Medicaid and the Supply of Entrepreneurs: Evidence from the Affordable Care Act

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Abstract

I examine whether the expansion of Medicaid eligibility under the Affordable Care Act increases the supply of entrepreneurs as measured by self-employment. Using the 2003–2017 Current Population Survey and focusing on childless adults in low-income households, I apply difference-in-differences, propensity score weighting, and instrumental variable (IV) methods. I find that expanding Medicaid eligibility raises the self-employment rate by 0.8 to 1.6 percentage points, without increasing self-employment exit. IV estimates imply that covered individuals have 8 to 11 percentage points higher probability to become self-employed. Exploiting additional variation by spousal coverage or poor health of individuals or their spouse within triple difference specifications, I also find evidence that the underlying mechanism of the effect was through the reduction of entrepreneurship lock. The results suggest that limited access to health insurance may be a barrier to entrepreneurship.

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1. Introduction

Does limited access to health insurance reduce entrepreneurship in the U.S? Most nonelderly US citizens receive health insurance through employers, while the self-employed tend to be excluded from group insurance and have little or no access to non-group insurance. As a result, the uninsured rate is considerably higher among the self-employed than employees (Perry and Rosen 2004). Limited access to health insurance may create an "entrepreneurship lock" that employees[1] (or wage and salary workers) with employer-sponsored insurance are less likely to leave their job and be self-employed (e.g. Fairlie, Kapur, and Gates 2011).[2] This may also influence new labor entrants to choose to become employees instead of self-employed. As a result, individual occupational choices to be self-employed are distorted. A large number of studies suggest that policies improving access to health insurance for the self-employed would therefore increase entrepreneurship (Becker and Tüzemen 2014; DeCicca 2010; Gumus and Regan 2014; Fairlie, Kapur, and Gates 2011; Niu 2014; Olds 2016).

In this paper, I study the 2014 Affordable Care Act (ACA) Medicaid eligibility expansion to examine whether improving access to health insurance increases the supply of entrepreneurs as measured by self-employment. The ACA expands Medicaid coverage to all individuals with household income below 138 percent of the Federal Poverty Level, with the biggest expansion among childless adults, who had been previously ineligible. Total 34 states have adopted the Medicaid expansion between 2014 and 2017. The target population of the ACA Medicaid expansion is markedly large compared to other health reforms, as the proportion under the eligibility threshold is about 24 percent of nonelderly citizens in the US (Finegold et al. 2015). Stephens et al. (2013) projected that approximately 21.3 million low-income adults will be newly covered by Medicaid under the eligibility expansion.

Theoretically, the effects of health insurance access on self-employment are ambiguous. On the one hand, access may reduce the entrepreneurship lock on starting a new business, raising

[1] In this paper, I use employees to refer wage and salary workers. The U.S. Bureau of Labor Statistics (BLS) defines wage and salary workers as "workers who receive wages, salaries, commissions, tips, payment in kind, or piece rates. The group includes employees in both the private and public sectors."

[2] The tight relationship between access to health insurance and jobs can create "job lock" whereby workers tend not to leave their jobs in order to keep their employer-sponsored insurance despite higher productivity in other jobs (e.g., Madrian 1994; Gruber and Madrian 2002). In a survey of over 50 empirical studies, Gruber and Madrian (2002) found suggestive evidence that health insurance coverage can distort workers' labor market choices including labor supply, retirement, and job mobility, but they do not study self-employment decisions.

the relative attractiveness of self-employment for both current employees and labor force entrants. On the other hand, access to free health insurance may have a negative income effect that reduces labor supply, including self-employment. If income effects are dominant, the self-employment rate may fall as some self-employed individuals reduce their working hours or even stop working.

Exploiting the geographic and time variation created by state policy implementation, I compare self-employment outcomes between expansion and non-expansion states, before and after the states' adoption of the ACA Medicaid expansion. I focus on low-income childless adults—the group experiencing the largest expansion in eligibility. My data are from the Annual Social and Economic Supplement of the Current Population Survey (CPS) from 2003 to 2017. My main outcome variable is the probability of self-employment, but I also analyze self-employment entry and exit, which may be useful in reflecting potential negative income effects. Exploiting the sample rotation design of the CPS, I also link individuals across years and create two-year panels with a large number of observations to capture self-employment transitions.

I estimate both intent-to-treat and local average treatment effects of the ACA Medicaid expansion. I use variations on a difference-in-differences model to estimate the intent-to-treat effects. The basic difference-in-differences approach relies on the assumption of common trends across expansion and non-expansion states. In the context of the Medicaid expansion, unbalanced covariates between expansion and non-expansion states may invalidate the common trend assumption. To address potential heterogeneity in individuals across states, I extend the difference-in-difference framework with propensity score weighting.

Although the ACA Medicaid expansion allowed all individuals under the eligibility threshold, only certain subpopulations enrolled in Medicaid ("compliers"). Previous studies on entrepreneurship lock focused on the intent-to-treat effect of the increase in access to health insurance. However, the effects on compliers have received much less attention. To estimate local average treatment effects, I apply an instrumental variable approach.[3] I use the states' adoption of the ACA Medicaid expansion as an instrument to see a causal relationship between Medicaid take-up and self-employment. I also apply propensity score weighting to the instrumental variable approach to balance covariates in the first stage.

[3] Finkelstein et al. (2012) examined the Oregon health experiment. They used lotter as an instrument to examine the local average treatment effects of Medicaid on health care utilization, financial burden, and health outcomes. Similarly, Baicker et al. (2013) used an instrumental variable approach to estimate the effects of being covered by Medicaid on labor market outcomes and social program participation.

I further associate the Medicaid expansion with variation in health insurance demand in triple difference specifications. The health insurance demand factors include access to spouses' employer-sponsored insurance and the existence of poor health status of respondents and/or spouses. If the increase in Medicaid eligibility reduces entrepreneurship lock, the effects on those with higher health demand would be larger than those with lower demand. The self-employment effects may be driven by consumer demand shocks. If Medicaid enrollees consume more local goods, this could increase not only the attractiveness of self-employment (new business) but also labor demand to produce more goods. Therefore, I also examine total employment effects to see whether Medicaid increases local demand for consumption goods.

There are three main findings. First, the ACA Medicaid expansion increased self-employment. I find that states that expanded Medicaid eligibility experienced an 0.8 to 1.6 percentage point increase in the self-employment rate among low-income childless adults relative to states that did not expand Medicaid eligibility. These are approximately 10 to 14 percent increases from the unconditional mean of the self-employment rate (7.6 percent). Results from self-employment transitions also indicate that the entry rate significantly increased while the exit rate remained steady, which suggests that income effects are not dominant for self-employed individuals. Second, Medicaid coverage engenders a higher propensity of entrepreneurship. My results suggest that only a fraction of the entire eligible population enrolled in Medicaid. Childless adults newly covered by Medicaid due to the increase in eligibility have higher propensity of being self-employed than those without Medicaid by 8 to 11 percentage points. Third, the mechanism of the ACA Medicaid expansion effects on entrepreneurship was through a reduction in entrepreneurship lock. I find that self-employment effects are larger for groups with factors associated with health insurance demand among childless married couples, and I find no evidence of growth in total employment.

My study contributes to the broad literature on health insurance and entrepreneurship by providing new evidence from the ACA Medicaid expansion.[4] Most related to my research are

[4] Early empirical studies identified the relationship between health insurance and self-employment using cross-sectional variation created by employer-sponsored insurance (ESI) and the access to spousal coverage within a difference-in-difference framework. These studies found mixed results, with some studies finding significant relationships (Wellington 2001; Zissimopoulos and Karoly 2007) and others finding no evidence (Bruce, Holtz-Eakin, and Quinn 2000; Holtz-Eakin, Penrod, and Rosen 1996). One major concern in these studies is that both ESI and spousal coverage are endogenously determined. To address endogeneity issues, recent studies have exploited exogenous variations created by health care reforms or regulations. One line of these studies examined health care

studies that examined the eligibility increase in public health insurance options. Some studies found positive and significant self-employment effects of public health insurance. The most influential study is Fairlie, Kapur, and Gates (2011), which exploited the eligibility threshold for Medicare at age 65 within a regression discontinuity framework. They found that eligibility for Medicare increased the rate of self-employment by those over age 65 by 14 percent from the sample mean of 24.6 percent. A limitation of this study is that it applies only to older workers around age 65, which makes it difficult to infer implications for other age groups. In addition, there might be retirement effects considering that the standard retirement age is 65. If retired individuals are more likely to be self-employed at age 65, the effects might be over-estimated. Similarly, Olds (2016) found that the State Child Health Insurance Program (SCHIP) raised the self-employment rate among parents by about 15 percent. He argued that although the SCHIP did not cover parents, it eased their worry about health insurance coverage for their children, thus allowing them to take the risk of starting a business.

On the other hand, other studies found limited evidence on the effects of public insurance on self-employment. in her analysis of Medicaid coverage for young children from 1986 to 1992, Dolan (2015) found that the expansion of Medicaid eligibility increased the likelihood of being self-employed among fathers, but not mothers. Boyle and Lahey (2010) examined the eligibility expansions of the US Department of Veterans Affairs (VA) health system in 2006. They found that after the reform, veterans with a university or more education were more likely to be self-employed compared to non-veterans, whereas veterans with a high school or less education were more likely to be not working compared to non-veterans. Finally, Bailey (2017) examined mandated dependent coverage under the ACA. He found no evidence of the dependent coverage mandate leading to an increase in the self-employment rate among young adults (19 to 25 years old), except for those who were disabled.

Considering that the effects on self-employment differ depending on the target population, reflecting varied economic environment or demand for health insurance, it is valuable to study different groups. My study provides evidence from previously understudied low-income childless

reforms that improve access to health insurance in the non-group insurance market (Becker and Tüzemen 2014; DeCicca 2010; Heim and Lurie 2014a; Heim and Lurie 2014b; Heim and Lurie 2017; Niu 2014). These studies found mixed results of the effects on entrepreneurship. Other relevant studies investigated the effects of tax reforms that reduce the cost of non-group health insurance for self-employed individuals (Gumus and Regan 2014; Heim and Lurie 2010; Velamuri 2012). These tax reform studies consistently found positive effects on the self-employment rate.

adults across all age groups. In addition, because the extent of the eligibility changes in the ACA Medicaid expansion is significantly larger for childless adults previously excluded from traditional state Medicaid programs, my study provides evidence for clarifying the relationship between health insurance and self-employment with a larger population. My identification strategies are different from previous studies in that I estimate the effects of being covered by Medicaid, in addition to the effects of eligibility increase.

I also contribute to the literature on the effects of the ACA Medicaid eligibility expansion on labor supply. I provide evidence that Medicaid increases labor supply by reducing distortion in occupational choice between employees and those who are self-employed. There is a debate on the unexpected consequences of Medicaid on labor market outcomes. Some studies have investigated state specific Medicaid programs that increase or decrease eligibility for low-income childless adults (Baicker et al. 2013; Dague, DeLeire, and Leininger 2017; DeLeire 2018; Garthwaite, Gross, and Notowidigdo 2014). Other empirical studies have directly examined the effects of the ACA Medicaid expansion on labor supply (Duggan, Goda, and Jackson 2017; Gooptu et al. 2016; Kaestner et al. 2017; Leung and Mas 2016). However, to the best of my knowledge, self-employment outcomes have not been studied in this literature, except for Duggan, Goda, and Jackson (2017).

My research differs from Duggan, Goda, and Jackson (2017) in several ways. Although they included self-employment in their analysis of labor market outcomes, it was not their main focus. In addition, because their sample was not restricted to low-income groups, the self-employment rate they found was computed based not only on the targeted low-income population but also on the nontargeted high-income population. If the proportion of the non-targeted group was large, the change in self-employment may have been small even if the targeted group responded. In my study, I narrow my sample to low-income childless adults who experience the largest eligibility changes.

One caveat in this study is that entrepreneurship is proxied by self-employment. Of course, the self-employed are heterogeneous in terms of their activities and the types of business they create. Nevertheless, self-employment has been used as a working definition (or proxy) for entrepreneurs in entrepreneurship studies (Parker 2009) because self-employment captures some aspects of entrepreneurship in terms of risk-taking and occupational choices. In addition, because the literature on health insurance and entrepreneurship used self-employment to measure entrepreneurial activities, using self-employment also allows the comparison of my estimates with those from previous studies. Finally, because the types of businesses low-income people start tend to be small and unsophisticated (Balkin 1989), self-employment is a relevant measure to capture entrepreneurship in low-income households.

Subsequent sections of this paper proceed as follows. Section 2 provides the background of Medicaid eligibility expansion under the ACA and describes the research design. In Section 3 and 4, I describe the data and methods used in the analysis. Section 5 discusses the results from the empirical analysis, and Section 6 provides a conclusion.

