Medicaid Expansion's Effect on Self-Employment, Independent Contracting, and the Online Gig Economy*

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* This is the current draft of the second chapter of my Dissertation. The most up-to-date version can be found at bglasner.com

This paper tests whether the expansion of Medicaid following the Affordable Care Act impacted the supply of labor toward work which does not offer employer supplied health insurance. I find evidence of a reduction in engagement in self-employment in states which expanded Medicaid, with roughly 350,000 fewer individuals reported earnings through tax filings through a nonemployer establishment among expansion states, or 18.9% of the expected number of nonemployer establishments among those states which took up Medicaid. This reduction is not a loss in employment though, but rather states which did expand Medicaid did not see the same increase in declared self-employment which states that did not expand experienced. Using data on the deployment of Uber, I test whether this effect is driven by an actual employment-lock effect, or if instead it is a tax evasion effect through a reduction in declared income. I find evidence that the reduction in declared self-employment is likely a result of tax evasion. This is inline with previous work on reported earnings from self-employment being manipulated in reference to means-tested programs (Andreoni, Erard and Feinstein, 1998; Saez, 2010; Chetty et al., 2012; Chetty, Friedman and Saez, 2013). *Keywords: Medicaid and Nonemployer Establishments*

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Introduction

The Patient Protection and Affordable Care Act (ACA) passed by Congress in 2010 introduced incentives for the expansion of Medicaid. Over this same period, the prevalence of alternative work arrangements (AWAs) and nonstandard work broadly are thought to have increased as a supplemental sources of income (Katz and Krueger, 2016; Sundararajan, 2016; Current Population Survey Staff, 2018; Abraham et al., 2018; Hyman, 2018; Katz and Krueger, 2019). This paper tests if the expansion of Medicaid to individuals below 138% of the Federal Poverty Line (FPL) impacted self-employment.

One of the hypothesized effects of the ACA was a reduction in job lock and an increase in the prevalence of work without employer-sponsored health insurance (ESI) (Blumberg, Corlette and Lucia, 2014). Job lock is defined here as the tendency for workers to feel they cannot leave a job due to the loss in benefits incurred by leaving. These benefits can range from paternal leave to retirement programs, and in the case of the ACA, ESI. Alternatively, employment lock, the tendency for workers to remain employed exclusively for access to, or to afford, health insurance may have led to a reduction in engagement in the labor market once more individuals had access to Medicaid.

This analysis utilizes data on Nonemployer Establishments to test the degree to which Medicaid expansion impacts the prevalence of self-employment. Data on Nonemployer establishments comes for Nonemployer Statistics (NES), which is aggregated tax data on the number of nonemployer establishments at a given geographic level annually. I also assess the degree to which Medicaid expansion interacts with the online gig economy in comparison with traditional independent contracting and self-employment. Independent contracting walks a line of self-employment as some workers act as solo enterprises contracting out services in project-oriented arrangements. Other independent contractors take up work under the hierarchy of an organization for extended periods of time.

Firms like Uber, Lyft, Airbnb, and TaskRabbit offer lower friction marketplaces and reduced transaction costs, lowering the start-up cost and reducing the risk of work on these platforms (Sundararajan, 2016; Hogan and Torpey, 2016). differences in organizational structure may attract substantially different types of workers, resulting in differing effects of Medicaid expansion. To test for differences between the self-employed, independent contracting broadly, and the online gig economy, data on where and when Uber was in operation in the U.S. is employed to identify workers who may be engaged in the online gig economy.

I find that Medicaid expansion results in a significant decline in engagement in self-employment. These results identify a reduction in the number of nonemployer establishments per person. The Medicaid expansion resulted in a reduction in the take up of self-employment. Roughly half a million fewer individuals reported earnings through a nonemployer establishment, or 25% of the expected number of nonemployer establishments among those who took up Medicaid. These results are robust across two-way fixed effects models, interacted fixed effect models, and synthetic control.

I. Background

The ACA intended to improve access to affordable health insurance through the use of state insurance exchanges, expanded dependent coverage on health plans, and subsidies for the purchase of health insurance on exchanges (David, Melinda and Rachel, 2015). In addition, the federal government funded the expansion of Medicaid to all individuals below 138 percent of the federal poverty line. After the supreme court ruled against the mandated expansion of Medicaid in National Federation of Independent Business (NFIB) v. Sebelius, expansion became optional. The states which expanded coverage can be seen in Figure 1.

The expansion of Medicaid meant that all individuals with incomes below 138 percent of the federal poverty line became eligible. This expansion in coverage had the greatest impact on non-elderly low-income adults without children younger than 18 (Leung and Mas, 2016). In 2016, 138% of the poverty line translated to $22,108, and the median earnings among the unincorporated self employed as a primary job was $30,510 (Christnacht, Smith and Chenevert, 2018).

The overlap between the population most effected by the Medicaid expansion and the male skew of self-employment (Kogut, Luse and Short, 2016) allows for a potentially greater impact of Medicaid expansion on self-employment then among the labor market more broadly. By December 2017, Medicaid enrollment had increased by 14,098,890 people among expansion states (Centers for Medicare & Medicaid Services, 2017). Estimates of the number of self-employed show that 7% of workers earn income solely from self-employment and an additional 6% earn income through a mixture of employment and self-employment (Jackson, Looney and Ramnath, 2017*a*). These estimates would imply that roughly 1.8 million of the additional Medicaid participants would be engaged in self-employment in some capacity, with no change in labor market behavior.

In the US, ESI has been the dominant form of health insurance since the early 20th century (Currie and Madrian, 1999). This is in part due to ESI's exemption from income taxes. Compensation packages which bundle ESI and monetary compensation can expand an individual worker's budget constraints in comparison to a fully taxable monetary package. This allows firms to create more attractive offers for workers at a lower cost, increasing labor recruitment and retention (Woodbury and

Huang, 1991; Gruber and Poterba, 1994; Gentry and Peress, 1994). The expansion in Medicaid is an expansion in the availability of non-ESI, which may have impacted individuals on the margin in their decision of how to supply their labor.

The availability of non-ESI predated the expansion in Medicaid though. In fact, the private market has acted as a mechanism for catching those who may not have access to ESI for a wide range of reasons, and this has resulted selection bias. Those workers who receive insurance through employers are less likely to purchase private insurance, and their dependents with access via shared family plans are also not pressured into the private market. Since health and productivity are positively correlated, the non-employed, and those without access to ESI, are likely to have a higher average cost of health insurance (Johnson and Lambrinos, 1985; Baldwin and Johnson, 1994, 2000; Jones, Latreille and Sloane, 2006; Jones, 2008). This relationship raises the cost of insurance in the private market on average, and this difference is increased by differences in bargaining power and pooling of risk across employees in firms (Service, 1988).

