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

By Benjamin Glasner*

Did the expansion of Medicaid following the Affordable Care Act result in an increase in the work which does not offer employer supplied health insurance, and if so, was the effect significantly different between types of work arrangements, including independent contracting and self-employment? I find evidence of a reduction in engagement in self-employment in areas which expanded Medicaid. *Keywords: Medicaid and Nonemployer Establishments*

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 in-

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crease 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. Job Lock vs Employment Lock

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 A1.

By December2017, Medicaid enrollment had increased by 14,098,890 people among expansion states (Centers for Medicare & Medicaid Services, 2017). This expansion in the availability of non-ESI may have impacted individuals in the labor market. In the US, ESI has been the dominant form of health insurance since the early 20th century (Currie and Madrian, 1999). Since ESI is exempt from income taxes, worker's budget constraints are expanded in comparison to a fully taxable monetary package. This is also an opportunity to compensate workers more at no additional cost to the firm, allowing for cheaper means of attracting and retaining labor than direct cash payments (Woodbury and Huang, 1991; Gruber and Poterba, 1994; Gentry and Peress, 1994).

This does not mean however that some individuals will not prefer to purcahse insurance on the private market, or that a private market was dysfunctional. In fact, the private market acts as a mechanism for catching those who may not have access to ESI for a wide range of reasons. The division between the participants in both markets does illustrate selection bias though. 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, and specifically independent contractors, are only going to get access to ESI if they are linked to a shared family plan, or if they are also an employee who for a firm which offers ESI, and have allocated enough hours. This means many actively purchase insurance in the private market, or receive their health insurance through a government program such as Medicaid. The higher cost of health insurance on the private market is seen as a deterrent from leaving work arrangements which offer ESI. How great of a deterrent this is depends on an individual's preferences for health insurance and differentials in the price and quality of insurance between markets.

Empirical testing of the effect of ESI and Medicaid have on labor force participation has 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). 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. 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). While the self-employed and independent contractors 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.

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. 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) as well as statistically insignificant effects when using experimental methods (Baicker et al., 2014) or looking at the medicaid expansion resulting from the ACA on survey data (Leung and Mas, 2016).

II. Data

Contrary to the work of Leung and Mas (2016), I use Nonemployer Statistics (NES) which collects annual data on nonemployer establishments and reports the count of establishments by geographic level and industry. I do this because my research question is focused on the self-employed broadly and independent contractors. Most nonemployer establishments are 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. This analysis uses the aggregate of all NAICS industries and measures the local propensity of engagement in self-employment.

While Previous work has leveraged the the American Community Survey (ACS) and the Current Population Survey (CPS), I favor the NES as it captures both primary and supplemental sources of income and allows for county level geographic information. Both the ACS and CWS focus on primary sources of income, which will fail to capture changes in supplemental sources of income. Both Abraham et al. (2018); 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.

I use NES data from 2000 to 2017 and create a balanced panel of counties throughout the sample. 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 industry-county-year. Those counties that have less than 3 establishments are censored for confidentiality concerns. While NES data are presented as counts at the county 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.

Taking advantage of the geographic and time varying rollout of Uber, it is possible to construct a treatment for a homogeneous, or nearly homogeneous, market for exempt labor, which varies in deployment timing and location. This market has relatively low-barriers to entry and exit and is composed of a labor force which is more similar to the general population than previous taxi industries (Hall and Krueger, 2018).

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 A2 shows this deployment strategy in action at the county level within the U.S. in relation to the expansion of medicaid. This initial expansion in locations was not random as Uber sought to operate in markets which would produce high initial take up of the service, but over time the deployment strategy grew less dependent on local market characteristics. As Uber's head of global expansion said in 2014 "At this point we go so quickly, I wouldn't say that it particularly matters" in response to questions about how Uber selects locations of operation. He went on to say, "If we're not there now, we'll be there in a week" (Huet, 2014).

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. 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 coding for the treatment of Uber is expanded to include the core-based statistical areas (CBSAs) in which a county is a member. CBSAs are defined by the Census Bureau as a geographic area which "consist of the county or 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). Linking Uber deployment to the CBSA level rather than an exclusively county level analysis will not only identify the effect of Uber deploying in a given county, but also capture the effect among counties related to any given CBSA. This reduces bias as a result of individuals commuting to areas where Uber is operational, as nonemployers will be recognized in counties where they file their taxes and not strictly where driving occurs. Annual county population estimates are also included using the Annual Estimates of the Resident Population data from the census bureau.