2. Medicaid Expansion under the Affordable Care Act

The initial ACA rendition mandated Medicaid expansion to all individuals in families with incomes below 138 percent of the federal poverty line (FPL) and subsidies to all individuals with incomes between 100 and 400 percent of the FPL, starting in 2014. However, the 2012 Supreme Court ruling made this mandate optional to individual states. On January 1, 2014, 25 states adopted this Medicaid expansion, and 7 states followed suit between 2014 and 2017, while 19 states opted out of the ACA's Medicaid expansion. In non-expansion states, individuals with incomes between 100 and 400 percent of the FPL still receive subsidies, but those with incomes below 100 percent of the FPL do not receive Medicaid or subsidies. This creates a huge coverage gap for low-income households. A list of states with their status regarding Medicaid expansion under the ACA is provided in Table 1.[5]

The target population of the Medicaid expansion is noticeably larger than other policy components of the ACA. The income level corresponding to 138 percent of the FPL was $12,060 for a single family and $24,600 for a family of four in 2017.[6] According to the US Department of Health and Human Services, about 16 percent of the population is below the FPL, and 8 percent of the nonelderly population is between 100 and 138 percent of the FPL.[7] Therefore, the eligibility

[5] The information of the state level Medicaid expansion is from the Kaiser Family Foundation's the Status of State Action on the Medicaid Expansion Decision, which is available at the following link. https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D

[6] See Federal Register notice of the 2017 poverty guidelines: http://www.kff.org/uninsured/issue-brief/the-coverage-gap-uninsured-poor-adults-in-states-that-do-not-expand-medicaid/view/footnotes/#footnote-201034-1

[7] See Figure 4. Distribution by Income: QHP-Eligible Uninsured vs. General Nonelderly Population: https://aspe.hhs.gov/basic-report/health-insurance-marketplace-uninsured-populations-eligible-enroll-2016

threshold of the ACA Medicaid expansion covers about 24 percent of nonelderly citizens in the US.

The Supreme Court decision resulted in exogenous geographical and time variations by states that adopted the Medicaid expansion between 2014 and 2017. The increase in eligibility was the largest for childless adults because they were previously excluded from most states' Medicaid programs. Figure 1 shows differences in the average eligibility threshold for childless adults between expansion and non-expansion states from 2011 to 2017. Before the implementation of the ACA, childless adults were ineligible for federally funded Medicaid in most states, except for some expansion states that made partial or full expansion before 2014. The average eligibility of expansion states was about 30 percent of the FPL. The eligibility threshold jumps to about 120 percent of the FPL in 2014 and then increases to 138 percent as late expansion states adopted the eligibility under the ACA. On the other hand, the average eligibility is zero percent of the FPL in non-expansion states before 2014. There is a slight increase in the eligibility threshold in 2014 since Wisconsin increased state level eligibility for childless adults up to 100 percent of the FPL without adopting the ACA Medicaid. Although there were some differences between expansion and non-expansion states, this figure indicates that the largest change in the eligibility threshold occurred in 2014.

Figure 2 highlights the geographic variation used in this study to create treatment and control groups. Using the status of the Medicaid expansion, I create the treatment (expansion states) and control (non-expansion states) groups. I exclude Alaska and Hawaii from the analysis due to different guidelines for the FPL, compared to the 48 contiguous states and the District of Columbia (DC). I also exclude 8 states that fully or partially expanded eligibility for childless adults (Arizona, Colorado, Connecticut, Delaware, District of Columbia, Minnesota, New York, and Vermont) from the treatment group. This is because full expansion states increased eligibility higher than 138 percent of the FPL, and most partial expansion states increased eligibility close to 100 percent of the FPL. Finally, I exclude Wisconsin from the control group because it increased state level eligibility to childless adults with income below 100 percent of the FPL. After excluding these states, the treatment group consists of 22 states while the control group includes 18 states. To counter the possibility that prior expansions may influence the estimated effects, I also estimate effects by including states that made full prior expansion as a robustness check.

3. Data

I use data from the Annual Social and Economic (ASEC) Supplement of the Current Population Survey (CPS).[8] The CPS is a nationally representative survey of US households on a monthly basis. It provides detailed demographic and labor force information in the previous week. The CPS ASEC provides additional information on work experience, income, migration, health insurance, household members' health conditions as well as receipt of noncash benefits in the previous calendar year. Since the CPS ASEC provides information for the previous year, I use the CPS ASEC 2004-2018 for the analysis between 2003 and 2017.

The sampling design of the CPS permits the creation of a two-year longitudinal data. In each month, a cohort of households is included in the CPS sample. These households are interviewed for four months, excluded from the survey for eight months, and then re-interviewed for four months. For linking individuals, I use person identifiers in the IPUMS CPS, which exclude Hispanic and the State Children's Health Insurance Program (SCHIP) oversamples of the ASEC.[9] I further validate the same individuals by using age, gender, and race. Theoretically, half of the CPS ASEC samples can be linked across two years. After excluding oversamples and validation process, about 35 percent of individuals under the CPS ASEC are linked. Using this longitudinal sample, I create self-employment transition variables. Because of different samples, self-employment transitions cannot be directly compared to self-employment levels. Nevertheless, transition variables provide a unique opportunity to separately examine the income effect of the Medicaid expansion (e.g. entry and exit).

I restrict the sample to non-disabled, childless adults aged between 26 and 64 to reduce potential bias from access to alternative health insurance. Disabled individuals are eligible for Medicaid. Those aged 65 or more are eligible for Medicare. The ACA mandated dependent coverage allows young adults to be covered by parents' ESI until they reach age 26. Since childless adults were previously excluded from the Medicaid eligible groups in most states, they are less likely to be influenced by the states' Medicaid programs before the ACA Medicaid expansion.

Given that the Medicaid expansion made all people under the 138 percent of the FPL eligible for insurance, low-income individuals are more likely to be influenced by the expansion.

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[8] The CPS ASEC data comes the Integrated Public Use Microdata Series (IPUMS) CPS (Flood, King, Ruggles, and Warren 2017). The IPUMS-CPS "harmonized" variables in CPS to make feasible cross-time comparisons.

[9] Drew et al. (2014) describes details on how IPUMS link individuals using the CPS micro data.

As a result, I further restrict sample based on household incomes. I use two low-income samples—those below 300 and 138 percent of the FPL—for some reasons. First, household incomes in the CPS ASEC are self-reported incomes so that they may differ from actual incomes applied to the Medicaid eligibility. For example, CPS ASEC includes non-disabled childless adults who are covered by Medicaid and report their household incomes above 138 percent of the FPL. If the sample is restricted to those below 138 percent of the FPL, many eligible people can be excluded from the analysis. Second, some self-employed individuals may adjust their incomes to below 138 percent of the FPL in order to be eligible for Medicaid. Sample below 300 percent of the FPL partially addresses these issues because it considers the self-employed who adjusted incomes as incumbents. Third, although using sample below 300 percent of the FPL partially addresses selection problems, they may be influenced by subsidies available for those with income below 400 percent of the FPL. Sample below 138 percent of the FPL excludes those who are eligible for subsidies. Because of reasons mentioned above, using two low-income samples are important to check potential biases. Using incomes to select sample may be problematic in that labor supply and income are endogenously determined. I check robustness of the estimates with an alternative sample with high school or less. This is because education levels are pre-determined before the eligibility expansions.

The main outcome variables are self-employment activities. The self-employed are defined as respondents who indicated self-employment as the longest job held in the previous calendar year.[10] I acknowledge that self-employment is not identical to entrepreneurship. But self-employment still captures the essential aspects of entrepreneurship, for example, risk taking aspects. Both economics and business literature often use self-employment to capture entrepreneurial activities. Moreover, given previous studies which used self-employment to study entrepreneurship lock, using self-employment is useful to compare my estimates with other studies. In addition to static self-employment variables, one-year transition variables are constructed based on the previous year's information. These variables include entry into and exit from self-employment.

[10] Star-ups may generate very low or no business earnings. Business earnings in the survey are also self-reported values. Using business earnings to define the self-employed may exclude start-ups. Therefore, I did not use business earnings to define the self-employed.

4. Methods

4.1 Difference-in-Differences

The baseline estimation approach is a difference-in-differences (DID) analysis that compares expansion states to non-expansion states before and after the states' adoption of the ACA Medicaid expansion. As mentioned earlier, the treatment group includes 22 states that expanded Medicaid between 2014 and 2017, whereas the control group consists of 18 states that did not expand Medicaid. The pre-time period is 2003 to 2013, and the post-time period is 2014 to 2017. The sample consists of non-disabled childless adults aged between the ages of 26 and 64. I estimate the following DID specification:

$$Y_{ist} = \alpha_0 + \beta(E_s * P_t) + X_{ist}\gamma + Unemp_{st} + \delta_s + \tau_t + \varepsilon_{ist}. \quad (1)$$

Y_{ist} represents the outcome variables by individual i in state s in time t. Outcome variables include self-employment level, entry, and exit. E_s and P_t are indicator variables for expansion states and post-time periods, respectively. X_{ist} is the set of demographic and human capital variables. $Unemp_{st}$ indicates the unemployment rate for state s in time t, which controls states' business cycles that may affect labor market outcomes differently. The model includes state fixed effects (δ_s) and time fixed effects (τ_t), which remove time invariant state-specific heterogeneity and contemporaneous shock respectively. Given that the focus of this study is the differences in conditional expected values between expansion and non-expansion states across time, I use linear probability models to estimate the equation (1). As a robustness check, I also estimate these equations with Logit and Probit models.

The key identifying assumption of the DID specification is a common trend assumption that in the absence of the Medicaid expansion, the trend of the rate of self-employment in expansion states would be the same as the trend in non-expansion states. If this assumption is true, the coefficient of the interaction term (β) captures the impact of the Medicaid expansion on outcome variables.

To check whether this identifying assumption is plausible, I conduct an event study. I estimate a new specification that interacts treatment states with time fixed effects in the following form.

$$Y_{ist} = \alpha_0 + \sum_{t=2003}^{2017} \beta_t (E_s * Year_t) + X_{ist}\gamma + Unemp_{st} + \delta_s + \tau_t + \varepsilon_{ist}. \quad (2)$$

In this specification, $\sum_{t=2003}^{2017} \beta_t (E_s * Year_t)$ captures changes in outcomes in the expansion states across time periods, relative to 2013. If the estimated differences between expansion and non-expansion states before 2014 ($\sum_{t=2003}^{2012} \beta_t$) are close to zero and statistically insignificant, the parallel trend assumption could be justified. The estimated effects from 2014 to 2017 ($\sum_{t=2014}^{2017} \beta_t$) differentiate short-term effects from long-term effects.

4.2 Propensity Score Weighting

One concern in the DID analysis is that the differences in characteristics between treatment and control groups may affect the trends of outcome variables if these characteristics are associated with outcome variables (Abadie 2005; Imbens and Wooldridge 2009). Additionally, repeated cross-sectional data (such as CPS or ACS) include random sample in each time period, which may lead to changes in compositions of samples over time (Abadie 2005; Blundell and Costa Dias 2009; Stuart et al. 2014).

To adjust unbalanced observable characteristics and composition changes resulting from repeated cross-section data over time, I apply multiple group propensity score weights to a parametric DID specification, as in Stuart et al. (2014).[11] I define four groups based on Medicaid expansion status as well as pre- and post-time periods: Group 1 (expansion states in pre-time period), Group 2 (expansion states in post-time period), Group 3 (non-expansion states in pre-time period), Group 4 (non-expansion states in post-time period). Group 1 is my baseline group to construct relative weights. I use multinomial logistic regression to compute propensity scores for the four groups based on observed characteristics, including age, gender, race/ethnicity, marital status, citizenship, education, and veteran status. Then, I construct weights with a following equation:

$$w_i = p_1(X_i)/p_g(X_i), \quad (3)$$

[11] Abadie (2005) originally proposed a similar approach using a propensity score weighing with a semiparametric difference-in-differences model. Blundell and Costa Dias (2008) also suggested a similar approach using a group propensity score matching with a parametric difference-in-differences model.

where w_i is the weight for an individual i and $p_g(X_i)$ is the propensity score for an individual i in Group g, for g=1-4. The weight is proportional to the probability of being in Group 1 (the expansion states in pre-time periods) relative to the probability of being in the observed Group g. Individuals in Group 1 receive an equal weight of 1, while those in Groups 2 to 4 receive proportional weights.

Applying the weights defined in Eq. (3) to the baseline model in Eq. (1), I estimate the propensity score weighted difference-in-differences (PSW-DID). The treatment effect of this model is specified as follows:

$$Effect = (w_i E[Y_{ist}|X_{ist} = x, E_s = 1, P_t = 1] - w_i E[Y_{ist}|X_{ist} = x, E_s = 0, P_t = 1]) \\ -(E[Y_{ist}|X_{ist} = x, E_s = 1, P_t = 0] - w_i E[Y_{ist}|X_{ist} = x, E_s = 0, P_t = 0]) \quad (4)$$

The third term is estimated from Group 1. The other three terms are estimated by weighting Group 2 (the first term), 3 (the fourth term), and 4 (the second term). This approach is similar to the inverse probability of treatment weighting (IPTW) in that the observations are weighted based on observable characteristics. But in this specification, weights are constructed to reflect not only treatment status but also time periods.

4.3 Instrumental Variable

Both DID and PSW-DID identify the intent-to-treat (ITT) effects of being eligible for Medicaid through the states' adoption of ACA Medicaid expansion. Even though the ITT estimates provide the net effects of expanding the eligibility of Medicaid to low-income childless adults, regardless of whether they opted for Medicaid coverage, it is also very important to understand outcomes of those who enrolled in Medicaid ("compliers").