The self-employed have traditionally been unable to access ESI unless they are linked to a shared family plan, or if they are also an employee for a firm which offers ESI and qualify. This means many self-employed individuals actively purchased insurance in the private market, or received their health insurance through a family plan or government program, including Medicaid. For individuals choosing where to allocate their labor, the higher cost of health insurance on the private market could be a deterrent from entering self-employment or leaving work arrangements which offer ESI. How great of a deterrent this is depends on an individual's preferences for health insurance and the differentials in the price and quality of insurance between markets.

Empirical tests of the effect of ESI and Medicaid on labor force participation have been difficult given the endogenous nature of employment matching markets. A number of scholars have used spousal insurance coverage to try and identify job lock effects (Gruber and Madrian, 1994; Monheit and Cooper, 1994; Holtz-Eakin, Penrod and Rosen, 1996; Buchmueller and Valletta, 1999; Anderson, 1997; Wellington, 2001; Heim and Lurie, 2010), the tendency for workers to feel they cannot leave a job due to the loss in benefits incurred by leaving, in this case ESI. Effect estimates from this literature appear to be sensitive to the data source and method used, but broadly identifies evidence that the job lock effects exists. Workers do have a tendency to value employer supplied benefits, including healthcare, and the price differential between the insurance marketplaces as well as the tax exempt status may prevent movements of labor.

Similarly, previous work has gone toward the study of age-based coverage effects, but found mixed results (DeCicca, 2007; Akosa Antwi, Moriya and Simon, 2013; Heim, Lurie and Simon, 2015; Depew, 2015; Bailey, 2017; Heim, Lurie and Simon, 2018). Both spousal and age-based coverage studies often do little to differentiate between the types of work which do not offer ESI. Instead it is treated as a binary based on coverage. While the self-employed have not been the focus of this research, these findings could generalize assuming that the self-employed are not significantly different in their valuation of health insurance then the labor market broadly. This may be an unreasonable assumption though, as the self-employed have been found to have a higher risk tolerance (Chell, Harworth and Brearley, 1991; Cramer et al., 2002; Caliendo, Fossen and Kritikos, 2009, 2014), which may result in them systematically having a lower valuation of health insurance. This would suggest that those most interested in self-employment would not be held back by uncertainty in their source of insurance, and job lock effects may be muted among this group of workers.

An alternative to the job lock hypothesis is employment lock. Employment lock is the tendency for workers to remain employed exclusively for access to, or to afford, health insurance. While job lock is focused on the transition between work arrangements, employment lock is focused on the withdraw of individuals from the labor market. Individuals who are attached to a source of employment exclusively for access to or to afford health insurance are likely not in need of that employment as a primary source of income. Health insurance is certainly not the only expense of a household. In households with multiple earners, one may stay attached to a source of ESI with better coverage than may be attainable in the private market, but leave to take up household labor or leisure if an alternative is available. Workers with multiple sources of income may also reduce hours to, or leave, a work arrangement if they no longer need to pay for health insurance.

There have been mixed results when studying the effects of Medicaid expansion on the labor market. Quasi-experimental research on the effects of Medicaid on labor supply have identified significant negative effects, implying an employment lock effect (Garthwaite, Gross and Notowidigdo, 2014; Dague, DeLeire and Leininger, 2017). Garthwaite, Gross and Notowidigdo (2014) use the disenrollment of Tennessee residents in 2005 to estimate the extensive marginal effect in labor supply. They find an increase in employment among individuals working at least 20 hours a week and who receive ESI. Dague, DeLeire and Leininger (2017) study "childless adults" in the context of an enrollment cap in Wisconsin by comparing enrollees to those on the waitlist. They find that enrollment in public insurance led to a 5% reduction in employment. These results differ from the conclusions of Baicker et al. (2014), who use a group of uninsured low-income adults in Oregon that were selected by lottery for the chance to apply for Medicaid. This experiment found no significant effects of being enrolled in Medicaid on labor market outcomes.

Similarly, Leung and Mas (2016) used data from the American Community Survey

(ACS) and Current Population Survey (CPS) to test how the state based expansion of Medicaid impacted employment. While they observed an increase in coverage of 3.0%, they found no significant effect on employment among "childless adults." Duggan, Goda and Jackson (2017) also use the expansion in Medicaid to test for impacts on labor market outcomes. Duggan, Goda and Jackson (2017) compares preexisting population shares of uninsured individuals, by income groups, interacted with each state's Medicaid expansion status. They also found no significant effect of Medicaid expansion on labor market outcomes in aggregate, but this was due to the offset of labor force participation reductions among high potential exchange enrollment areas and increases in labor force participation among high potential Medicaid enrollment areas.

These assessments of employment lock are focused on the aggregate effects of access to public health insurance on employment and earnings, but given the concerns of generalizability to the self-employed, it is worth exploring how they might differ from employment arrangements in their response to a means-tested public health insurance program. Previous work has already identified that reported earnings from self-employment are often manipulated in reference to means-tested programs (Andreoni, Erard and Feinstein, 1998; Chetty et al., 2012). Chetty, Friedman and Saez (2013) show the ways in which self-employment earnings are reported in a way to maximize the Earned Income Tax Credit (EITC) refund. This is supported by the work of Saez (2010) which identified that self-employed tax files tend to report income at the kink in the EITC schedule which maximizes tax refunds.

This is not unexpected though given that wage earnings are double reported by employers and employees to the IRS, but self-employment has no secondary report. We can imagine then that self-employed workers may have a tendency to not only experience job lock or employment lock, but may also participate in tax evasion to gain access to Medicaid. Effects of tax evasion appear larger on the extensive margin in general, which would imply that any effect of Medicaid expansion on self-employment would likely be best seen on the number of workers, as opposed to the intensive margin (Piketty and Saez, 2012). This would imply that the number of self-employed would likely be lower among states where Medicaid expands, but not due to an actual reduction in labor, but as a result of tax evasion. This effect would not be seen though among the online gig economy where platforms act as a secondary report to the IRS. As a result, we can expect that the traditional self-employed would have access to a response which gig workers would not.