III. Methodology

I define a variable for the extensive marginal effect of the medicaid expansion on the nonexempt labor market by measuring the number of establishments per person in a county. This creates a proxy measure for the likelihood that an individual will engage in the exempt labor market in a given county. This is defined as:

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

where E_{it} is the number of nonemployer establishments in county i and year t, and P_{it} is county i's population estimate in year t. Since the NES is a count of establishments, I am unable to measure an individual's intensity of engagement in this type of work, but this measure can act as an aggregate proxy for the local intensity of engagement in the exempt labor market.

This analysis leverages a two-way fixed effect model on a balanced panel of counties 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 county experienced medicaid expansion. I include one, two, and three year lags of M_{it} to calculate the total effect of medicaid expansion from 2014 to 2017.

$$e_{it} = \beta_0 + \beta_1 M_{i,t} + \beta_2 M_{i,t-1} + \beta_3 M_{i,t-2} + \beta_4 M_{i,t-3} + \alpha_i + \tau_t + \mu_{it} \tag{1}$$

This method 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. This is shown in equation (2).

$$
\begin{aligned}
e_{it} = \beta_0 + \beta_1 M_{i,t} + \beta_2 M_{i,t-1} + \beta_3 M_{i,t-2} + \beta_4 M_{i,t-3} + \\
\beta_5 M_{it} * Uber_{it} + \beta_6 M_{i,t-1} * Uber_{it} + \beta_7 M_{i,t-2} * Uber_{it} + \beta_8 M_{i,t-3} * Uber_{it} + \\
\beta_9 Uber_{it} + \alpha_i + \tau_t + \mu_{it}
\end{aligned} \tag{2}
$$

These models control for time invariant geographic characteristics, α_i, which is preferred at the county level given the inclusion of local 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.

Given concerns over parallel trends violations discussed later, I repeat the analysis using both interacted fixed effects (Bai, 2009) and synthetic control designs Xu (2017).

IV. Results

Before introducing the two-way fixed effect approach I assess the validity of the parallel trends assumption. I do this by comparing the trends in the average number of establishments per person in counties which do and do not receive an expansion in medicaid following the ACA. This is shown in Figure A3. While counties which receive the expansion in medicaid, the treatment group, appear to have more establishments per person in the early 2000s, but the counties which do not receive an expansion, control group, overtake the treatment group in 2005. They appear to be growing at a faster rate throughout the whole sample. This is a violation in parallel trends, and will likely lead to an overestimate of a negative effect of medicaid expansion on the number of establishments per person.

Figure A3 is expanded by breaking counties out by if they ever receive Uber, shown in Figure A4. The difference in slope across treatment and control groups remains, but a level difference is also clear as the two lines defining if a county ever receives Uber appear higher than their relative counterpart throughout the sample. Interestingly, we do see a significant jump across all four lines in the number of establishments per person in 2014, which is consistent with Figure A3.

With the observed difference in trends in mind, I utilize a two-way fixed effect model, interactive fixed effect model, an EM synthetic control design, and a matrix completion method. The results of each of these methods are shown in Table A1. As was expected from the descriptive figures, the two-way fixed effect approach produces the larges negative coefficient as it is capturing the difference in trends and attributing it to the treatment effect of medicaid expansion.

Both the interactive fixed effects and synthetic control designs appear to do a better job of addressing this difference in trends. These coefficients show the change in the number of establishments per person at the county level, using the total population of the county. Within the sample used in this analysis, a total of 165,986,713 people lived in counties which received Medicaid expansion in 2014. Using this, I estimate the number of establishments which were not created as a result of the expansion in Medicaid across all of these models from 2014 to 2017.

While the negative coefficients are consistent across models for the treatment effect of Medicaid expansion on the number of nonemployer establishments, the negative coefficient actually shows a slower growth in the number of establishments. Figures A5 and A6 show the counterfactual path of the treatment group in comparison to the observed treatment group. The average treatment effect is depicted in Figures A7 and A8. Figures A5 through A8 demonstrate that the observed effect is likely fewer people taking up nonstandard work instead of individuals exiting self-employment.

Jackson, Looney and Ramnath (n.d.) 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-employment. I create an estimate of the percent reduction in establishment formation from this number across each of the models, as shown in Table A1.

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. Roughly half a million fewer individuals reported earnings through a nonemployer establishment among expansion states, 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.

REFERENCES

Abraham, Katharine G, John C Haltiwanger, Kristin Sandusky, and James R Spletzer. 2018. "Measuring the Gig Economy: Current Knowledge and Open Issues." National Bureau of Economic Research Working Paper 24950.

Akosa Antwi, Yaa, Asako S Moriya, and Kosali Simon. 2013. "Effects of federal policy to insure young adults: evidence from the 2010 Affordable Care Act's dependent-coverage mandate." *American Economic Journal: Economic Policy*, 5(4): 1–28.