The relationship between Medicaid coverage and self-employment outcomes can be specified as in the following equation.

$$Y_{ist} = \alpha_0 + \pi Medicaid_{ist} + X_{ist}\gamma + Unemp_{st} + \delta_s + \tau_t + \varepsilon_{ist}, \quad (5)$$

where $Medicaid_{ist}$ is an indicator of being covered by Medicaid. Other variables are the same as in the previous specification. The coefficient of $Medicaid_{ist}$ captures the average difference in outcomes between individuals with and without Medicaid coverage.

However, because Medicaid coverage is endogenously determined, directly estimating Eq. (5) with the ordinary least square (OLS) provides a biased estimate of the Medicaid coverage. To get the bias-corrected estimates, I apply an instrumental variable (IV) approach using the ACA Medicaid expansion as an instrument.[12] I estimate Eq. (5) using two-stage least squares with the following first stage equation:

$$Medicaid_{ist} = \alpha_0 + \theta(E_s * P_t) + X_{ist}\gamma + Unemp_{st} + \delta_s + \tau_t + \varepsilon_{ist}. \quad (6)$$

In this equation, the instrumental variable is the interaction term ($E_s * P_t$), which indicates the ACA Medicaid expansion status. Following Angrist and Pischke (2009), I estimate both first and second equations with a linear probability model and examine whether F-statistic of the first stage is larger than 10 to check a possibility of a weak instrument. The first stage in Eq. (6) is a standard DID specification. As in Eq. (1), the first stage equation relies on a common trend assumption. Therefore, I also apply the PSW to IV (PSW-IV) estimation, which reduces potential bias in the first stage equation.

The instrumental variable approach estimates a local average treatment effect (LATE) for compliers, which is the ratio of the reduced form estimate in Eq. (1) to the first stage estimate in Eq. (6). The compliers are a subpopulation of childless adults who enrolled in Medicaid in the expansion states because of the states' adoption of the ACA Medicaid eligibility expansion. The assumption of the LATE is that being eligible for Medicaid affects self-employment outcomes only through being covered by Medicaid.

4.4 Triple Differences

In order to empirically test whether the Medicaid expansion reduces entrepreneurship lock, I exploit the variation of cost factors for health insurance within a triple difference framework. I use three different cost factors separately: spousal ESI, poor health status of family members, or

[12] Baicker et al. (2013) and Finkelstein et al. (2012) applied an instrumental variable approach to estimate the effects on compliers in their analyses of Oregon's Medicaid expansion.

poor health status of spouse. I estimate a specification by interacting the difference-in-differences estimate with a cost factor. Using either spouse or family information, here my sample is restricted to married couples. The specification of the model is as follows:

$$Y_{ist} = \alpha_0 + \beta_1(E_s * P_t) + \beta_2(E_s * P_t * C_{ist}) + X_{ist}\gamma + Unemp_{st} + \delta_s + \tau_t + \varepsilon_{ist}, \qquad (8)$$

where C_{ist} is an indicator of health insurance cost factors. β_1 provides the effects on married couples with low cost factors, and β_2 is the triple difference estimate indicating how much larger the effect is for those with high cost factors. To capture the effects on married couples with high cost factors, I also compute $\beta_1 + \beta_2$ and test $\beta_1 + \beta_2 > 0$.

Those with spousal coverage are less likely to experience entrepreneurship lock, because they have access to alternative health insurance. Therefore, they are less likely to worry about employer-sponsored insurance. Likewise, other cost factors may affect accessibility to health insurance in the non-group insurance market. If the Medicaid expansion increases the access to health insurance by reducing entrepreneurship lock, positive and significant β_2 would be expected.

5. Results

5.1 Descriptive Statistics

Table 2 provides the descriptive statistics of demographics and health insurance status for non-disabled childless adults aged 26 to 64 with household incomes below 300 percent of the FPL. The first column provides the descriptive statistics for the full sample. The second and third columns shows descriptive statistics for the self-employed and employees. The remaining two columns show descriptive statistics by the status of expansion in the pre-treatment periods.

The upper panel provides demographic characteristics, including age, gender, race/ethnicity, marital status, foreign born status, veteran status, and education. Compared to employees, the self-employed are more likely to be older, white, married, and male. They also tend to have higher education levels, but their family income is lower than employees' by about 4,200 dollars on average. Although my sample is restricted to low-income households, the characteristics of self-employment are still similar to factors found in the self-employment literature.[13] The

[13] See Parker (2009) for a literature review of the determinants of self-employment.

comparison between expansion and non-expansion states before the implementation of the Medicaid expansion in 2014 shows that average demographic characteristics are very similar, except for race/ethnicity, foreign born, and never married variables. While the proportion of Hispanics is very similar, the expansion states include more non-Hispanic whites and Asians while the non-expansion states include more non-Hispanic blacks. The expansion states also include a larger proportion of foreign born or never married individuals. Since state heterogeneity may drive self-employment outcomes differently in expansion and non-expansion states, I adjust all demographic characteristics to estimate the effects of the Medicaid expansion.

The lower panel shows descriptive statistics on health insurance coverages. The rate of the uninsured is high among low-income childless adults, which is about 40 percent. Half of the sample is covered by private insurance. It should be noted that ESI coverage is the main source of insurance coverage (37 percent)[14]. By comparison, the uninsured rate is higher among the self-employed than employees. Self-employed individuals are more likely to be covered by Medicaid and less likely to have private insurance. Notably, the coverage rate of ESI is significantly lower among the self-employed, and the majority of the ESI coverage is explained by spousal ESI. Although the rate of non-group insurance in self-employment is much higher, the magnitude is smaller than the reduction in the ESI coverage. This reflects limited access to non-group health insurance for self-employed individuals. Compared to non-expansion states, expansion states tend to have lower rates of uninsured and higher rates of Medicaid coverage. The rate of private insurance coverage is very similar between expansion and non-expansion states. Since the Medicaid expansions affect health insurance outcomes, I do not adjust health insurance status when I estimate the effects of the ACA Medicaid expansion on self-employment outcomes. Instead, the effect of Medicaid coverage on self-employment is directly estimated in the instrumental variable approach.

Table 3 presents the descriptive statistics of self-employment and other employment status. The first column provides the descriptive statistics for the full sample. The remaining four columns show descriptive statistics by the status of expansion and the pre/post-treatment periods.

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[14] The coverage rate of the ESI for low-income childless adults with ages 26-64 (37 percent) is lower than that for all individuals with ages 26-64 (65 percent). But it should be emphasized that low-income childless adults include the larger proportion of non-employed individuals. When the sample is restricted to employees, the coverage rate of the ESI for low-income childless adults increases to 48 percent. Furthermore, the rate of the uninsured is large for low-income childless adults (40 percent), which reflect limited access to health insurance for this group. These numbers together suggest that entrepreneurship lock is an issue for this population.

The upper panel includes self-employment levels and flows. About 8 percent of low-income childless adults are self-employed. Among the self-employed, the share of unincorporated self-employment (84 percent) is much higher than that of incorporated self-employment (16 percent). This suggests that unincorporated self-employment is the major type of self-employment for low-income households. The entry rate into self-employment is slightly lower than the exit rate. In the pre-time period, self-employment levels and flows are qualitatively similar in expansion and non-expansion states. But in the post-time period, the self-employment level increased to 7.9 percent in expansion states while it decreased to 7.2 percent in non-expansion sates. Similar changes are found in the unincorporated self-employment rates but not in incorporated ones. When looking at self-employment flows, an increase in the entry rate was larger in expansion states. Despite the increased exit rate, the difference between expansion and non-expansion states was still small. In sum, these descriptive statistics suggest that the ACA Medicaid expansion might lead to a higher self-employment rate.

The lower panel in Table 3 depicts the comparison of labor market characteristics between expansion and non-expansion states in terms of other employment related variables, including labor force participation, private sector employment, full time status, and hours worked. The labor force participation rate is 61 percent. As with self-employment, both expansion states and non-expansion states have on average similar employment characteristics in the pre-time period. Also, employment related variables do not significantly change in the post time period. These descriptive statistics are consistent with previous research that found no significant effects of the ACA Medicaid expansions on labor supply.[15]

One concern in the descriptive statistics is that the self-employment rate increased in expansion states while it declined in non-expansion states. This may result from different trends, which invalidates the common trend assumption for difference-in-differences analyses. Therefore, I check the trends in average self-employment, entry, and exit rates for the low-income childless adult sample in Appendix Figure A2. The pre-trends of the average self-employment rates in both expansion and non-expansion states are quite similar from 2003 to 2013. Then, the self-employment rate increased only in expansion states in 2014. These trends suggest that the decrease

[15] The different composition of industries and occupations might also lead to differential outcomes. I check this possibility by computing the share of 2-digit industries and 2-digit occupations in Appendix Figure A1. Like other labor market variables, the distribution of industries and occupations were very similar between expansion and non-expansion states.

in the average self-employment rate in non-expansion states in the post-time period is not driven by different trends. In addition to visual inspection of trends, I also conduct event studies to do the formal statistical test for the common trend assumption, which is explained in detail in the section of event study analysis.

5.2 Effects on Self-Employment Levels

The estimated effects of the ACA Medicaid expansion are provided in Table 4. The first and second columns provide the results of the propensity of becoming self-employed from the DID and PSW-DID, respectively. The last two columns show the results of the likelihood of being an employee. The upper and lower panels show the results from the samples of childless adults with incomes below 300 and 138 percent of the FPL, respectively.

The estimated effect from the baseline DID specification indicates that the self-employment rate in the expansion states statistically significantly increased by 1.1 percentage points, relative to non-expansion states across time. This is an approximate 14 percent increase from the unconditional mean of the self-employment rate (7.6 percent). While the DID estimates are adjusted to individual characteristics, some of which were different between expansion and non-expansion states, controlling for these characteristics may not be enough if they affect the trends of the propensities of being self-employed differentially. The PSW-DID specification addresses this issue by balancing observable characteristics for treatment and control states before and after adopting the ACA Medicaid expansion. The result from the PSW-DID shows that the Medicaid expansion increased the rate of self-employment by 0.8 percentage points, which is about a 10 percent increase from the unconditional mean. The estimate from the PSW-DID is slightly lower, but it is not statistically different from the DID. These results indicate that the estimate from the DID is not driven by differences of observable covariates in treatment and control states.

The time period in this study coincides with the financial crisis of 2007–2008 and subsequent economic recovery from it. In this respect, one may be concerned that various states' business cycles or economic recovery influenced the self-employment rate differentially. To address this issue, all specifications control for state level unemployment rates. In addition, the estimated effects on the employment rates are also reported in columns (3) and (4). If better economic conditions or higher demand in expansion states have raised the self-employment rate, it would have also increased the employment rate. However, the estimates on the employment rates from both DID and PSW-DID are close to zero and statistically insignificant, which suggests that the influence from the business cycle or higher demand is of less concern.

The Panel B shows the results from the sample below 138 percent of the FPL. The patterns of the estimated effects in the sample below 138 percent of the FPL are similar to the sample below 300 percent of the FPL. In states that adopted the ACA Medicaid expansion, the self-employment rate increased while the employment rate remained constant. But the magnitudes of estimates on the self-employment rate are slightly higher in the sample below 138 percent of the FPL. The DID and PSW-DID estimates indicate 1.6 and 1.2 percentage point increases in the self-employment rates, respectively. The different sizes of the estimates may result from the fact that the sample below 138 percent of the FPL include more relevant population. However, as explained in the method section, the sample below 138 percent of the FPL may also capture the self-employed who adjusted household incomes to become eligible for Medicaid, which leads to some overestimation biases in estimated effects. I further examine these issues in the instrumental variable approach.

Overall, the analysis of self-employment levels suggests that the ACA Medicaid expansion raised the self-employment rate among childless adults in low-income households. The magnitudes of ITT estimates are consistent with previous studies on Medicare (Fairlie, Kapur, and Gates 2011) and the SCHIP (Olds 2016). Also, findings on the employment rate are consistent with recent empirical studies that found the ACA Medicaid expansion did not have significant effects on labor supply (Duggan, Goda, and Jackson 2017; Gooptu et al. 2016; Kaestner et al. 2017; Leung and Mas 2016).

Since not all eligible individuals enroll in Medicaid, the baseline estimates captured the ITT effects of being eligible for Medicaid through the states' adoption of ACA Medicaid expansion. Previous studies found that the estimated effects of the Medicaid expansion on Medicaid coverage range from 2 to 7 percentage points (Couremanche et al. 2017; Duggan, Goda, and Jackson 2017; Frean, Gruber, and Sommers 2017; Kaestner et al. 2017; Leung and Mas 2016; Siomon, Soni, and Cawley 2017; Wherry and Miller 2016). Even in the randomized control study in the Oregon health insurance experiment, about 30 percent of eligible people enrolled in Medicaid (Baicker et al. 2013; Finkelstein et al. 2012). The IV approach estimates the LATE of being covered by Medicaid ("compliers").