II. Data

Following the work of Leung and Mas (2016), I use both the Current Population Survey (CPS) and the American Community Survey (ACS). Both the ACS and CPS are nationally representative surveys with information on demographics, health, and labor. I use the 1% sample of U.S. households from the ACS from 2001 to 2017, and the CPS Annual Social and Economic Supplement (ASEC) sample from 2001-2017. I also include Nonemployer Statistics (NES) which collect annual data on nonemployer establishments and report the count of establishments by geographic level and industry.[1] Both Abraham et al. (2018) and Katz and Krueger (2019) discuss the advantages and disadvantages of using survey and administrative data sources when studying the self-employed, and specifically independent contractors. The primary difference between both is their assessment of primary and secondary sources of income. The ACS and CPS supplements focus on primary sources of

[1]The NES is composed of self-employed individuals running small unincorporated businesses. Each establishment is defined as a business that has no paid employees, has annual business receipts of 1,000 dollars or more (1 dollar or more in the construction industry), and is subject to federal income taxes.

income, but the NES captures changes in supplemental sources of income which are missed by the survey data. This analysis uses the aggregate of all NAICS industries and measures the local propensity of engagement in self-employment.

To create some consistency in definition across all three data sources, I treat the count of nonemployer establishments as a count of individuals who are participating in the labor market as unincorporated self-employed, and I identify the equivalent set of workers in the CPS and ACS using the worker classification tag. Unlike Leung and Mas (2016), this analysis does not subset the sample to childless adults because no equivalent subset can be made out of the NES. I use NES data from 2001 to 2017 and create a balanced panel of counties throughout the sample.[2] While NES data are presented as counts at the specified geographic level, a given NAICS industry code may not always be available across each year in each county. As a result, a balanced panel of counties used in the analysis will vary in the number of counties by industry specification, as some counties are dropped from the panel due to missing data or concerns of anonymity.[3]

Using the ACS and CPS, I create balanced panels at the state level of participation in unincorporated self-employment as the primary source of income. These two panels are intended to be a comparable comparison to the state level NES. As shown in Figure 2, both the ACS and CPS appear to capture a stable level of respondents who identify unincorporated self-employment as their primary source of income. The NES on the other hand has seen a steady increase in the number of nonemployer

[2]The NES county panel is balanced at the county-industry-year level, the state panel is balanced for each state-industry-year.

[3]Counties which have no nonemployer establishments in a given industry code are not included in the data, and can therefore be assumed to have zero in a given county-industry-year. Those counties that have less than 3 establishments, but are non-zero, in a given year are censored for confidentiality concerns. As a result I assume that any censored county has two establishments, and any structural zero is excluded from the analysis. The results of this analysis are not sensitive to this decision.

establishments per member of the labor force. Differences between the two trends can be attributed to both the difference in definition, and the difference in methodology, as the ACS and CPS are surveys and the NES is administrative data built on reported tax fillings.

As outlined in the background of this paper, tax evasion may prove to be a biasing impact in the comparison of effects between the survey sources of data and the administrative. As a result, data on the geographic and time varying rollout of Uber is used to construct an indicator for likely workers in the online gig economy. The addition of platform moderating work reduces the likelihood of tax evasion among Uber drivers. Using Uber drivers in comparison to the general transportation and warehousing industry, as well as a the unincorporated self-employed broadly, can help differentiate job lock, employment lock, and tax evasion. Uber deployed across the United States in a series of waves starting in 2011 in San Francisco. It then spread nationally and internationally over the following years. Figure 1 shows this deployment strategy in action at the county level within the U.S. in relation to the expansion of Medicaid. This expansion in locations was not random, but over time the deployment strategy grew less dependent on local market characteristics.[4] By linking Uber deployment locations to FIPS state-county codes as defined in the NES, the presence or absence of Uber's marketplace is established for a given year. This data is only merged with the NES county panel though, as no comparable panel can be formed with the ACS or CPS data.

The treatment of Uber is expanded to include the core-based statistical areas (CBSAs) in which a county is a member.[5] This is done to capture the effect of commuting

[4]For the purposes of identifying the effect of Uber, the date of operation of Uber in a given county is used to create an indicator for a homogeneous exempt labor market. This deployment data was supplied by Uber upon request.

[5]CBSAs are defined by the Census Bureau as a geographic area which "consist of the county or

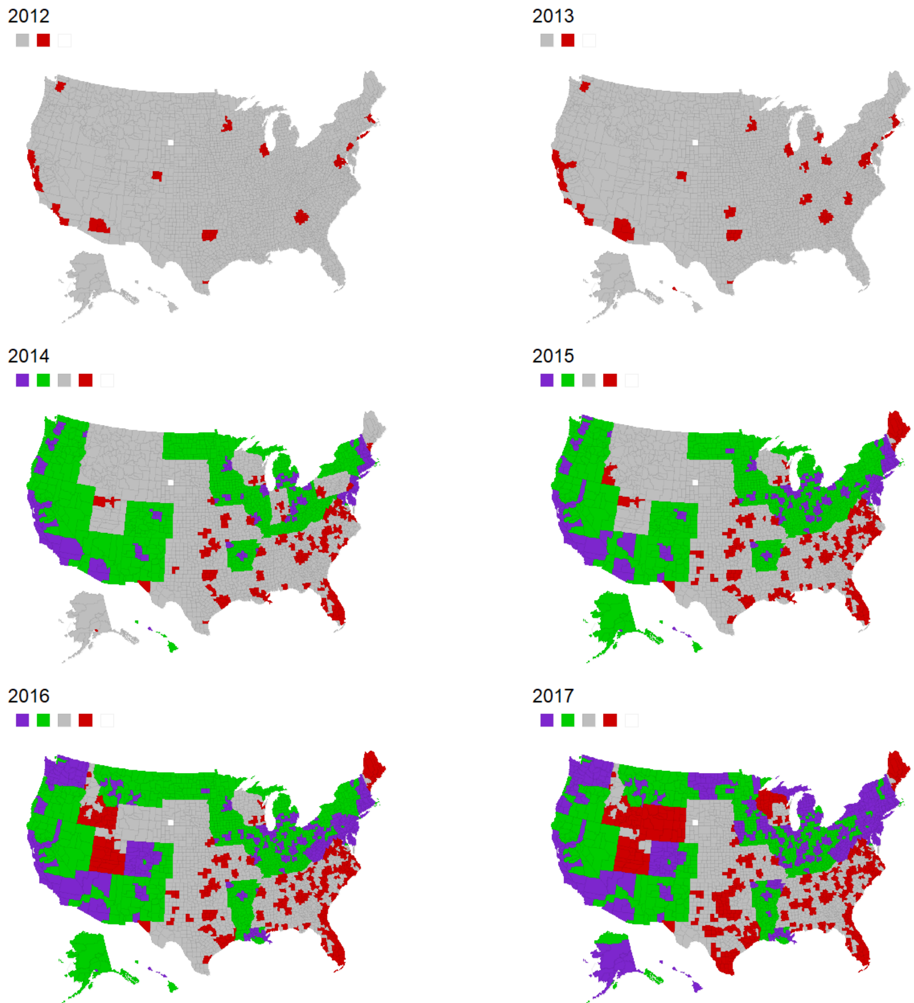

Figure 1. : The figures above depict the counties in which Medicaid expansion occurs 2014-2017. Grey counties are areas which do not experience a Medicaid expansion, but green counties are where the expansion does occur. Red counties and purple counties show where Uber is active in a given year, split by if Medicaid expansion has or has not occurred in that state. White counties are counties which either do not appear in every year of the panel or are structural zeros and are dropped from the analysis.

