Eligibility ∗ Post	0.140**	0.035	0.211**	0.031	0.076	0.110	0.057	0.118**
	(0.058)	(0.064)	(0.084)	(0.045)	(0.060)	(0.064)	(0.060)	(0.056)
	[1,009]	[1,047]	[817]	[1,239]	[1,023]	[1,033]	[853]	[1,203]
Panel D: PT Employment (20-34 Hrs)								
Eligibility ∗ Post	0.029	0.046	-0.088	0.123	0.073	0.049	-0.010	0.078
	(0.082)	(0.079)	(0.109)	(0.077)	(0.081)	(0.086)	(0.093)	(0.076)
	[1,009]	[1,047]	[817]	[1,239]	[1,023]	[1,033]	[853]	[1,203]
Panel E: PT Employment (<35 Hrs)								
Eligibility ∗ Post	0.168	0.081	0.124	0.154	0.149	0.159	0.047	0.196**
	(0.091)	(0.094)	(0.123)	(0.082)	(0.096)	(0.098)	(0.101)	(0.091)
	[1,009]	[1,047]	[817]	[1,239]	[1,023]	[1,033]	[853]	[1,203]

Notes: The sample is restricted to ±4% FPL around the elgibility cutoff in expansion states. All of the specifications include control variables (excluding the subgroup), state fixed effects, period effects (year and month dummies), and state time-varying effects. See Table 3 for a complete list of control variables. State time-varying effects include both state unemployment rate and state GDP (% change). The standard errors are bootstrapped with 400 replications and clustered by state. The number of observations are denoted in brackets. Significance levels are: ***0.01 and **0.05.

Table 7: Covariate Smoothness Test

	Female	Age	Married	Divorced	Widowed	Separated	White	African-American	Asian	Less than HS	HS Dropout	HS Grad
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Eligibility * Post$	0.020	1.489	-0.039	0.074	-0.048	-0.012	-0.040	0.057	0.005	-0.003	-0.014	-0.007
	(0.051)	(1.242)	(0.027)	(0.051)	(0.028)	(0.024)	(0.042)	(0.039)	(0.013)	(0.033)	(0.046)	(0.049)
Constant	0.539***	49.51***	0.003	0.411***	0.140***	0.028	0.620***	0.270***	0.028**	0.130***	0.165***	0.709***
	(0.038)	(0.831)	(0.016)	(0.037)	(0.026)	(0.018)	(0.035)	(0.031)	(0.011)	(0.026)	(0.033)	(0.034)

Notes: N =4,140 in each column. The sample is restricted to ±4% FPL around the elgibility cutoff. The regressions exclude covariates and state time-varying effects and include the remaining terms defined in Equation(6). Constant shows the predicted value for childless adults who are about to be eligible at 138% FPL given that d = FPL - 138. The standard errors are bootstrapped with 400 replications and clustered by state. Significance levels are: ***0.01 and **0.05.

Table 8: Robustness and Falsification Checks

	Include Early Expansion States		Double Bandwidth (±8% FPL)		Quadratic Running Variable		Cubic Running Variable		Age > 64	
	Expansion States	Non-Expansion States	Expansion States	Non-Expansion States	Expansion States	Non-Expansion States	Expansion States	Non-Expansion States	Expansion States	Non-Expansion States
Panel A: Labor Force Participation										
$Eligibility * Post$	0.010	-0.032	0.032	-0.052	0.033	-0.017	0.033	-0.012	-0.008	-0.036
	(0.047)	(0.064)	(0.033)	(0.040)	(0.039)	(0.043)	(0.035)	(0.038)	(0.027)	(0.041)
Panel B: Employed										
$Eligibility * Post$	-0.037	0.094	-0.003	0.032	-0.005	0.063	-0.006	0.055	0.168	-0.201
	(0.039)	(0.048)	(0.030)	(0.034)	(0.035)	(0.034)	(0.032)	(0.030)	(0.119)	(0.106)
Panel C: PT Employment (<20 Hrs)										
$Eligibility * Post$	0.081**	0.053	0.073***	0.030	0.081**	0.042	0.074**	0.038	0.288	-0.324
	(0.036)	(0.041)	(0.028)	(0.032)	(0.032)	(0.030)	(0.029)	(0.027)	(0.286)	(0.232)
Panel D: PT Employment (20-34 Hrs)										
$Eligibility * Post$	0.062	0.013	0.040	-0.014	0.042	-0.015	0.040	-0.023	-0.005	0.177
	(0.050)	(0.066)	(0.042)	(0.048)	(0.046)	(0.049)	(0.042)	(0.044)	(0.236)	(0.222)
Panel E: PT Employment (<35 Hrs)										
$Eligibility * Post$	0.143**	0.066	0.113**	(0.016)	0.123**	0.027	0.115**	0.015	0.283	-0.147
	(0.057)	(0.072)	(0.048)	(0.054)	(0.049)	(0.055)	(0.046)	(0.048)	(0.306)	(0.257)

Notes: All of the specifications include control variables, state fixed effects, period effects (year and month dummies), and state time-varying effects. See Table 3 for a complete list of control variables. State time-varying effects include both state unemployment rate and state GDP (% change). The standard errors are bootstrapped with 400 replications and clustered by state. Significance levels are: ***0.01 and **0.05.