Table 5 provides estimates for OLS, IV, and PSW-IV. The simple OLS estimate shows that Medicaid coverage is negatively associated with the propensity of being self-employed.

However, this OLS estimate suffers from selection bias. If the self-employed are more ambitious individuals who start their businesses regardless of health insurance, then they are less likely to take Medicaid. On the other hand, the IV estimate captures effects for compliers who do not start their business only because of limited access to health insurance. Therefore, these latent entrepreneurs are very sensitive to obtaining health insurance. The IV estimate indicates that being covered by Medicaid due to increased Medicaid eligibility led to an 11 percentage point higher propensity of being self-employed. The PSW-IV estimate was slightly smaller (8 percentage points), but it is also positive and statistically significant. Both IV and PSW-IV estimates suggest that receiving Medicaid leads to a significant increase in the propensity of becoming self-employed for latent entrepreneurs.

It is also interesting to see that the sizes of estimates are similar regardless of sample changes based on different income cutoffs, which reflects the fact that the IV approach captures effects on compliers in both samples. These results suggest that the ITT estimates in the sample below 138% of the FPL do not suffer from overestimation bias. If the sample below 138% of the FPL capture the self-employed who adjusted household incomes, the estimates on Medicaid coverage should be much larger than the estimates on self-employment, which leads to smaller magnitudes of the LATEs compared to the sample below 300% of the FPL. The F-statistics for the first stage estimates are over 100, which suggests that the indicator for the ACA Medicaid expansion is not a weak instrument. Looking at the employment rate, the OLS estimate shows a much larger negative relationship. But the IV and PSW-IV indicate that being covered by Medicaid did not have significant effects on the probability of being an employee.

It requires some caution to interpret the IV results. The first stage estimate on Medicaid shows that the eligibility expansion raised the rate of Medicaid coverage by about 10 percentage points. Since I include longer time periods, the size of this estimate is slightly larger than previous studies on the ACA Medicaid expansion (2 to 7 percentage points). Nevertheless, the Medicaid take-up rate is relatively small given a large number of eligible childless adults. Because of a low take-up rate, the size of the LATEs are about 10 times larger than the ITT effects. Considering the unconditional mean of the self-employment rate, the IV estimates suggest those newly covered by Medicaid under the ACA have a double or higher likelihood of becoming self-employed.

5.3 Effects on Self-Employment Transitions

Table 6 provides the DID and PSW-DID estimates on self-employment transitions. Each set of columns shows the self-employment entry, self-employment exit, and transition from self-employment to non-employed status.

The estimates indicate that the self-employment entry rate increased by 8 to 9 percentage points in the sample below 300 percent of the FPL. The increase in the self-employment rate was statistically significant, and its magnitude is similar to the estimates on the self-employment rate. In contrast, the self-employment exit did not significantly change. Since the self-employment exit includes both transitions to employees and non-employed status, it may raise a concern that this estimate does not capture those exiting from labor market. But the estimates on the transition from self-employed to non-employed status are also close to zero and statistically insignificant. The estimates using the sample below 138 percent of the FPL show similar patterns.

The estimates from IV and PSW-IV are provided in Table 7. Similar to the self-employment entry, the simple OLS estimate shows a negative association between Medicaid and the self-employment entry. However, both IV and PSW-IV estimates indicate that being covered by Medicaid due to the eligibility expansion increased the propensity of entering self-employment. The results also show that Medicaid coverage did not change the self-employment exit and transition from self-employed to non-employed status.

The PSW-DID and PSW-IV estimates on self-employment entry are statistically insignificant in the sample below 138 percent of the FPL. This is because the low incidence of self-employment entry and the small sample size increase the standard errors. But the direction and size of the estimates are very similar to the sample below 300 percent of the FPL.

Overall, the ACA Medicaid expansion raised self-employment entry, but not self-employment exit. The negative income effects were not huge enough to make the self-employed stop working. These results of self-employment transitions imply that changes in the self-employment rate is mainly driven by new self-employment entrants and negative income effects are of less concern.

5.4 Event Study Analysis and Falsification Test

As described earlier, the key identifying assumption for all my specifications is that the self-employment rates (or other self-employment outcomes) in expansion states would evolve as in non-expansion states in the absence of the eligibility increase in Medicaid under the ACA. In order to check the validity of this assumption, I apply event study approaches to the self-employment level, entry, and exit. In Figure 3, For DID and PSW-DID, the coefficients of the interaction terms between the treatment indicator and year dummies in Eq (2) are provided with 95 percent confidence intervals. Each coefficient is estimated relative to 2013, a year before the implementation of the Medicaid expansion.

The patterns of event studies are very similar across different specifications. The DID event study estimates of self-employment levels, entry, and exit before 2014 are close to zero and statistically insignificant at 95 percent of the confidence interval, except for self-employment exit in 2003. There are no specific upward or downward pre-trends. Compared to the DD specification, the event study estimates from the PSW-DID are slightly less fluctuating and closer to zero, but the differences across specifications are minor. These results suggest the plausibility of the parallel trend assumption and support the validity of my baseline estimates.

Since the Medicaid expansion is one of many components in the ACA, other changes related to access to health insurance in expansion states may drive estimated effects. In Table 8, I conduct falsification tests with high-income childless adults (above 300 or 400 percent of the FPL) not affected by the Medicaid expansion. The results show that the Medicaid eligibility expansion did not make noticeable changes in self-employment outcomes among high-income people. The magnitudes of estimates are close to zero and statistically insignificant. I conclude that there is no evidence to ascertain that changes in self-employment in low-income individuals are not driven by other changes in expansion states.

5.5 Analysis of the Entrepreneurship Lock Mechanism

To check whether the Medicaid expansion reduced entrepreneur lock, I apply a DDD approach by interacting the DID estimate with health insurance cost factors such as spousal ESI, poor health status of respondent or spouse, and poor health status of spouse. Since cost factors are from the spouse's information, the sample is restricted to married childless adults. Table 9 provides the results by specifications with different cost factors. The estimate of the DID (β_1) shows the estimated impact on married couples with low insurance costs. The estimate of the DDD (β_2) provides the additional insurance cost effect. The linear combination of these two estimates ($\beta_1 + \beta_2$) indicates the effects on married couples with high insurance costs.

In column (1), the estimate of the DDD using no access to spousal ESI (β_2) shows a positive and significant 1.9 percentage point increase in the propensity of being self-employed. These results suggest that the ACA Medicaid expansion increased the self-employment rate for those without access to alternative health insurance. In columns (2) and (3), β_2 is statistically insignificant in most specifications, except for two estimates from the specification with spouse health condition. However, $\beta_1 + \beta_2$ is positive and statically significant. That is, although those with poor health in family members have slightly higher propensities of being self-employed, the difference in propensities are not statistically different. These results suggest that the main mechanism of the effects of the ACA Medicaid expansion is through a reduction in entrepreneurship lock by improving access to health insurance.

5.6 Business Characteristics

One important concern is the business characteristics of newly self-employed individuals. Considering that Medicaid beneficiaries are low-income households, their characteristics may be different from middle- or high-income groups. It is difficult to check business characteristics without detailed information on the business. Using limited information, some business characteristics related variables are examined in Table 10.

The results show that the Medicaid expansion increased the self-employed with positive business incomes by 0.9 percentage points. Given the baseline DID estimate on self-employment (1.1 percentage points), more than 80 percent of newly self-employed people make positive incomes. To capture different types of self-employment activities, I examine incorporated and unincorporated self-employment. Incorporated self-employment tends to be more successful than unincorporated self-employment. But since entrepreneurs tend to incorporate their business after it has grown, the rate of incorporation is low among newly self-employed individuals (e.g., Evans and Jovanovic 1989). In addition, unincorporated self-employment is the major form of business among low-income households. The results indicate that the rate of incorporated self-employment changed insignificantly, whereas the rate of unincorporated self-employment increased significantly by 1.2 percentage points. These findings are consistent with my expectation that the ACA Medicaid expansion increased the number of newly self-employed individuals among low-income households.

The previous findings showed no significant negative income effects on the extensive margin of self-employment supply. But there might be adjustment in the intensive margin of self-employment. Or the newly self-employed individuals might consider self-employment as a part-time job and not be fully committed to self-employment. However, the results in in columns (4) and (5) show an increase in weeks worked and a decline in hours worked among the self-employed. Both estimates are statistically insignificant. The results suggest that adjustment in the intensive margin of self-employment or an increase in part-time self-employment is of less concern.

5.7 Heterogeneous Effects of the Medicaid Expansion

The treatment effects may be heterogeneous for different genders. The literature suggests that women have higher demand for health insurance and are more risk averse, compared to men. The heterogeneous effects by gender are provided in Figure 4. Both DID and PSW-DID estimates show that the Medicaid expansion significantly increased the rate of self-employment among low-income childless women by 1.5 to 1.8 percentage points. These estimates are statistically significant. In contrast, the increase in the self-employment rate among male childless adults are positive but relatively small and statistically insignificant. It seems that latent entrepreneurs among low-income female childless adults significantly benefit from the Medicaid expansion.

5.8 Robustness Check

I conduct several robustness checks of the main results with different models, thresholds, and samples. The results of the robustness checks are provided in Appendix C.

First, I apply a synthetic control group method as an alternative approach. Like DID and PSW-DID, the SCGM estimates the ITT effects. The detailed description of the SCGM is provided in Appendix B. Table C1 provides the estimated effects of the Medicaid expansion on self-employment levels and transitions. Since the permutation test is used for SCGM, the p-value of the root mean square prediction error (RMSPE) ratio for the expansion states is reported in brackets. The results of the SCGM indicate that the self-employment rate statistically significantly increased in treatment states after the Medicaid expansion. The magnitude of the estimate is a 0.95 percentage point, which is similar to the DID and PSW-DID estimates. The SCGM estimate on the self-employment entry is positive and two times larger than the estimate on the self-employment exit, but it is statistically insignificant. Similar to the event study, the difference of self-employment outcomes between treatment and synthetic control groups for each year are provided with placebo estimates for using each non-expansion state as a treatment group in Figure C1. The pre-trends for all self-employment outcomes are pretty close to zero. When looking at the optimal weights to create a synthetic control group in Table C2, both included states and weights are somewhat different across all self-employment outcomes. In general, the SCGM seems slightly more sensitive to estimate a small incidence of self-employment transitions. This may be because the SCGM uses aggregated information at the state and year level, which reduces the sample size. Nevertheless, the overall patterns of estimated effects are qualitatively similar.

Second, since self-employment outcome variables are binary variables, I estimate the DID and PSW-DID specifications with Logit and Probit models. The results are provided in Table C3. To compare with the linear probability model (LPM), I computed the average marginal effects for nonlinear models. The overall patterns and magnitudes of the estimated effects from logit and probit models are very similar to LPM estimates in previous tables. These results show that my estimates are robust to different linear and nonlinear models.

Third, I estimate the DID and PSW-DID specifications using the sample with high school or less in Table C5. Kaestner et al. (2017) suggested that the robustness of a sample would increase by defining a sample comprising individuals with low education levels rather than income levels because the education levels tended to be determined before the ACA Medicaid expansion and individuals with a high school or less are more likely to be covered by Medicaid. On the other hand, Simon et al. (2017) claimed that low education is not a strong predictor for low income. Selecting samples based on education levels also includes high-income people with low education levels, which may result in noise in the estimates. My results for the sample with low education individuals show qualitatively similar and slightly smaller estimates compared to the sample below 300 percent of the FPL. But standard errors in the low-education childless adult sample become slightly larger, and the estimate on self-employment entry becomes statistically insignificant. As Simon et al. (2017) suggested, this could be because selecting samples with low education levels leads to the inclusion of the ineligible.

Fourth, I control for different health insurance market conditions in Table C5. The DID and PSW-DID specifications include state fixed effects that control time invariant unobserved state heterogeneities. But they do not address time varying state heterogeneities, especially insurance market conditions. I use individual and small group market Herfindahl-Hirschman Indexes (HHI) as proxies to control time varying insurance market conditions. For example, some states with few insurance companies having high market share may have a limited number of insurance options and higher insurance premiums on average. Since the HHI indexes from the Kaiser Family Foundation are available for only 2011–2016, the study time period is further restricted. In most specifications, both the individual and small group market HHI are negatively associated with self-employment outcomes. That is, states with low insurance market competition tend to have lower self-employment outcomes, which is consistent with the entrepreneurship lock hypothesis. But even after controlling for insurance market conditions, the estimated effects are similar to previous results. These results suggest that state fixed effects already control most state heterogeneities and that my estimates are robust to remaining heterogeneities.

Finally, I check the sensitivity of my estimates using different treatment and control groups as shown in Table C6. In Panel A, I estimate the effects by excluding late expansion states since these states may have different economic or political reasons to adopt the Medicaid eligibility. This exclusion slightly increases my estimates, but estimates are qualitatively the same. In Panel B, I include Wisconsin in the control group. Wisconsin increased the state's own eligibility threshold for Medicaid up to 100 percent of the FPL for all adults, but it did not adopt the ACA Medicaid expansion. In Panel C, I include prior expansion states in the treatment group. Most prior expansion states partially increased their eligibility before 2014 and additionally increased it to 138 percent of the FPL in 2014. In Panel D, I include both Wisconsin and prior expansion states. The results show that the baseline estimates are very robust even after including Wisconsin and/or late expansion sates.