to work, where drivers may commute to counties or zones which have Uber active, but file their earnings from an address where Uber is not. Nonemployers are recognized in counties where they file their taxes and not strictly where driving occurs. Annual county labor force estimates and unemployment rates are included using the Bureau of Labor Statistics Local Area Unemployment Statistics. Annual county population estimates are also included using the Annual Estimates of the Resident Population data from the Census Bureau.

III. Methodology

Data

I begin this analysis with a comparison between administrative and survey sources of data. Access to Medicaid among both expansion and non-expansion states is determined by an individuals reported income. This may lead individuals to report their income differently between a survey and their taxes. To address this, I compare the ACS, CPS, and NES. To make this comparison, I construct two different measures of self-employment which can be compared.

Within the ACS and CPS, I identify if an individual's primary source of income was through unincorporated self-employment at the time of being surveyed. This creates a proxy for the number of individuals who would be classified as nonemployer establishments within both the ACS and CPS. I then calculate the number of unincorporated self-employed per person at the state level. Within the NES, this is done by using the count of nonemployer establishments and dividing it by the state's population. In the ACS and CPS, I create a weighted aggregation of the unincorporated self-employed and divide it by the state population. Both versions, in the

counties or equivalent entities associated with at least one core (urbanized area or urban cluster) of at least 10,000 population, plus adjacent counties having a high degree of social and economic integration with the core as measured through commuting ties with the counties associated with the core" (US Census Bureau, 2010).

survey and administrative data, offer a measure for the likelihood that an individual will engage in the exempt labor market, as shown below:

$$e_{it} = \frac{E_{it}}{P_{it}}$$

where E_{it} is the number of unincorporated self-employed or nonemployer establishments in state or county i and year t, and P_{it} is state or county i's labor force estimate in year t. If individuals respond truthfully and accurately on the ACS and CPS and do not participate in tax evasion, then any difference between the two should represent a difference in behavior between individuals treating self-employment as their primary source of income, or as a secondary or tertiary source of income.

While neither of the survey data sources include information on the revenues of business managed by the unincorporated self-employed, the NES does include information on the total receipts taken in by nonemployer establishments at a given geographic level. Using the receipts data included in the NES, I construct a measure of the average receipts of the nonemployer establishments at the county level. Treating R_{it} as the total receipts taken in by nonemployer establishments in county i and year t, the average receipts are defined as:

$$r_{cit} = \frac{R_{it}}{E_{it}}$$

This analysis leverages a two-way fixed effect model to ground effect estimates, similar in specification to that used by Leung and Mas (2016) as shown by equation (1), where M_{it} is a dummy variable identifying if the state, s, or county, c, experienced Medicaid expansion, with both geographic levels identified as i. I estimate this equation for both e_{it} and r_{it}, but will use Y_{it} to represent both.

$$Y_{it} = \beta_0 + \beta_1 M_{it} + \alpha_i + \tau_t + \mu_{it} \tag{1}$$

This equation is expanded through the inclusion of a dummy variable identifying if Uber is active in a county-year, $Uber_{it}$, and an interaction between this dummy and the expansion of Medicaid. By including this interaction effect, I test the degree to which any relationship between Medicaid expansion and engagement in self-employment differs across traditional self-employment and the online gig economy. This equation is used on the transportation and warehousing subset of nonemployer establishments at the county level, as shown in equation (2).

$$Y_{it} = \beta_0 + \beta_1 M_{ct} + \beta_2 Uber_{ct} + \beta_3 M_{ct} * Uber_{ct} + \alpha_c + \tau_t + \mu_{ct} \tag{2}$$

Two-way fixed effect models include control for time invariant geographic characteristics, α_i. When making comparisons between the ACS, CPS, and NES α_i is at the state level,α_s, but when looking at the Uber interaction, α_i must be at the county level, α_c, given the inclusion of county level Uber treatment. Year fixed effects, τ_t, control for shocks which occurred nationally. When utilizing τ_t the analysis is controlling for federal policy changes which are uniform across all states and counties, which is necessary given the deployment of the ACA nationally.

Both equation (1) and equation (2) offer conservative tests for the effect of Medicaid expansion on self-employment, but this is heavily reliant on the parallel trends assumption: that states which expanded Medicaid following the passage of the ACA would have continued on a similar path as those which did not expand Medicaid, and deviated from the path as a result of this treatment. The take up of expansion was not random though, and was at minimum somewhat politically motivated, and this raises concerns about the validity of the parallel trends assumption.

To help address this, I use a generalized synthetic control model (GSCM) Abadie, Diamond and Hainmueller (2010, 2015) following the methodology of Bai (2009), Gobillon and Magnac (2016), and Xu (2017). GSCMs rely on an approach similar to the difference-in-difference estimator, but with a weighted control group to create a minimized difference control group. This weighted control group may better meet the parallel trends assumption as it approximates the pretreatment trends. Xu (2017)'s methodology generates a counterfactual for each treated unit from the control group by estimating a linear, interactive two-way fixed effect model. This method then allows for the estimation of average treatment effects from comparisons between each treated unit and it's specific synthetic control.

When construction the GSCM for this analysis I utilize an interactive fixed effects estimator following Gobillon and Magnac (2016) which is designed to estimate the treatment effects in regional policy evaluation. Appendix Figure A2 shows how the optimal number of factors to be included is selected. The matching process in the pretreatment period is on the dependent variable[6], the county labor force, the labor market concentration as measured by the county HHI[7], if Uber is active in the county, and either the number of nonemployer establishments in the county or the total receipts taken in by nonemployer establishments in the county.[8]

This could be clearer — explain what a match means

While the GSCM method helps address the issue of parallel trends, two-way fixed

[6]number of establishments per member of the labor force or average receipts
[7]This measure is identical to that defined in the first chapter of this dissertation.
[8]If the dependent variable is the number of nonemployer establishments per member of the labor force I include the total receipts taken in by nonemployer establishments in the county in the pretreatment matching. If the dependent variable is the average receipts of nonemployer establishments then I include the number of nonemployer establishments in the county in the pretreatment matching.

explain

are you saying GSCM is a 2-way FE model?

explain

effect approaches have been challenged on a variety of issues. These critiques include the use of negative weights, a failure to validate parallel trends, and a nonconformity with event study designs (Borusyak and Jaravel, 2017; Abraham and Sun, 2018; Goodman-Bacon, 2018; Imai, Kim and Wang, 2018; Athey and Imbens, 2018; Callaway and Sant'Anna, 2019; de Chaisemartin and d'Haultfoeuille, 2019). To further support the conclusions of this analysis, I use the difference-in-difference design outlined by Callaway and Sant'Anna (2019) to estimate the average treatment on the treated effect. I also use the Callaway and Sant'Anna (2019) method to construct an event study on Medicaid expansion, further supporting the parallel trends assumption of the two-way fixed effect model. These results are included in the appendix.