Anderson, Patricia M. 1997. "The Effect of Employer-Provided Health Insurance on Job Mobility: Job-Lock or Job-Push?" *unpublished paper (Dartmouth University).*

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman. 2014. "The impact of Medicaid on labor market activity and program participation: evidence from the Oregon Health Insurance Experiment." *American Economic Review*, 104(5): 322–28.

Bai, Jushan. 2009. "Panel data models with interactive fixed effects." *Econometrica*, 77(4): 1229–1279.

Bailey, James. 2017. "Health insurance and the supply of entrepreneurs: new evidence from the affordable care act." *Small Business Economics*, 49(3): 627–646.

Baldwin, Marjorie, and William G. Johnson. 1994. "Labor market discrimination against men with disabilities." *Journal of Human Resources*, 1–19.

Baldwin, Marjorie L., and William G. Johnson. 2000. "Labor Market Discrimination against Men with Disabilities in the Year of the ADA." *Southern Economic Journal*, 66(3): 548–566.

Blumberg, L. J., S. Corlette, and K. Lucia. 2014. "The Affordable Care Act: Improving Incentives for Entrepreneurship and Self-Employment." *Public Policy & Aging Report*.

Buchmueller, Thomas C., and Robert G. Valletta. 1999. "The effect of health insurance on married female labor supply." *Journal of Human Resources*, 42–70.

Centers for Medicare & Medicaid Services. 2017. "Monthly Medicaid & CHIP Application, Eligibility Determination, and Enrollment Reports & Data | Medicaid."

Current Population Survey Staff. 2018. "Electronically mediated work: new questions in the Contingent Worker Supplement." U.S. Bureau of Labor Statistics.

Currie, Janet, and Brigitte C. Madrian. 1999. "Chapter 50 Health, health insurance and the labor market." In *Handbook of Labor Economics*. Vol. 3, 3309–3416. Elsevier.

Dague, Laura, Thomas DeLeire, and Lindsey Leininger. 2017. "The Effect of Public Insurance Coverage for Childless Adults on Labor Supply." *American Economic Journal: Economic Policy*, 9(2): 124–154.

David, Blumenthal, Abrams Melinda, and Nuzum Rachel. 2015. "The Affordable Care Act at 5 Years." *The New England Journal of Medicine*, 8.

DeCicca, Philip. 2007. "Health Insurance Availability and Entrepreneurship: Evidence from New Jersey." Social Science Research Network SSRN Scholarly Paper ID 1003309, Rochester, NY.

Depew, Briggs. 2015. "The effect of state dependent mandate laws on the labor supply decisions of young adults." *Journal of health economics*, 39: 123–134.

Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo. 2014. "Public Health Insurance, Labor Supply, and Employment Lock." *The Quarterly Journal of Economics*, 129(2): 653–696.

Gentry, William M, and Eric Peress. 1994. "Taxes and Fringe Benefits Offered by Employers." National Bureau of Economic Research Working Paper 4764.

Gruber, Jonathan, and Brigitte C. Madrian. 1994. "Health insurance and job mobility: The effects of public policy on job-lock." *ILR Review*, 48(1): 86–102.

Gruber, Jonathan, and James Poterba. 1994. "Tax Incentives and the Decision to Purchase Health Insurance: Evidence from the Self-Employed." *The Quarterly Journal of Economics*, 109(3): 701–733.

Hall, Jonathan V., and Alan B. Krueger. 2018. "An analysis of the labor market for Uber's driver-partners in the United States." *ILR Review*, 71(3): 705–732.

Heim, Bradley, Ithai Lurie, and Kosali Simon. 2015. "The impact of the affordable care act young adult provision on labor market outcomes: evidence from tax data." *Tax Policy and Economy*, 29(1): 133–157.

Heim, Bradley, Ithai Lurie, and Kosali Simon. 2018. "Did the Affordable Care Act Young Adult Provision Affect Labor Market Outcomes? Analysis Using Tax Data." *ILR Review*, 71(5): 1154–1178.

Heim, Bradley T., and Ithai Z. Lurie. 2010. "The effect of self-employed health insurance subsidies on self-employment." *Journal of Public Economics*, 94(11): 995–1007.

Hogan, Andrew, and Elka Torpey. 2016. "Working in a gig economy : Career Outlook: U.S. Bureau of Labor Statistics."

Holtz-Eakin, Douglas, John R. Penrod, and Harvey S. Rosen. 1996. "Health insurance and the supply of entrepreneurs." *Journal of Public Economics*, 62(1): 209–235.