6. Discussion and Conclusion

In this paper, I study whether the Medicaid eligibility expansions increased the supply of entrepreneurs measured by self-employment among low-income childless adults who were previously excluded from state Medicaid programs. Using geographic and time variations created by the states' adoption of the ACA Medicaid expansion, I use the difference-in-differences and propensity score weighting specifications to estimate the intent-to-treatment effects (being eligible for Medicaid). I also apply the instrumental variable and propensity score weighting approaches to estimate the local average treatment effects (being covered by Medicaid).

I find that the Medicaid expansion increased the self-employment rate by 0.8 to 1.6 percentage points in expansion states. My estimates are consistent with previous studies on the self-employment effects of Medicare (Fairlie, Kapur, and Gates 2011) and SCHIP (Olds 2016). Concerning self-employment flows, the Medicaid expansion significantly increased self-employment entry, but did not change self-employment exit. The latter can be interpreted that there is no evidence of large negative income effects on self-employment. The estimates are also robust to several sensitivity analyses. Using an instrumental variable approach, I estimate the effect of being covered by Medicaid on entrepreneurship. I found that childless adults covered by Medicaid have a higher propensity of being self-employed than those without Medicaid by 8 to 11 percentage points. The triple difference specification using insurance cost factors suggests that the main mechanism of the Medicaid expansion is through reduction of the entrepreneurship lock. I find consistent evidence that married childless adults with no access to alternative health insurance experienced a large and significant increase in the propensity for being self-employed.

Estimates from different specifications provide evidence that improving limited access to health insurance may increase entrepreneurship. My findings are consistent with the entrepreneurship lock hypothesis that the tight connection between employer-sponsored insurance and workplace may create distortion in the supply of entrepreneurs (Fairlie, Kapur, and Gates 2011; Olds 2016). My results differ from studies that found limited evidence on the entrepreneurship effects in other aspects of the ACA, for example, the dependent coverage mandate (Bailey 2017) or health exchange market (Heim and Yang 2017).

The different findings may be explained by differences in the target population and the sizes of policies. First, the dependent coverage mandate improve access to health insurance for young adults with ages below 26 who have better health conditions and lower demand for health insurance than older adults. Second, the main beneficiaries in the health exchange market are middle income groups. As the amount of subsidies decrease as income increases, the size of the effects may not be large enough to allow individuals to become self-employed. Finally, Frean, Gruber, and Sommers (2017) suggest that Medicaid expansion explains about 60 percent of the reduction in the rate of the uninsured. These differences suggest that my study includes larger changes in health insurance status compared to previous studies. Nevertheless, these different findings on the entrepreneurship effects of the ACA require further exploration in future research.

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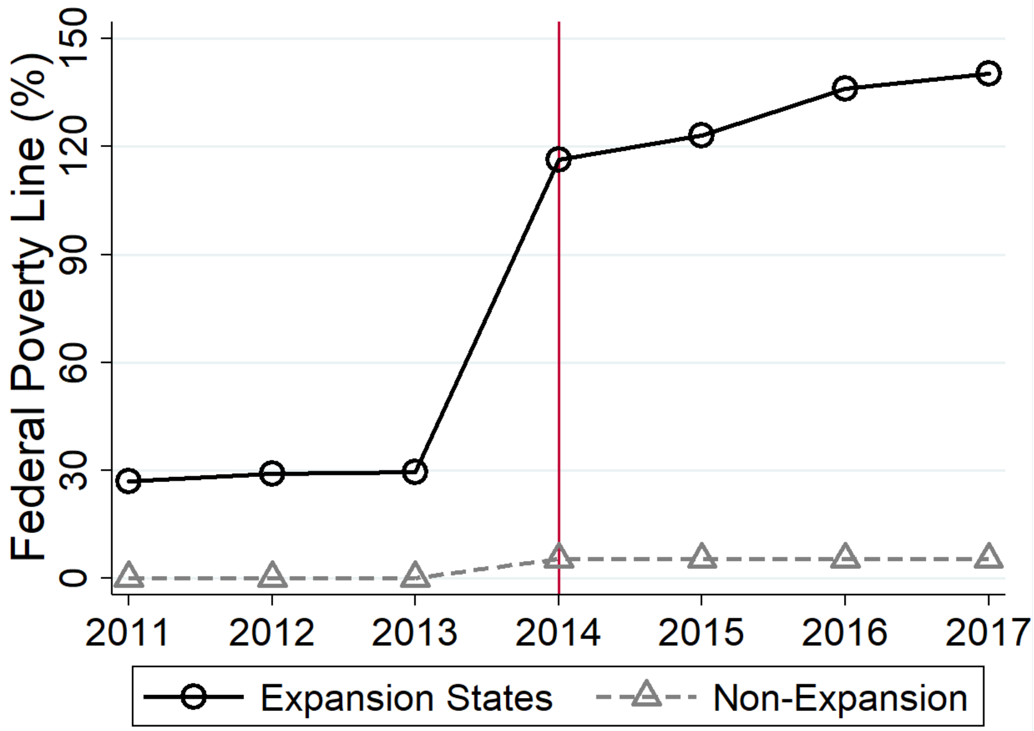
Table 1. Status of States by Medicaid Expansion and Prior Expansion

No ACA Medicaid Expansion	ACA Medicaid Expansion	
	Prior Expansion	**No Prior Expansion**
Alabama, Florida, Georgia, Idaho, Kansas, Mississippi, Missouri, Nebraska, North Carolina, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Wisconsin[†], Wyoming	Arizona‡, Colorado, Connecticut, Delaware, District of Columbia[⁋], Hawaii, Minnesota, New York, Vermont[⁋]	Alaska[§], Arkansas[‡], California, Illinois, Indiana[§‡], Iowa[‡], Kentucky, Louisiana[§], Maryland, Massachusetts[*], Michigan[§‡], Montana[§‡], Nevada, New Hampshire[§‡], New Jersey, New Mexico, North Dakota, Ohio, Oregon, Pennsylvania[§], Rhode Island, Washington, West Virginia

Note: [†] Wisconsin did not adopt the ACA Medicaid expansion, but increased Medicaid eligibility to childless adults up to 100% FPL in 2014. [⁋] indicates states that made full prior expansions before 2014. [§] identifies states that adopted the Medicaid expansion after January 1, 2014: Michigan (4/1/2014), New Hampshire (8/15/2014), Pennsylvania (1/1/2015), Indiana (2/1/2015), Alaska (9/1/2015), Montana (1/1/2016), and Louisiana (7/1/2016). [‡] specifies states that have approved Section 1115 waivers for the Medicaid expansion: Arizona, Arkansas, Indiana, Iowa, Michigan, Montana, and New Hampshire. [*] Under the MassHealth Medicaid waiver, parents and childless adults up to 133% of the FPL were covered in Massachusetts.

Figure 1. Medicaid Eligibility for Childless Adults by ACA Medicaid Expansion, 2011–2017



Notes: Data is from Kaiser Family Foundation, "Medicaid Income Eligibility Limits for Other Non-Disabled Adults, 2011–2018." Income eligibility limits for coverage that provides full Medicaid benefits (federal matching funds). Waiver programs or fully state-funded programs are not included. Arizona, Colorado, Connecticut, Delaware, District of Columbia, Hawaii, Minnesota, New York, and Vermont fully or partially adopted the ACA Medicaid expansion between 2011 and 2013. Michigan, New Hampshire, Pennsylvania, Indiana, Alaska, Montana, and Louisiana expanded Medicaid between 2014 and 2016. Wisconsin did not adopt the ACA Medicaid expansion but expanded Medicaid eligibility to childless adults up to 100% FPL.

Figure 2. States That Adopted ACA Medicaid Expansion Between 2014 and 2017

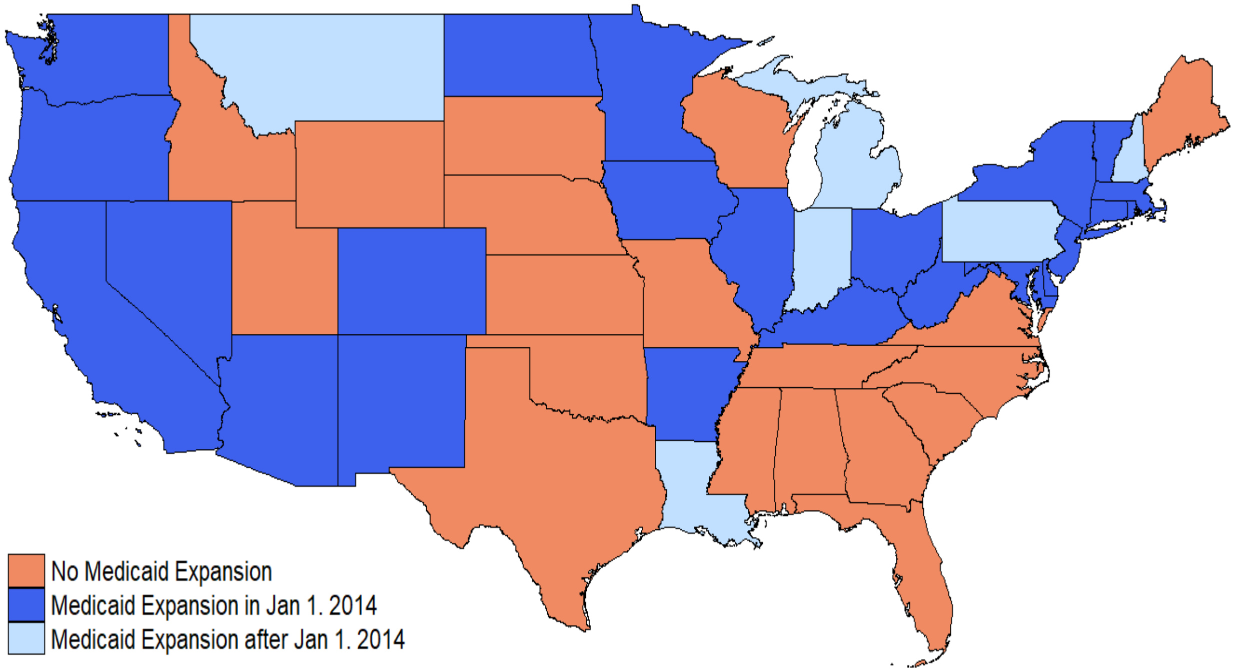


Table 2. Descriptive Statistics of Demographics and Health Insurance, Low-Income (FPL < 300%) Childless Adults Sample, CPS ASEC 2003–2016

	(1)	(2)	(3)	(4)	(5)
				Pre (2003–2013)	
	All	Self-employed	Employee	Expansion	No Expansion
Demographics					
Age	47.165	48.549	44.103	47.158	47.191
Female	0.502	0.343	0.470	0.502	0.497
Hispanic	0.132	0.112	0.164	0.124	0.134
Non-Hispanic White	0.681	0.781	0.650	0.713	0.658
Non-Hispanic Black	0.136	0.060	0.135	0.104	0.174
Non-Hispanic Asian	0.034	0.033	0.035	0.043	0.019
Non-Hispanic Other	0.017	0.014	0.016	0.016	0.016
Foreign Born	0.169	0.176	0.197	0.180	0.145
Married	0.375	0.426	0.307	0.365	0.393
Divorced or Separated	0.257	0.271	0.277	0.255	0.271
Widowed	0.050	0.036	0.038	0.049	0.053
Never Married	0.318	0.267	0.378	0.331	0.283
Veteran	0.079	0.083	0.066	0.082	0.091
< High School	0.181	0.132	0.172	0.181	0.208
High School	0.392	0.357	0.404	0.395	0.390
Some College	0.261	0.285	0.276	0.257	0.255
University	0.119	0.165	0.114	0.120	0.109
> University	0.046	0.061	0.035	0.047	0.038
Family Income	24,562	24,111	28,268	23,808	23,751
Insurance					
Uninsured	0.395	0.487	0.370	0.404	0.450
Private Insurance	0.470	0.446	0.563	0.464	0.445
ESI	0.366	0.199	0.484	0.375	0.364
Spouse ESI	0.134	0.142	0.119	0.140	0.130
Non-group Insurance	0.103	0.247	0.079	0.089	0.081
Medicaid	0.135	0.067	0.067	0.132	0.105
Observations	156,257	12,050	74,197	66,601	51,705

Notes: Sample is restricted to non-disabled childless adults aged 26-64. The estimates are calculated by using weights provided by the US Census. For transition variables including SE Entry, SE Exit, and SW to SE, the sample is restricted to individuals with labor force information for the last year. The sample size for transition variables in CPS ASEC 2002-2016 is 76,999, which are about 35 percent of the entire sample of CPS ASEC.