IV. Results

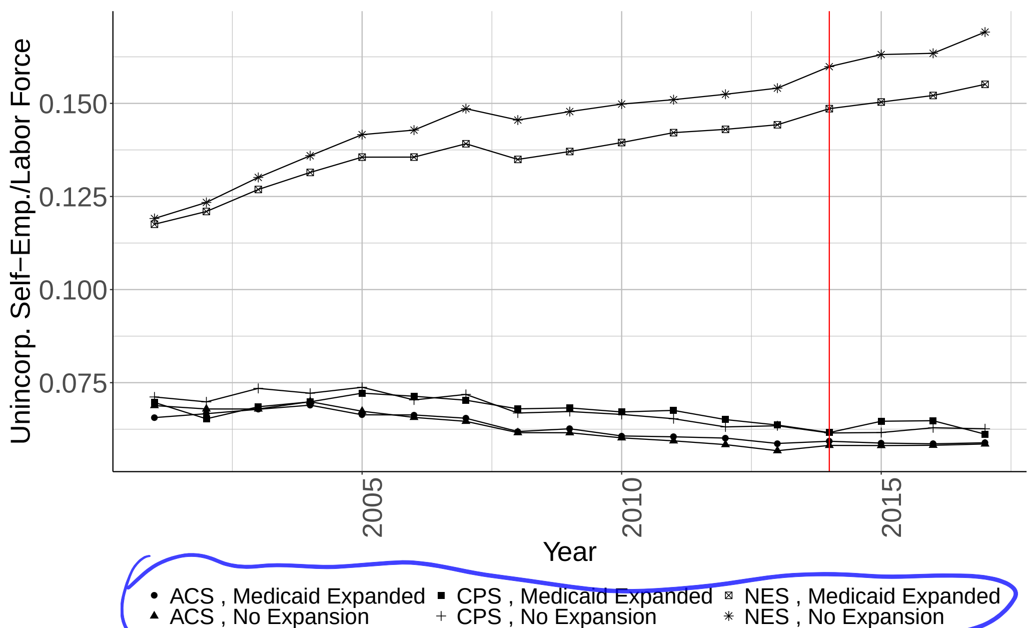

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Figure 2.

NES, no
NES, yes
CPS, no
CPS, yes
ACS, no
ACS, yes

← one column

Before introducing the two-way fixed effect approach I assess the trends in unincorporated self-employment. Figure 2 compares the trends in the average number of unincorporated self-employed and nonemployer establishments per member of the labor force in states which do and do not receive an expansion in Medicaid following the passage of the ACA. This figure also highlights the divergence in trends between declared self-employment earnings for tax purposes and survey responses regarding self-employment as a primary source of income. These trends match those reported by Abraham et al. (2018). While no consistent difference seems to exist among the survey data, states which do not receive the expansion in Medicaid appear to grow at a faster rate in the NES than those which do receive the Medicaid expansion. This is may represent a violation in parallel trends, and could lead to an overestimate of a negative effect of Medicaid expansion on the number of establishments per person.

modestly

When comparing the effect estimates of the Medicaid expansion on self-employment across the ACS, CPS, and NES, we find similar results to that which is seen in Figure 2. Neither the ACS or CPS find a significant difference in engagement in exempt work resulting from the expansion in Medicaid. The NES on the other hand does find a significant difference when using the GSCM interactive fixed effects. I find that the ATE of Medicaid expansion results in a decline of -0.0036 nonemployer establishments per member of the labor force. In 2018, those states which have expanded Medicaid accounted for 98,219,447 members of the labor force in my sample. This means that the ATE of -0.0036 is an estimated reduction in nonemployer establishments of 353,590.

3?,

what is this referring to?,

table 7?,

the number of

The difference in effects measured across the ACS, CPS, and NES points to a key difference in the samples being collected. While the ACS and CPS are focused on primary sources of income, the NES collects any source of reported earnings from nonemployer establishments. This includes secondary and supplemental sources of

Synthetic Control Results, NES v ACS v CPS:

NES:

ACS:

CPS:

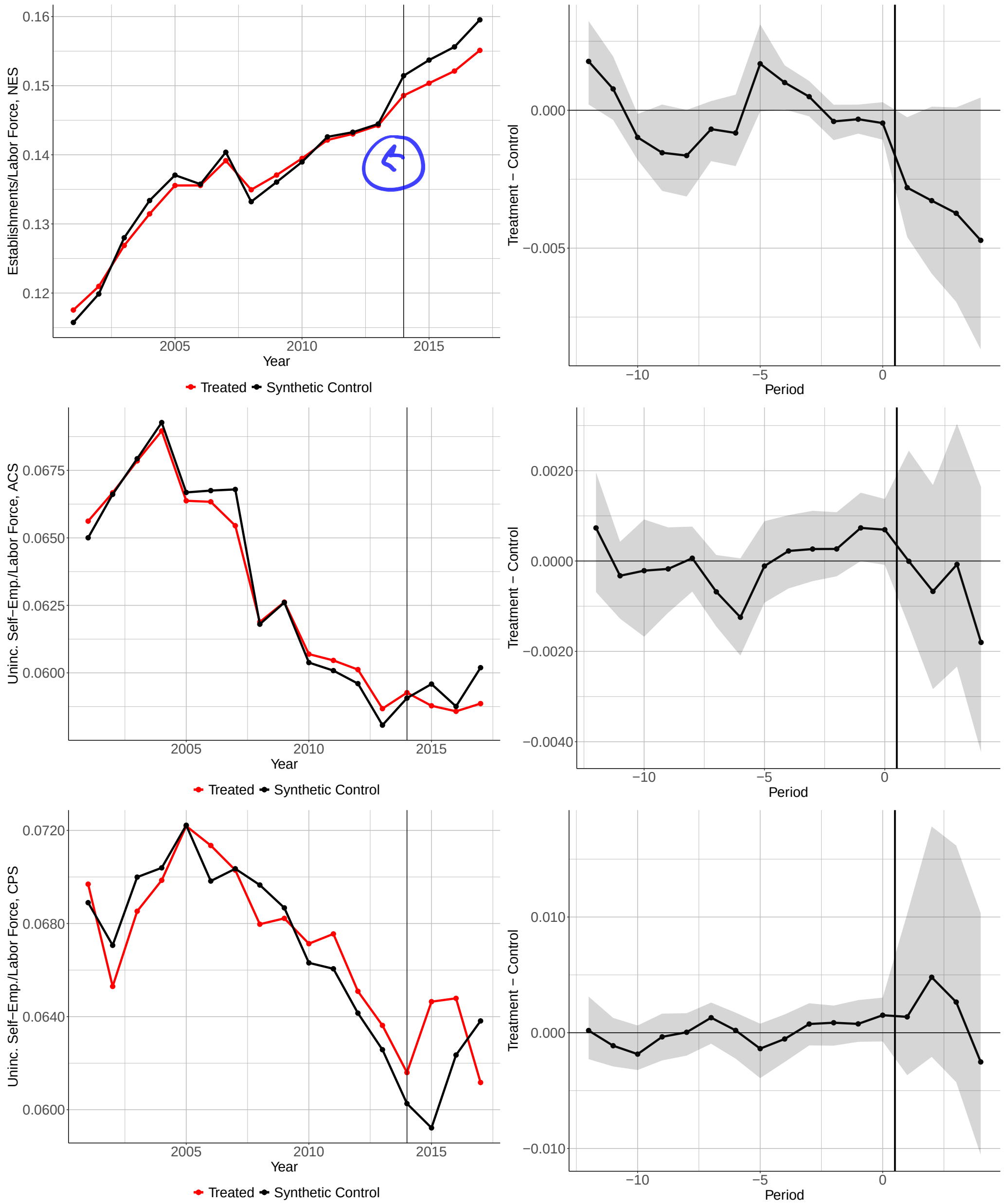


Figure 3. : These figures show the results of the Generalized Synthetic Control Method across the NES, ACS, and CPS, in order from top to bottom.

Table 1—: ADD DESCRIPTIVE OBS R2 and so on

	Dependent variable:		
	Establishments/ Labor Force	Unincorporated Self-Employed/ Labor Force	
Data	NES	ACS	CPS
Medicaid Expansion (Two-Way)	−0.0039 (0.0037)	0.0003 (0.0009)	0.0014 (0.0015)
Medicaid Expansion (Generalized Synthetic Control)	-0.0036** (0.0015)	-0.0006 (0.0011)	0.0016 (0.0039)
Note:			*p<0.1; **p<0.05; ***p<0.01

is this the ave. of 4-years after?

income which may be missed among the ACS and CPS. The NES also relies on declared income sources for tax purposes, and may be susceptible for bias through tax evasion. Table 1 points to two explanations then: (1) individuals are less likely to take up supplemental sources of income through self-employment when they have access to health insurance, or in order to meet the income threshold of Medicaid expansion, or (2) individuals are less likely to report self-employed income (primary, secondary, or supplemental) as a result of the income threshold of Medicaid expansion.

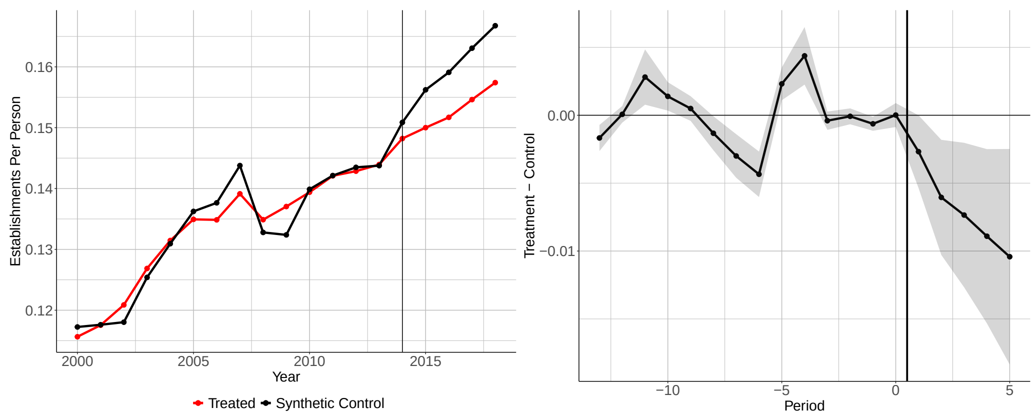
This would require (1) as well, correct?

Explanation (1) falls in line with the employment lock hypothesis and disemployment effects (Garthwaite, Gross and Notowidigdo, 2014; Dague, DeLeire and Leininger, 2017). Explanation (2) falls in line with the tax evasion literature among the self-employed (Andreoni, Erard and Feinstein, 1998; Saez, 2010; Chetty et al., 2012; Chetty, Friedman and Saez, 2013). Figure 3 shows what the identified negative effect among the NES looks like in comparison to the ACS and CPS for the GSCM. Interestingly, the significant negative effect on nonemployer establishments is not a reduction in the number of individual s with declared nonemployer income, but instead fewer new individuals declaring self-employment income in expansion states in comparison to non-expansion states.

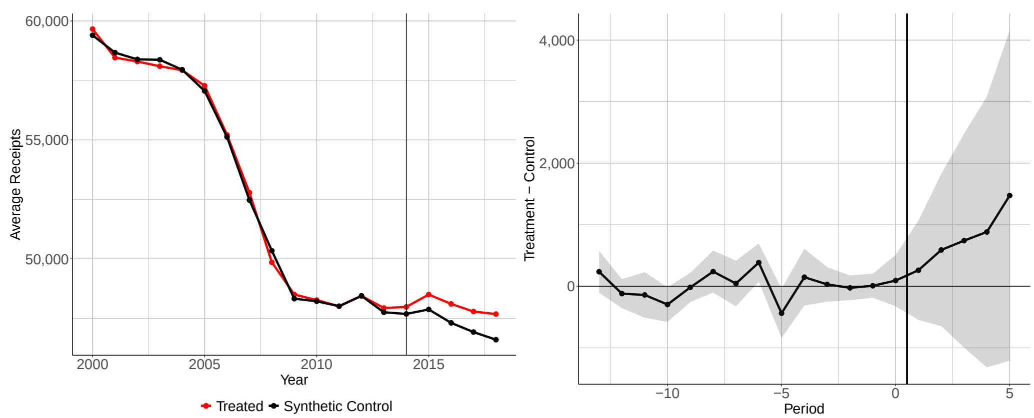
took me a while to understand - NES right?
also, we don't know this because not panel data

All Nonemployer Establishments, Synthetic Control Results:

Establishments/Labor Force



Average Receipts



Move down

Figure 4. : The figures on the left show both the treated and counterfactual group averages from 2001 to 2018 for e_{cit} and r_{cit}. The figures on the right show the average effect of the treatment on the treated with a bootstrapped 95% confidence interval.