Table 9: The Effect of Medicaid Expansion on Labor Market Outcomes:
Difference-in-Differences (DD) Model

	(1)	(2)	(3)
Panel A: Labor Force Participation			
$Expansion * Post$	0.078**	0.052	0.007**
	(0.039)	(0.028)	(0.003)
Panel B: Employed			
$Expansion * Post$	-0.003	0.014	0.002
	(0.029)	(0.018)	(0.002)
Panel C: PT Employment (<20 Hrs)			
$Expansion * Post$	0.011	0.020	-0.002
	(0.018)	(0.014)	(0.001)
Panel D: PT Employment (20-34 Hrs)			
$Expansion * Post$	0.048	0.030	-0.002
	(0.039)	(0.033)	(0.003)
Panel E: PT Employment (<35 Hrs)			
$Expansion * Post$	0.059	0.050	-0.004
	(0.037)	(0.037)	(0.004)
Sample	±4% FPL	±8% FPL	Full Sample

Notes: All of the specifications include control variables, state fixed effects, period effects (year and month dummies), and state time-varying effects. See Table 3 for a complete list of control variables. State time-varying effects include both state unemployment rate and state GDP (% change). The standard errors are clustered by state and observations are weighted using the individual-level weights in the CPS. Significance levels are: ***0.01 and **0.05.

Appendix

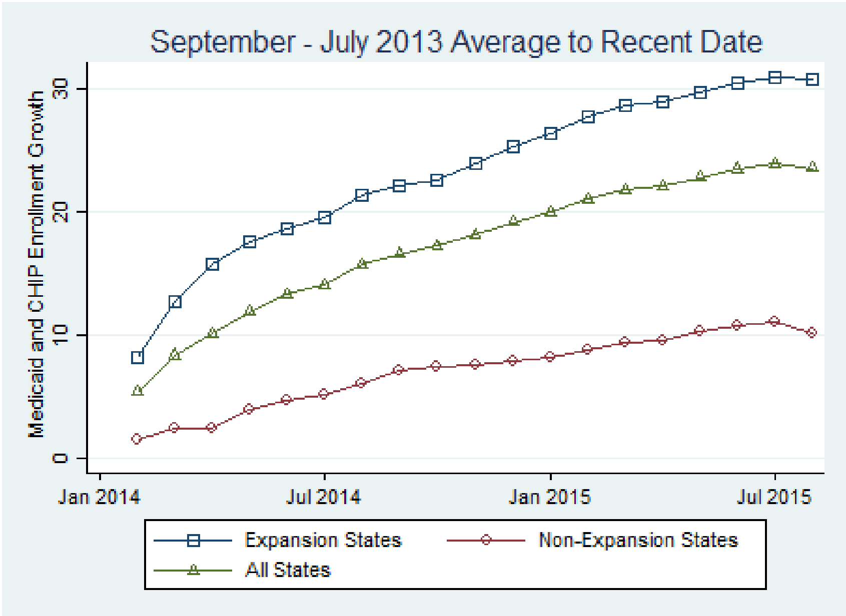

Figure A1: Medicaid and CHIP Enrollment Growth Rate

Notes: The graph is constructed by the author using the Medicaid enrollment data from Centers for Medicare & Medicaid Services (CMS).

Table A1: Guidelines on the Federal Poverty Level (FPL)

Household Size	100% FPL						
	2010 FPL	2011 FPL	2012 FPL	2013 FPL	2014 FPL	2015 FPL	2016 FPL
1	\$10,830	\$10,890	\$11,170	\$11,490	\$11,670	\$11,770	\$11,880
2	\$14,570	\$14,710	\$15,130	\$15,510	\$15,730	\$15,930	\$16,020
3	\$18,310	\$18,530	\$19,090	\$19,530	\$19,790	\$20,090	\$20,160
4	\$22,050	\$22,350	\$23,050	\$23,550	\$23,850	\$24,250	\$24,300
5	\$25,790	\$26,170	\$27,010	\$27,570	\$27,910	\$28,410	\$28,440
6	\$29,530	\$29,990	\$30,970	\$31,590	\$31,970	\$32,570	\$32,580

Notes: Hawaii and Alaska have different guidelines for the poverty thresholds and those are taken into account.
Source: U.S. Department of Health & Human Services.