Table 3. Descriptive Statistics of Employment and Insurance, Low-Income (FPL < 300%) Childless Adults Sample, CPS ASEC 2003–2016

	(1)	(2)	(3)	(4)	(5)
		Pre (2003–2013)		Post (2014–2017)	
	All	Expansion	No Expansion	Expansion	No Expansion
Self-Employment					
Self-employed (SE)	0.076	0.074	0.078	0.079	0.072
Incorporated SE	0.012	0.011	0.013	0.012	0.014
Unincorporated SE	0.064	0.063	0.065	0.067	0.058
SE Entry	0.028	0.025	0.029	0.036	0.031
SE Exit	0.031	0.030	0.030	0.035	0.036
Other Employment					
Labor Force	0.610	0.599	0.616	0.626	0.621
Employee (Private Sector)	0.473	0.468	0.472	0.485	0.483
Full Time	0.474	0.452	0.494	0.473	0.495
Usual Working Hours	22.956	22.223	23.483	23.374	23.669
Observations	156,257	66,601	51,705	21,169	16,782

Notes: Sample is restricted to non-disabled childless adults aged 26-64. The estimates are calculated by using weights provided by the US Census. For transition variables including SE Entry, SE Exit, and SW to SE, the sample is restricted to individuals with labor force information for the last year. The sample size for transition variables in CPS ASEC 2002-2016 is 76,999, which are about 35 percent of the entire sample of CPS ASEC.

Table 4. Difference-in-Differences Estimates for the Intent-to-Treat Effects of Medicaid Expansion on Self-Employment, Low-Income Childless Adult Sample

	(1)	(2)	(3)	(4)
	Self-Employed		Employee	
	DID	PSW-DID	DID	PSW-DID
Panel A: FPL<300%				
Expansion*Post	0.0112***	0.0082***	0.0008	-0.0017
	(0.0036)	(0.0029)	(0.0060)	(0.0089)
Panel B: FPL<138%				
Expansion*Post	0.0161***	0.0124**	-0.0019	0.0008
	(0.0061)	(0.0049)	(0.0057)	(0.0080)
Individual Characteristics	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Unemployment Rate	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL<300% and FPL<138% full samples are 156,257 and 57,478, respectively.

Table 5. Instrumental Variable Estimates for the Local Average Treatment Effects of Medicaid Expansion on Self-Employment, Low-Income Childless Adult Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employed			Employee		
	OLS	IV	PSW-IV	OLS	IV	PSW-IV
Panel A: FPL<300%						
Medicaid	-0.0380***	0.1124***	0.0776***	-0.2740***	0.0185	-0.0144
	(0.0020)	(0.0376)	(0.0284)	(0.0070)	(0.0602)	(0.0532)
1st Stage Medicaid		0.0994***	0.1065***		0.0994***	0.1065***
		(0.0069)	(0.0065)		(0.0069)	(0.0065)
F-statistics		106.5	135.4		106.5	135.4
Panel B: FPL<138%						
Medicaid	-0.0516***	0.1118***	0.0795**	-0.1747***	0.0215	0.0219
	(0.0029)	(0.0430)	(0.0314)	(0.0067)	(0.0640)	(0.0525)
1st Stage Medicaid		0.1454***	0.1588***		0.1454***	0.1588***
		(0.0109)	(0.0106)		(0.0109)	(0.0106)
F-statistics		89.54	113.5		89.54	113.5
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL<300% and FPL<138% full samples are 156,257 and 57,478, respectively.

Table 6. Difference-in-Differences Estimates for the Intent-to-Treat Effects of Medicaid Expansion on Self-Employment Transitions, Low-Income Childless Adult Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	SE Entry		SE Exit		SE to NE	
	DID	PSW- DID	DID	PSW- DID	DID	PSW- DID
Panel A: FPL<300%						
Expansion*Post	0.0093**	0.0084**	-0.0012	0.0009	-0.0029	-0.0012
	(0.0038)	(0.0034)	(0.0036)	(0.0033)	(0.0022)	(0.0021)
Panel B: FPL<138%						
Expansion*Post	0.0138**	0.0095	-0.0048	-0.0068	-0.0061	-0.0024
	(0.0070)	(0.0059)	(0.0071)	(0.0064)	(0.0048)	(0.0044)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL<300% and FPL<138% transition samples are 57,166 and 20,106, respectively.

Table 7. Instrumental Variable Estimates for the Local Average Treatment Effects of Medicaid Expansion on Self-Employment Transitions, Low-Income Childless Adult Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SE Entry			SE Exit			SE to NE		
	OLS	IV	PSW-IV	OLS	IV	PSW-IV	OLS	IV	PSW-IV
Panel A: FPL<300%									
Medicaid	-0.0135***	0.0874**	0.0738**	-0.0036	-0.0122	0.0069	0.0015	-0.0262	-0.0108
	(0.0020)	(0.0365)	(0.0300)	(0.0025)	(0.0327)	(0.0283)	(0.0019)	(0.0205)	(0.0176)
1st Stage		0.1081***	0.1170***		0.1081***	0.1170***		0.1081***	0.1170***
		(0.0108)	(0.0098)		(0.0108)	(0.0098)		(0.0108)	(0.0098)
F-statistics		50.55	71.23		50.55	71.23		50.55	71.23
Panel B: FPL<138%									
Medicaid	-0.0243***	0.0758*	0.0517	-0.0081**	-0.0273	-0.0371	-0.0031	-0.0351	-0.0132
	(0.0028)	(0.0393)	(0.0321)	(0.0038)	(0.0391)	(0.0347)	(0.0032)	(0.0263)	(0.0238)
1st Stage		0.1787***	0.1842***		0.1787***	0.1842***		0.1787***	0.1842***
		(0.0187)	(0.0174)		(0.0187)	(0.0174)		(0.0187)	(0.0174)
F-statistics		47.53	58.12		47.53	58.12		47.53	58.12
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL<300% and FPL<138% transition samples are 57,166 and 20,106, respectively.

Figure 3. Event Study Analysis, Low-Income Sample

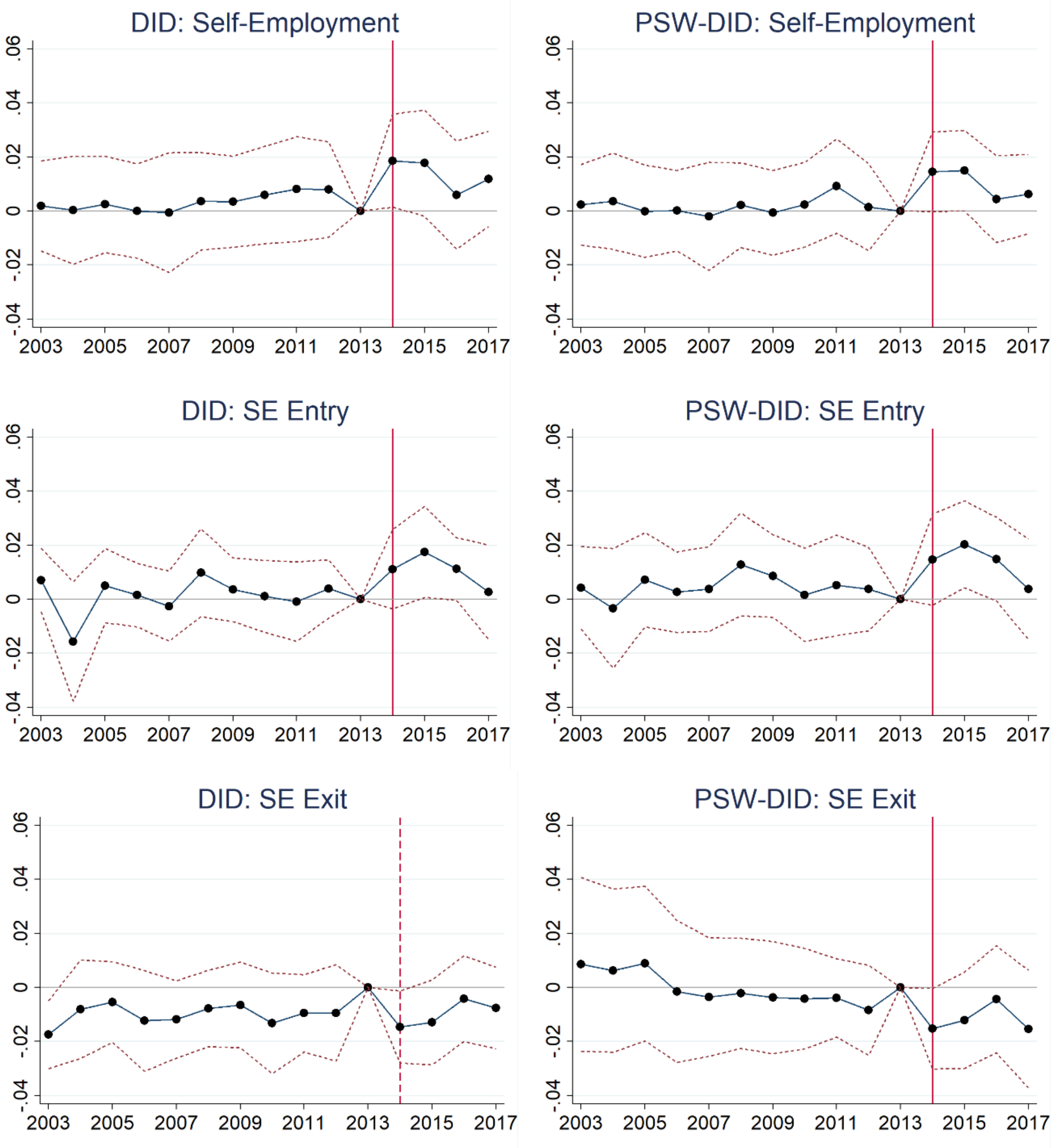


Table 8. Falsification Test, High-Income Childless Adult Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-employed		SE Entry		SE Exit	
	DID	PSW- DID	DID	PSW- DID	DID	PSW- DID
Panel A: FPL>300%						
Expansion*Post	-0.0028	-0.0028	0.0021	0.0012	-0.0011	-0.0011
	(0.0026)	(0.0024)	(0.0027)	(0.0024)	(0.0031)	(0.0026)
Panel B: FPL>400%						
Expansion*Post	-0.0032	-0.0018	0.0025	0.0020	0.0006	0.0003
	(0.0030)	(0.0026)	(0.0032)	(0.0027)	(0.0033)	(0.0029)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL>300% and FPL>400% full samples are 227,787 and 288,822, respectively. The numbers of observations for the FPL>300% and FPL>400% transition samples are 92,790 and 116,529, respectively.

Table 9. Triple Difference with Health Insurance Demand Factor, Low-Income Married Childless Adult Sample

	(1)	(2)	(3)
	No Access to Spouse's ESI	Poor Health of Respondent or Spouse	Poor Health of Spouse
	DDD	DDD	DDD
Expansion*Post (β_1)	0.0033	0.0156**	0.0169***
	(0.0089)	(0.0070)	(0.0063)
Expansion*Post*Demand (β_2)	0.0186**	0.0119	0.0071
	(0.0091)	(0.0082)	(0.0067)
Test: $\beta_1 + \beta_2 > 0$	0.0219***	0.0275***	0.0240***
[p-value]	[0.0003]	[0.0000]	[0.0004]
Characteristics	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes

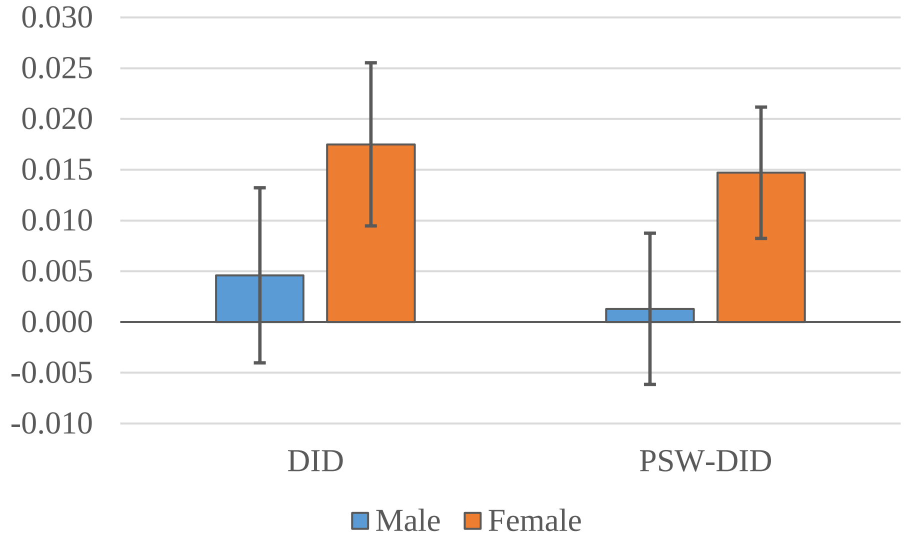
Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The number of observations for the FPL<300% married sample is 60,956.

Table 10. Business Characteristics, Low-Income Childless Adult Sample

	(1)	(2)	(3)	(4)	(5)
		All		Self-Employed	
	Biz Income (Positive)	Inc. SE	Uninc. SE	Weeks Worked	Hours Worked
Panel A: FPL<300%					
Expansion*Post	0.0092***	-0.0005	0.0117***	0.1141	-0.5065
	(0.0031)	(0.0016)	(0.0032)	(0.6434)	(0.7937)
Characteristics	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Unemployment Rate	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observation for the FPL<300% is 156,257.