To help differentiate between explanation (1) and explanation (2), I utilize the NES county level data on nonemployer establishments, the receipts taken in by these establishments, and data on Uber deployment by county over time. Figure 4 shows the effect of Medicaid expansion on both the number of nonemployer establishments per member of the labor force and the average receipts of those establishments using GSCM when able to match on county level data. The effect of Medicaid expansion remains consistently negative on the number of nonemployer establishments per member of the labor force, similar to Table 1. The additional information supplied by the NES, and unavailable in the ACS or CPS, is the receipts taken in by nonemployer establishments. Using this data, I find that Medicaid expansion is insignificantly positively related to the average receipts taken in by nonemployer establishments.

These results suggest that it is not actually a reduction in the number of nonemployer establishments, but is actually fewer new entrants among expansion states. ? The lack in a of significant change in receipts, while also being relatively stable in the post period, implies that the growing number of self-employed is not impacting the reported earnings of nonemployer establishments in expansion states, but is leading to a reduction in average receipts in non-expansion states. ? We can interpret the nonemployer establishment market to have slowed it's growth relative non-expansion states. This is shown in the counterfactual plots of Figure 4.

While the treatment in this case is access to Medicaid expansion, it is important to note that this expansion takes place in the context of the ACA broadly. Multiple aspects of the ACA were thought to potentially increases the amount of self-employment taken up, including state insurance exchanges, expanded dependent coverage on health plans, and subsidies for the purchase of health insurance on exchanges (David, Melinda and Rachel, 2015). This could be implying that the ACA without Medicaid expansion is related to an increase in self-employment, but with

This what?

the expansion in Medicaid, the growth is reduced. If this is a true reduction, then this slowed growth would be a reduction in secondary or supplemental sources of income through self-employment, given the lack of an aggregate effect in the CPS and ACS.

Occurring during a similar time frame as Medicaid expansion was the increased availability of Uber across the US. Uber, and other online gig platforms, act as a potential secondary report to the IRS of earnings, and this would discourage tax evasion as a response to Medicaid expansion. Using nonemployer establishment data on transportation and warehousing services and where/when Uber is active in reference to the expansion in Medicaid can allow for a test of the true reduction in self-employment. Table 2 shows equations (1) and (2) for the two-way fixed effect model on both transportation and warehousing services and across all nonemployer establishments. preferred?

Table 2 identifies a very different relationship among transportation and warehousing services in aggregate then is seen across all nonemployer establishments. Medicaid expansion among transportation and warehousing services is shown to be positively related to the number of nonemployer establishments per member of the labor force. Using equation (2), when Uber is not active among expansion counties, the effect is negative and significant, similar to the effect reported among all nonemployer establishments. Once accounting for the interaction though, the aggregate effect switches signs. This flip implies that when in an environment where a secondary reporter is not active, fewer individuals report earnings through a transportation and warehousing nonemployer establishment. Once a prominent secondary reporter enters, we see a flip in this effect and a substantial increase in self-employment is found.

The effect of Medicaid expansion on the average receipts of nonemployer establishments without Uber active is somewhat positive, similar to all nonemployer estab-

Table 2—

	Establishments/Labor Force, e_{cit}			
	NAICS 48-49		NAICS 00	
	(1)	(2)	(1)	(2)
Medicaid	0.0016*	−0.0015**	−0.0039	−0.0070***
	(0.0009)	(0.0006)	(0.0030)	(0.0026)
Medicaid*Uber Active		0.0041***		0.0041*
		(0.0007)		(0.0020)
Observations	56,525	56,525	56,620	56,620
R^2	0.808	0.816	0.922	0.923
Adjusted R^2	0.797	0.806	0.918	0.918
	Average Receipts, r_{cit}			
	NAICS 48-49		NAICS 00	
	(1)	(2)	(1)	(2)
Medicaid	−3,013.6	2,398.7*	1,602.1*	2,091.7**
	(2,192.1)	(1,342.0)	(947.6)	(876.0)
Medicaid*Uber Active		−7,030.1***		−636.0
		(1,912.9)		(646.0)
Observations	56,525	56,525	56,620	56,620
R^2	0.818	0.820	0.913	0.913
Adjusted R^2	0.808	0.810	0.908	0.908
Uber Active	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01			

lishments, but the interaction is negative. These two effects work against each other and result in an insignificant effect in aggregate. Due to concerns of parallel trends already discussed, Figure 5 shows the GSCM for transportation and warehousing and supports the identified aggregate positive effect on the number of nonemployer establishments per member of the labor force, and the insignificant effect on average receipts.

Can this be split by UBER/Non-UBER?

Viewing these results on transportation and warehousing services in the context of the aggregate effect outlined earlier, it appears likely that a substantial amount of tax evasion is occurring. Before introducing the secondary reporter, the explanation for the negative effect in the number of nonemployer establishments, without tax evasion, was a reduction in the number of new nonemployer establishments. This effect would not be expected to vary by type of work, and given the expansion in availability and use of independent contracting through the online gig economy, it would be reasonable to expect that the reduction in new firms would be consistent across both traditional self-employment and the online gig economy. The results of Table 2 indicate that is not the case. In fact, it appears that the job lock hypothesis is the best explanation when looking at the online gig economy and a secondary reporter.