Huet, Ellen. 2014. "Uber's Global Expansion In Five Seconds."

Hyman, Louis. 2018. *Temp: How American Work, American Business, and the American Dream Became Temporary.* Penguin.

Jackson, Emilie, Adam Looney, and Shanthi Ramnath. n.d.. "The Rise of Alternative Work Arrangements: Evidence and Implications for Tax Filing and Benefit Coverage." 50.

Johnson, William G., and James Lambrinos. 1985. "Wage discrimination against handicapped men and women." *Journal of Human Resources*, 264–277.

Jones, Melanie K. 2008. "Disability and the labour market: a review of the empirical evidence." *Journal of Economic Studies*, 35(5): 405–424.

Jones, Melanie K., Paul L. Latreille, and Peter J. Sloane. 2006. "Disability, gender, and the British labour market." *Oxford Economic Papers*, 58(3): 407–449.

Katz, Lawrence F., and Alan B. Krueger. 2016. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015." *ILR Review*, 72(2): 382–416.

Katz, Lawrence F., and Alan B. Krueger. 2019. "Understanding Trends in Alternative Work Arrangements in the United States." *National Bureau of Economic Research Working Paper Series.*

Leung, Pauline, and Alexandre Mas. 2016. "Employment effects of the ACA Medicaid expansions." National Bureau of Economic Research.

Monheit, Alan C., and Philip F. Cooper. 1994. "Health Insurance and Job Mobility: Theoryand Evidence." *ILR Review*, 48(1): 68–85.

Service, Congressional Research. 1988. "Cost and Effects of Extending Health Insurance Coverage." Congressional Research Service.

Sundararajan, Arun. 2016. *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism.* MIT Press. Google-Books-ID: 2Zz2CwAAQBAJ.

US Census Bureau. 2010. "2010 census summary file 1." *Using American FactFinder.*

Wellington, Alison J. 2001. "Health Insurance Coverage and Entrepreneurship." *Contemporary Economic Policy*, 19(4): 465–478.

Woodbury, Stephen, and Wei-Jang Huang. 1991. "The Tax Treatment of Fringe Benefits." *Upjohn Press.*

Xu, Yiqing. 2017. "Generalized synthetic control method: Causal inference with interactive fixed effects models." *Political Analysis*, 25(1): 57–76.

APPENDIX

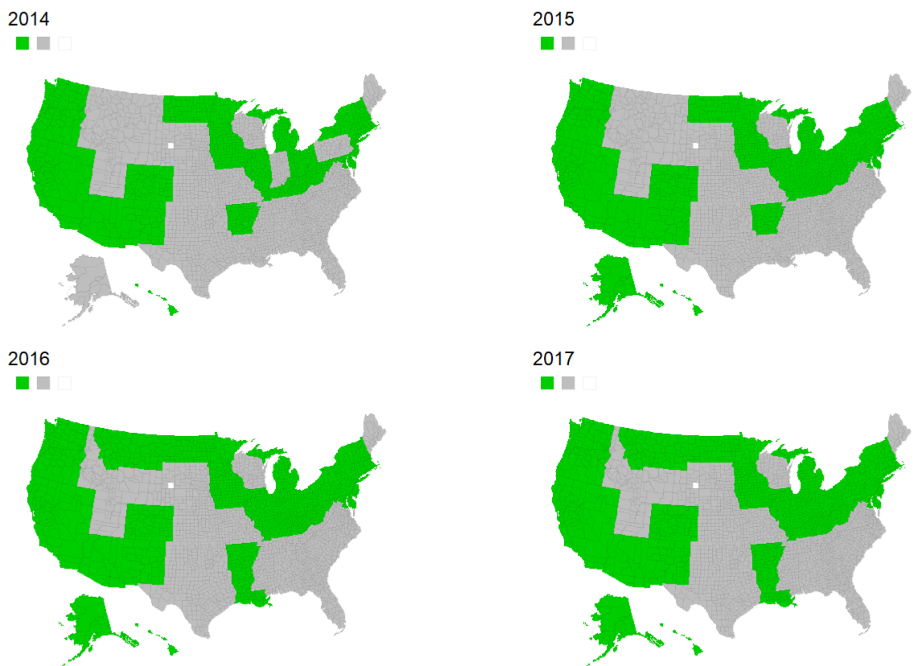


Figure A1. : The figures above depict the counties in which Medicaid expansion occurs 2014-2017. Grey counties are areas which do not experience a medicaid expansion, but green counties are where teh expansion does occur. White counties are counties which either do not appear in every year of the panel or are structural zeros and are dropped from the analysis.