Figure 4. Heterogeneous Effects of Medicaid Eligibility Expansion by Gender, Low-Income Sample



Appendix A

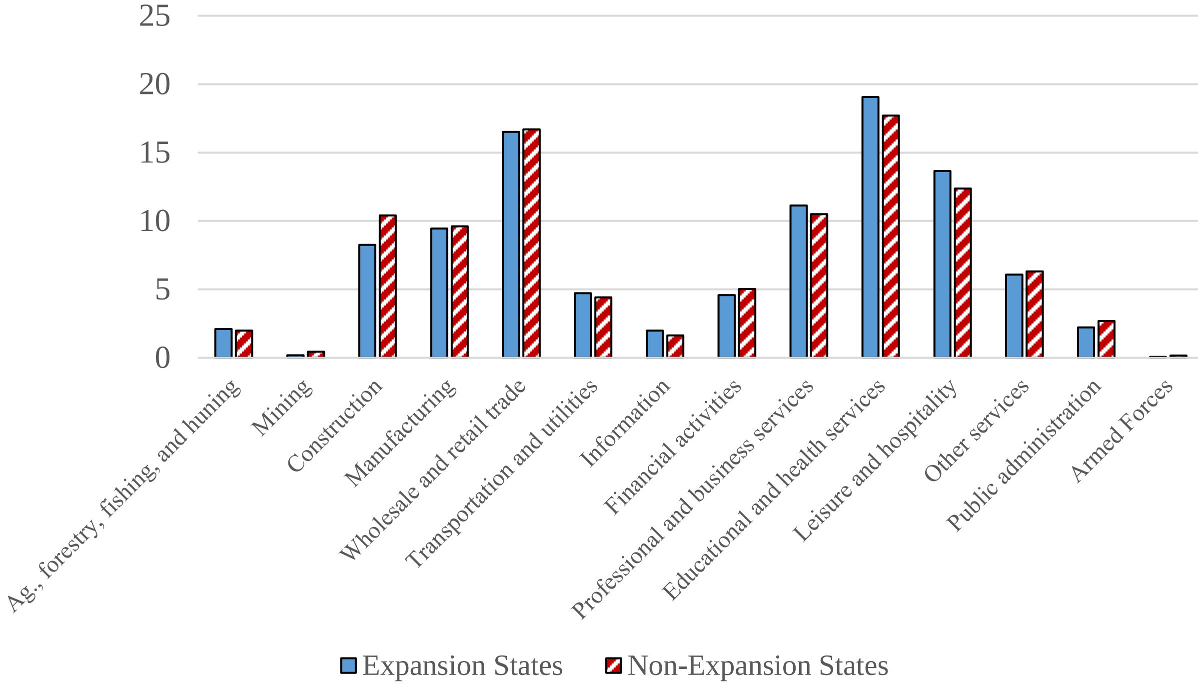
Table A1. Annual Income Thresholds of the ACA Medicaid Eligibility for Childless Adults in 2016

Size of family unit	138% of the FPL for Childless Adults (No related children under 18 years)
One person (unrelated individual)	
Under 65 years	16,996
65 years and over	15,669
Two people	
Householder under 65 years	21,877
Householder 65 years and over	19,746
Three people	25,555
Four people	33,697
Five people	40,637
Six people	46,739
Seven people	53,780
Eight people	60,149
Nine people or more	72,353

Notes: These numbers are computed based on the official federal poverty line available in the following link: https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html

Figure A1. Share of 2-Digit Industries and 2-Digit Occupations by Expansion and Non-Expansion States, CPS ASEC 2007–2013

Panel A. Share of 2-Digit Industries



Panel B. Share of 2-Digit Occupations

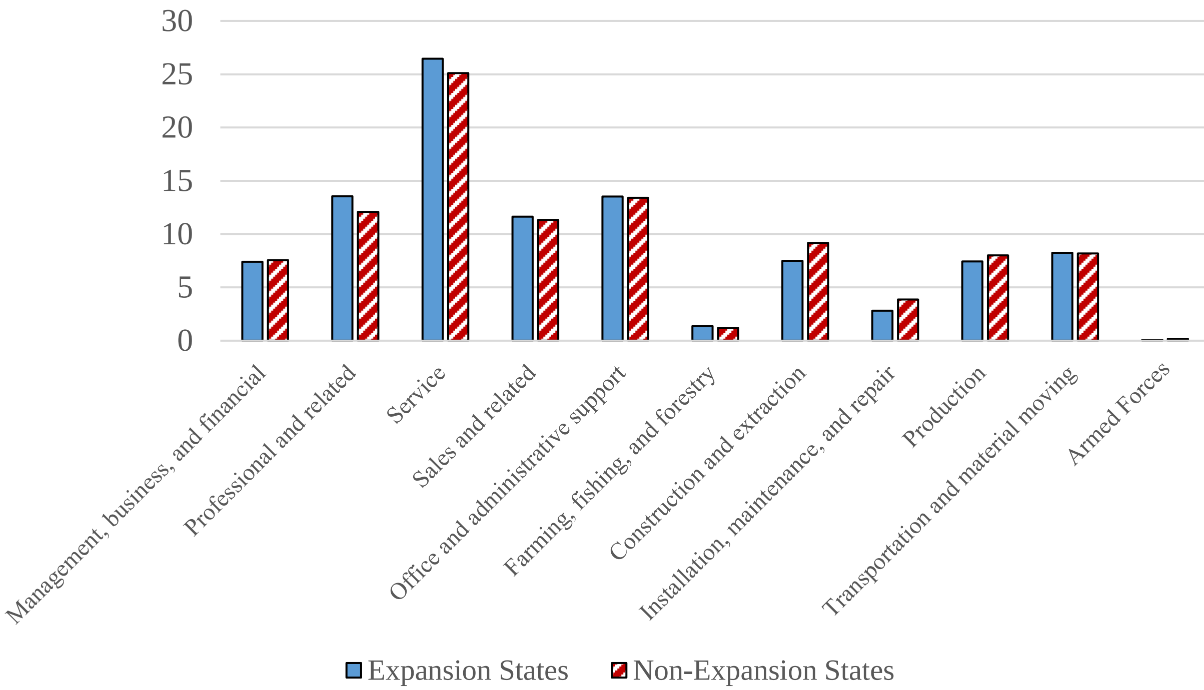


Figure A2. Trends of Self-Employment, Low-Income Childless Adult Sample (FPL < 300%)

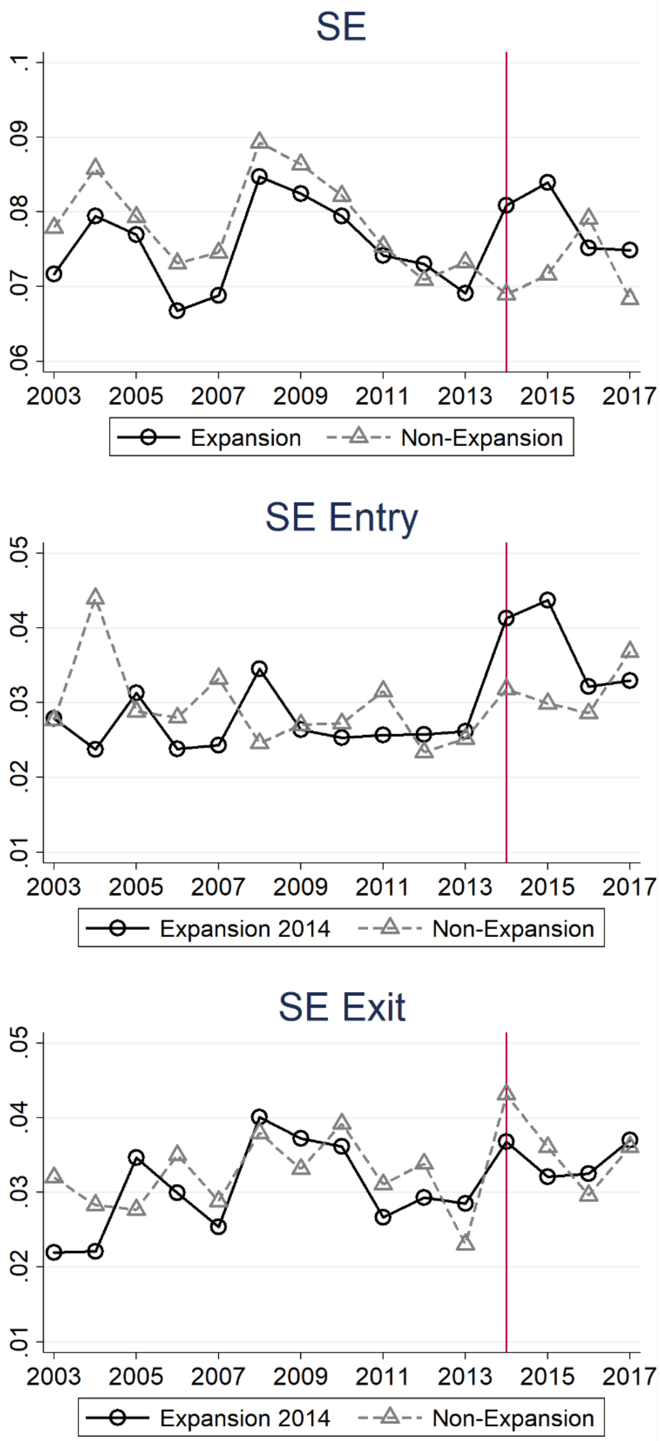


Table A2. Event Study Analysis, Low-Income Sample (<300% FPL)

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employed		SE Entry		SE Exit	
	DID	PSW- DID	DID	PSW- DID	DID	PSW- DID
Expansion*Yr2003	0.0018	0.0023	0.0070	0.0042	-0.0175***	-0.0064
	(0.0085)	(0.0076)	(0.0060)	(0.0078)	(0.0064)	(0.0066)
Expansion*Yr2004	0.0003	0.0036	-0.0157	-0.0034	-0.0081	-0.0065
	(0.0102)	(0.0091)	(0.0113)	(0.0113)	(0.0093)	(0.0080)
Expansion*Yr2005	0.0024	-0.0001	0.0050	0.0072	-0.0054	-0.0022
	(0.0091)	(0.0087)	(0.0070)	(0.0089)	(0.0076)	(0.0073)
Expansion*Yr2006	-0.0000	0.0001	0.0015	0.0026	-0.0124	-0.0108
	(0.0089)	(0.0076)	(0.0060)	(0.0076)	(0.0095)	(0.0093)
Expansion*Yr2007	-0.0006	-0.0020	-0.0026	0.0037	-0.0119	-0.0117*
	(0.0113)	(0.0102)	(0.0066)	(0.0080)	(0.0073)	(0.0069)
Expansion*Yr2008	0.0036	0.0021	0.0098	0.0128	-0.0078	-0.0087
	(0.0092)	(0.0080)	(0.0083)	(0.0097)	(0.0072)	(0.0082)
Expansion*Yr2009	0.0034	-0.0007	0.0035	0.0086	-0.0065	-0.0093
	(0.0086)	(0.0080)	(0.0060)	(0.0078)	(0.0081)	(0.0092)
Expansion*Yr2010	0.0059	0.0023	0.0010	0.0016	-0.0133	-0.0085
	(0.0092)	(0.0080)	(0.0068)	(0.0088)	(0.0095)	(0.0091)
Expansion*Yr2011	0.0081	0.0092	-0.0009	0.0051	-0.0096	-0.0067
	(0.0099)	(0.0089)	(0.0075)	(0.0095)	(0.0073)	(0.0073)
Expansion*Yr2012	0.0079	0.0014	0.0038	0.0037	-0.0095	-0.0100
	(0.0090)	(0.0082)	(0.0055)	(0.0079)	(0.0091)	(0.0086)
Expansion*Yr2014	0.0186**	0.0145*	0.0111	0.0146*	-0.0147**	-0.0135**
	(0.0088)	(0.0075)	(0.0075)	(0.0086)	(0.0068)	(0.0068)
Expansion*Yr2015	0.0177*	0.0149**	0.0175**	0.0203**	-0.0130	-0.0083
	(0.0100)	(0.0076)	(0.0086)	(0.0082)	(0.0080)	(0.0083)
Expansion*Yr2016	0.0059	0.0044	0.0112*	0.0148*	-0.0042	0.0012
	(0.0102)	(0.0082)	(0.0059)	(0.0079)	(0.0081)	(0.0075)
Expansion*Yr2017	0.0118	0.0062	0.0026	0.0037	-0.0076	-0.0068
	(0.0090)	(0.0075)	(0.0089)	(0.0095)	(0.0077)	(0.0075)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL<300% full and transition samples are 156,257 and 57,166, respectively.

Table A3. Heterogeneous Effects on Self-Employment by Gender, Low-Income Childless Adult Sample

	(1) DD	(2) PSW-DID
Men	0.0046	0.0013
	(0.0044)	(0.0038)
Women	0.0175***	0.0147***
	(0.0041)	(0.0033)
Controls	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes
Unemp. Rate	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The number of observations for the FPL<300% full sample is 156,257.