In 2018, those states which have expanded Medicaid accounted for 98,219,447 members of the labor force in my sample. Jackson, Looney and Ramnath (2017*b*) estimates that in 2014, among those with non-zero earnings, 7.2 percent earned income solely from self-employment and the remaining 6.1 percent earned from a mix of both self-employment and wage income reported on a W2. A rough estimate can be made then of how many of the 14,098,890 additional Medicaid recipients would have been expected to fall into the nonemployer data. From the additional Medicaid recipient population, we would estimate that 1,875,152 would be participating in self-

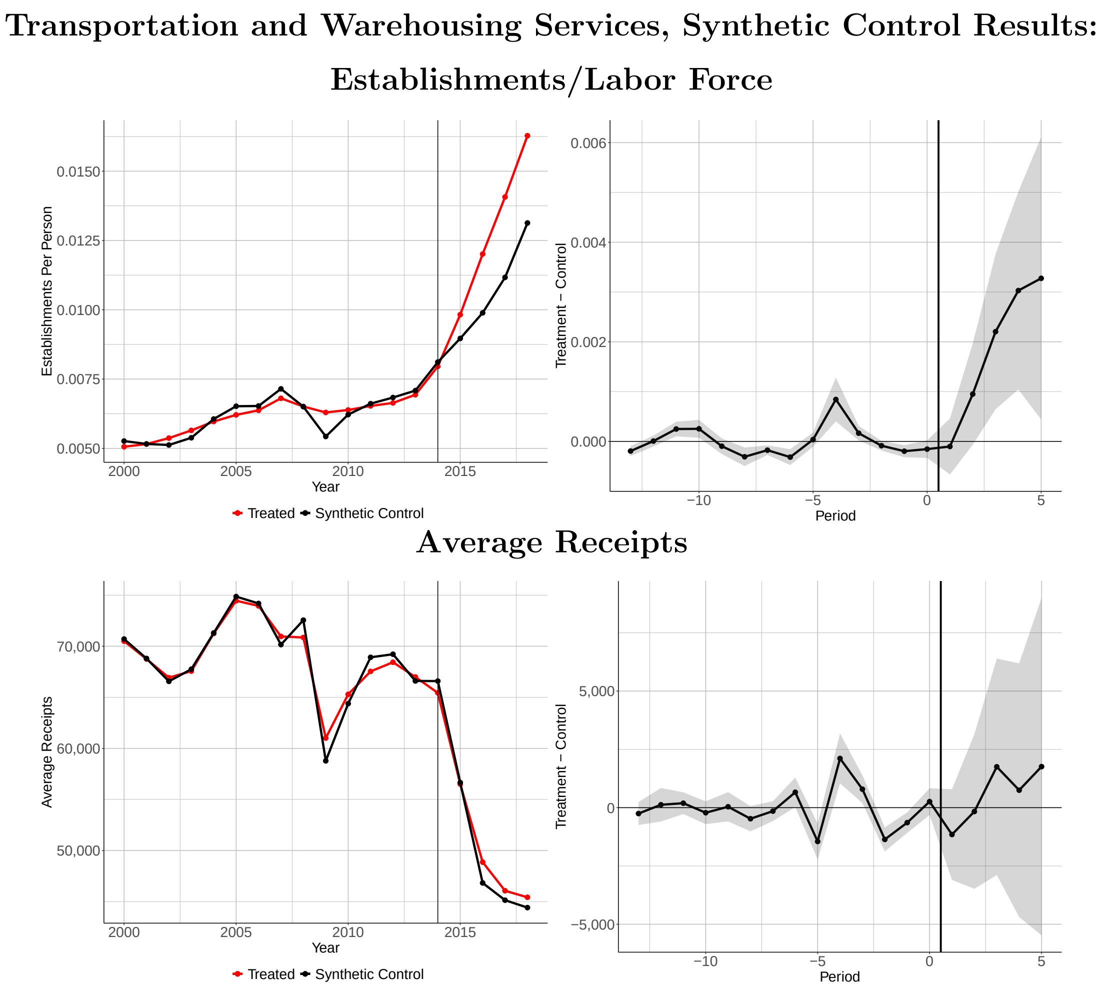


Figure 5. : The figures on the left show both the treated and counterfactual group averages from 2001 to 2018 for e_{cit} and r_{cit}. The figures on the right show the average effect of the treatment on the treated with a bootstrapped 95% confidence interval.

employment. The number of nonemployer establishments which were not reported on tax filings as a result of the expansion in Medicaid by 2018 was 353,590, or an 18.9% reduction compared to the expected number of self-employed.

V. Conclusion

This analysis focused on exploring the impact of the expansion of Medicaid on individual's propensity to take up self-employment and independent contracting. I find that the Medicaid expansion resulted in a significant decline in engagement in self-employment. Approximately 350,000 fewer individuals reported earnings through a nonemployer establishment among expansion states, or 18.9% of the expected number of nonemployer establishments among those who took up Medicaid.

Remind us why - many

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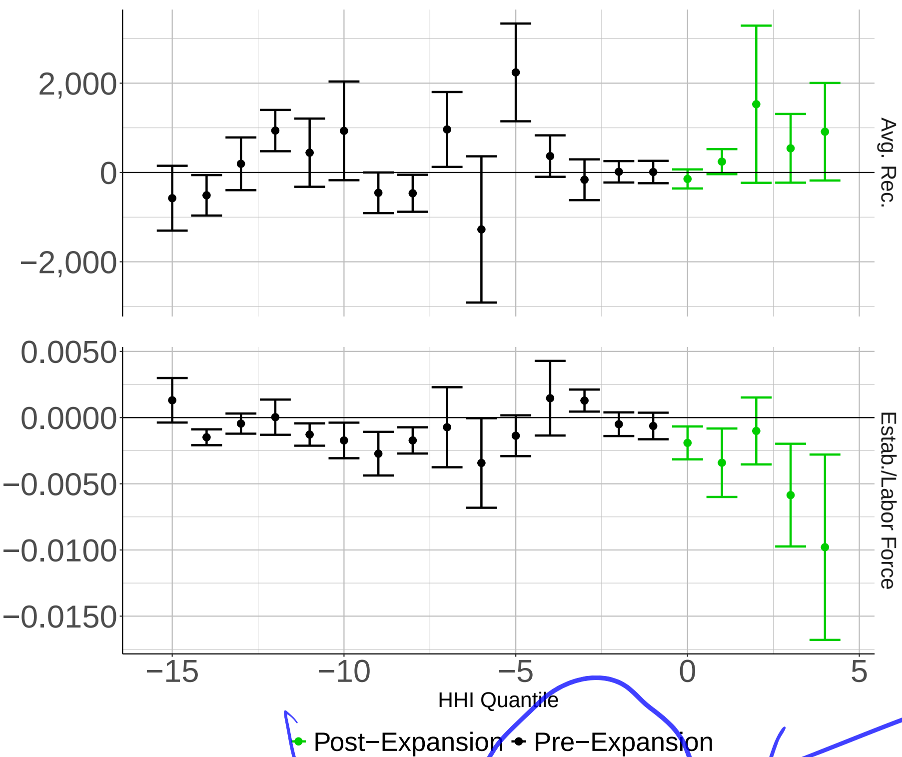
APPENDIX



Revise

Figure A1. : Callaway and Sant'Anna (2019)'s method for the assessment of parallel trends.

Figure A2. : Include this factor figure soon