Appendix B. Synthetic Control Group Method

As an alternative approach to estimate the effects of the Medicaid expansion on self-employment, I use the synthetic control group method (SCGM) invented by Abadie, Diamond, and Hainmueller (2010). The synthetic control method weights outcome measures from control groups before the policy intervention to construct a counterfactual outcome measure for the treated group in the absence of the treatment effects. Then, it estimates the causal effect by using the differences between the treated and the synthetic control group after the implementation of the policy. The main advantage of using the synthetic control method is to allow the effects of unobserved characteristics on the outcome to vary across time, which addresses concerns about the potential bias due to unobserved heterogeneity across states.

Following the notation used in Abadie, Diamond, and Hainmueller (2010), I specify the observed outcome can be specified below.

$$Y_{jt} = Y_{jt}^{N} + \alpha_{jt} D_{jt} \qquad (6)$$

Y_{jt} is the observed outcome at group j and time t. Y_{jt}^{N} is the unobserved outcome in the absence of the Medicaid expansion. α_{jt} is the effect of the Medicaid expansion for group j and time t. D_{jt} is an indicator variable for the treated group in the post intervention, which is equal to one if $j = 1$ and $t > T_0$ and zero otherwise. Because of the indicator variable, only the treated group in the post-time period can have the effect of the intervention.

In order to estimate the effect of the Medicaid expansion (α_{1t}), I need both Y_{1t} and Y_{1t}^{N}. Since Y_{1t} is the observed outcome, I estimate the treatment-free outcome variable Y_{jt}^{N} with following specification.

$$Y_{jt}^{N} = \delta_t + \lambda_t \mu_j + \theta_t Z_j + \varepsilon_{jt} \qquad (7)$$

δ_t are time effects; μ_j are time-invariant unobserved variables with time varying coefficients λ_t; Z_j are the observed time-invariant covariates with time-varying coefficients θ_t; and ε_{jt} are unobserved transitory shocks at group across time. The assumption is the linearity between pre-treated covariates and post-untreated outcomes.

By weighting covariates among control groups, the SCGM constructs a synthetic control group that produces an approximation for covariates of the treated group in pre-intervention time periods, which is the linear combination of observed outcomes in the control groups: $\widehat{Y_{1t}^{N}} =$

$\sum_{j=2}^{J+1} w_j^* Y_{jt}$. As in Abadie, Diamond, and Hainmueller (2010), I select weights that minimize the root mean square prediction error (RMSPE) in the pre-intervention time period, which is specified as

$$RMSPE = \sqrt{\frac{\sum_t^{T_0}(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt})^2}{T_0 - t + 1}} \quad (8)$$

where w_j^* is the optimal weights that minimizes RMSPE. t is the beginning and T_0 is the end of the time periods. $T_0 - t + 1$ computes the number of periods. The RMSPE measures the difference between observed outcomes of the treatment group and synthetic control estimates. If the synthetic counterparts are not close to the observed outcomes of the treatment group, the value of RMSPE increases.

Then, the effect of the Medicaid expansion for the treated groups can be estimated by subtracting counterfactual outcomes from the observed outcomes as follows.

$$\widehat{\alpha_{1t}} = Y_{1t} - \widehat{Y_{1t}^N} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \quad (9)$$

I aggregate data up to the state level with the weights from the CPS. This process creates 24 treatment states and 21 control states, excluding late expansion states and the District of Columbia. For the case of multiple treatment groups, Abadie, Diamond, and Hainmueller (2010) suggested to aggregate all treatment groups into a single treatment group. I create a new single treatment group by aggregating 24 treatment states.

For inference of the treatment effects, I use a permutation test as suggested in Abadie et al. (2015). Using the RMSPE equation with the optimal weight structure, I first compute both pre- and post-intervention RMSPE as well as RMSPE Ratio (=$\text{RMSPE}_{\text{pre}}/\text{RMSPE}_{\text{post}}$) for my treatment group. I also run placebo estimates by changing treatment status and compute RMSPE ratios for all placebo estimates. After I rank these RMSPE ratios of treatment and placebo estimates, I calculate p-values by using the percentile of the rank of the RMSPE for treatment estimate. Since I have one treatment and 19 placebo estimates, the smallest p-value would be 0.05. Considering the small number of states, I take a conservative perspective and consider a significant treatment effect only if the RMSPE ratio of treatment estimate is the first rank of a distribution of RMSPE ratios.

Appendix C. Robustness Check

Table C1. Synthetic Control Group Method: Average Treatment Effects of Medicaid, Low-Income Childless Adult Sample (<300% of the FPL)

	(1) Self-Employed	(2) SE Entry	(3) SE Exit
Panel A: FPL<300%			
Treatment Effect	0.0095*	0.0038	0.0015
P-value	[0.0526]	[0.8421]	[0.7895]
RMSPE	0.003	0.005	0.011

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Weights are chosen based on individual characteristics that include age, sex, race, education, marital status, foreign-born status, and citizenship status. P-values of the permutation tests are provided in brackets. The number of observations is 285 at the state-year level.

Figure C1. Treatment Effects 2003–2017, Low-Income Childless Adult Sample

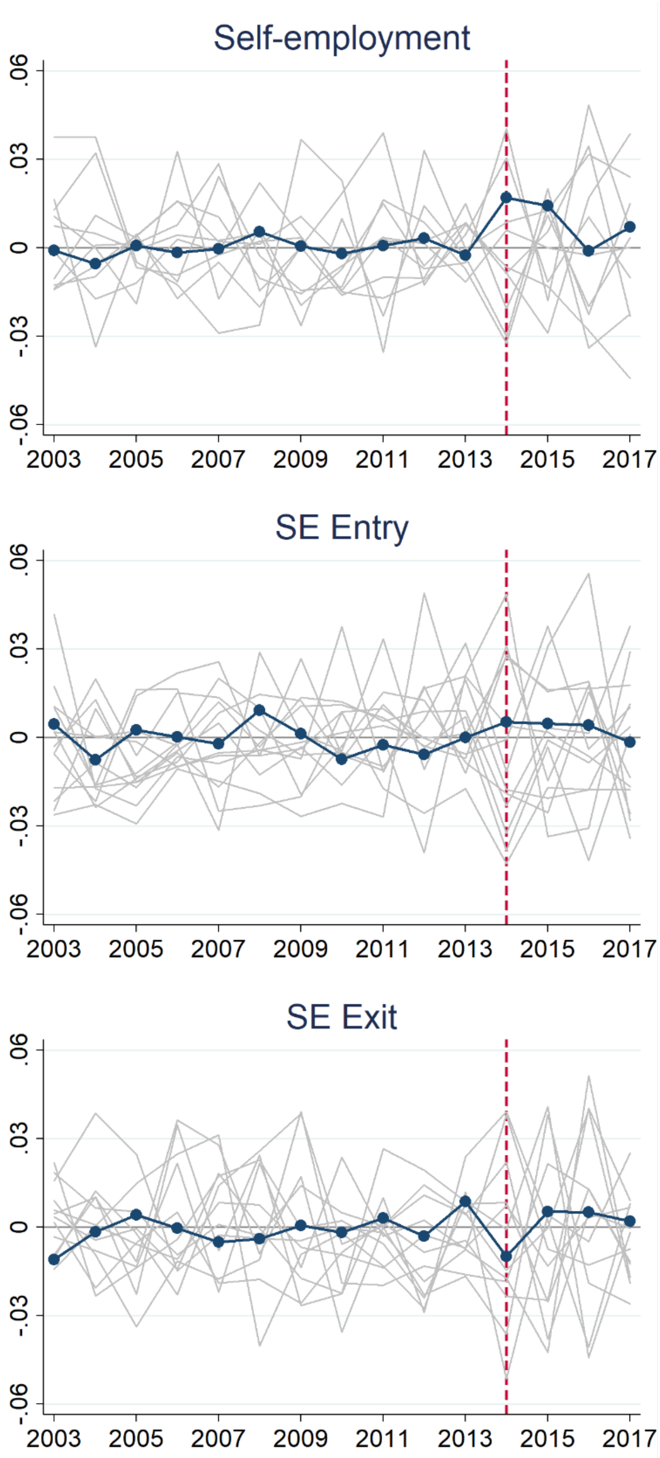


Table C2. Optimal Weights for the Synthetic Control Group

States	Self-Employed	SE Entry	SE Exit
Alabama	0.097	0.005	0
Florida	0.217	0.455	0.305
Georgia	0.071	0.107	0.018
Idaho	0	0.032	0
Kansas	0	0	0.038
Maine	0	0.006	0
Mississippi	0	0	0
Missouri	0	0	0.29
Nebraska	0	0.018	0
North Carolina	0.152	0.038	0.025
Oklahoma	0.011	0.009	0.027
South Carolina	0	0	0
South Dakota	0.023	0.063	0.004
Tennessee	0	0.118	0
Texas	0.231	0.147	0.167
Utah	0.052	0	0.016
Virginia	0.145	0	0.11
Wyoming	0	0.001	0

Table C3. Difference-in-Differences: Logit and Probit Models, Low-Income Childless Adult Sample (<300% FPL)

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employed		SE Entry		SE Exit	
	DID	PSW- DID	DID	PSW- DID	DID	PSW- DID
Panel A: Logit						
Expansion*Post	0.0110***	0.0077***	0.0085**	0.0083**	-0.0013	0.0009
	(0.0036)	(0.0030)	(0.0034)	(0.0033)	(0.0033)	(0.0032)
Panel B: Probit						
Expansion*Post	0.0111***	0.0080***	0.0088***	0.0082**	-0.0015	0.0007
	(0.0035)	(0.0029)	(0.0033)	(0.0032)	(0.0033)	(0.0032)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL<300% full and transition samples are 156,257 and 57,166, respectively.

Table C4. Difference-in-Differences, Low-Education Childless Adult Sample (High School or Less)

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employed		SE Entry		SE Exit	
	DID	PSW- DID	DID	PSW- DID	DID	PSW- DID
Panel A: Low Education						
Expansion*Post	0.0064*	0.0049	0.0086**	0.0070**	0.0008	0.0004
	(0.0034)	(0.0030)	(0.0040)	(0.0033)	(0.0036)	(0.0030)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the low-education full and transition samples are 183,762 and 70,300, respectively.

Table C5. Difference-in-Differences: Control Herfindahl-Hirschman Index (HHI), Low-Income Childless Adult Sample (<300% of the FPL)

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employed		SE Entry		SE Exit	
	DID	PSW- DID	DID	PSW- DID	DID	PSW- DID
Panel A: Individual and Small Group Insurance Market Competition						
Expansion*Post	0.0114**	0.0070*	0.0089**	0.0082*	-0.0048	-0.0009
	(0.0051)	(0.0040)	(0.0043)	(0.0042)	(0.0047)	(0.0043)
Individual	-0.0002	0.0003	-0.0044**	-0.0024*	-0.0020	-0.0009
Market HHI/1,000	(0.0014)	(0.0014)	(0.0017)	(0.0013)	(0.0020)	(0.0017)
Small Group	-0.0001	-0.0017	-0.0026	-0.0057*	-0.0019	-0.0024
Market HHI/1,000	(0.0033)	(0.0030)	(0.0031)	(0.0033)	(0.0032)	(0.0031)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Because of data limitation, the sample period is restricted to 2011-2016. The Herfindahl-Hirschman Index (HHI) for the health insurance market is from Kaiser Family Foundation. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for the FPL<300% full and transition samples with HHI information are 60,075 and 21,466, respectively.

Table C6. Difference-in-Differences: Different Treatment and Control Groups, Low-Income Childless Adult Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employed		SE Entry		SE Exit	
	DID	PSW- DID	DID	PSW- DID	DID	PSW- DID
Panel A: Excluding Late Expansion States						
Expansion*Post	0.0116***	0.0088***	0.0100**	0.0087**	-0.0021	-0.0003
	(0.0039)	(0.0032)	(0.0043)	(0.0037)	(0.0039)	(0.0036)
Panel B: Including Wisconsin in Control Group						
Expansion*Post	0.0115***	0.0084***	0.0082**	0.0073**	-0.0004	0.0013
	(0.0036)	(0.0029)	(0.0038)	(0.0035)	(0.0035)	(0.0032)
Panel C: Including Prior Expansion States in Treatment Group						
Expansion*Post	0.0105***	0.0076***	0.0076**	0.0069**	-0.0000	0.0020
	(0.0034)	(0.0028)	(0.0036)	(0.0033)	(0.0035)	(0.0032)
Panel D: Including Both Wisconsin and Prior Expansion States						
Expansion*Post	0.0109***	0.0079***	0.0065*	0.0059*	0.0008	0.0021
	(0.0033)	(0.0028)	(0.0036)	(0.0033)	(0.0034)	(0.0031)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Unemp. Rate	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Estimates are calculated using CPS ASEC weights. Individual characteristics include age, sex, race, education, marital status, foreign-born status, and citizenship status. Standard errors clustered at the state-year level are provided in parentheses. The numbers of observations for Panels A, B, C, and D full samples are 141,933, 159,344, 185,205, and 188,292, respectively. The numbers of observations for Panels A, B, C, and D transition samples are 51,724, 58,338, 67,736 and 68,908, respectively.