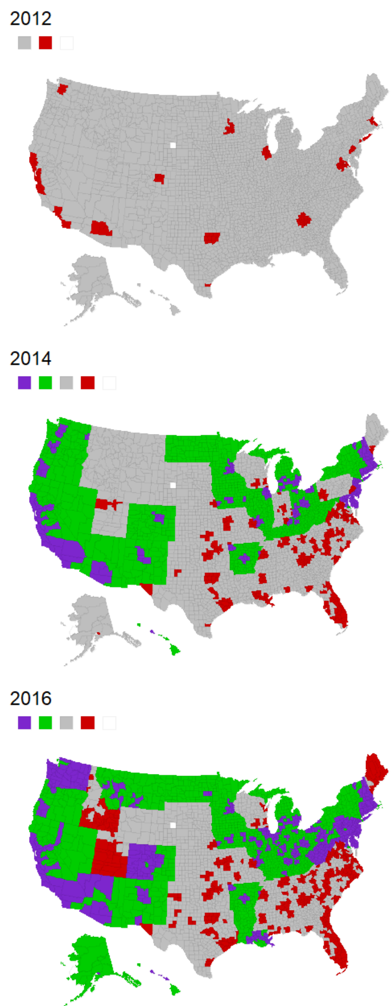
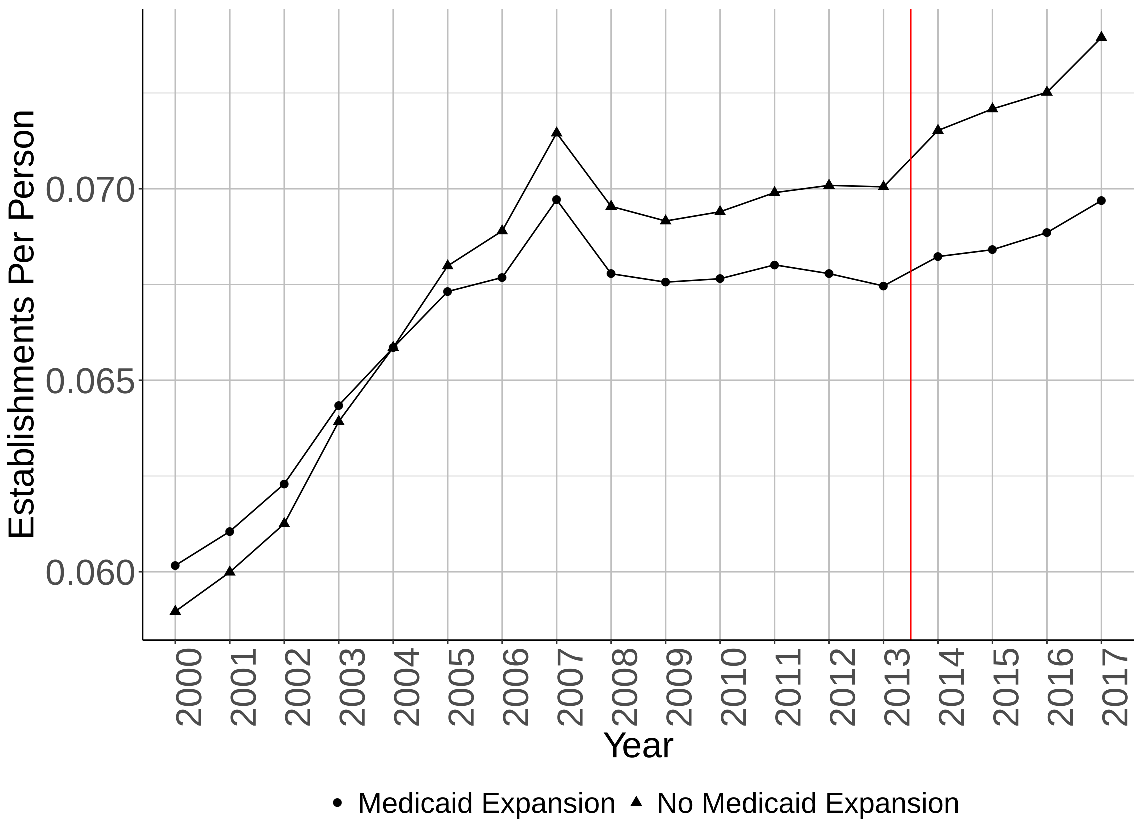


Figure A2. : The figures above depict the counties in which Medicaid expansion occurs 2014-2017. Grey counties are areas which do not experience a medicaid expansion, but green counties are where teh expansion does occur. White counties are counties which either do not appear in every year of the panel or are structural zeros and are dropped from the analysis.


Establishments Per Person
0.070
0.065
0.060
2000
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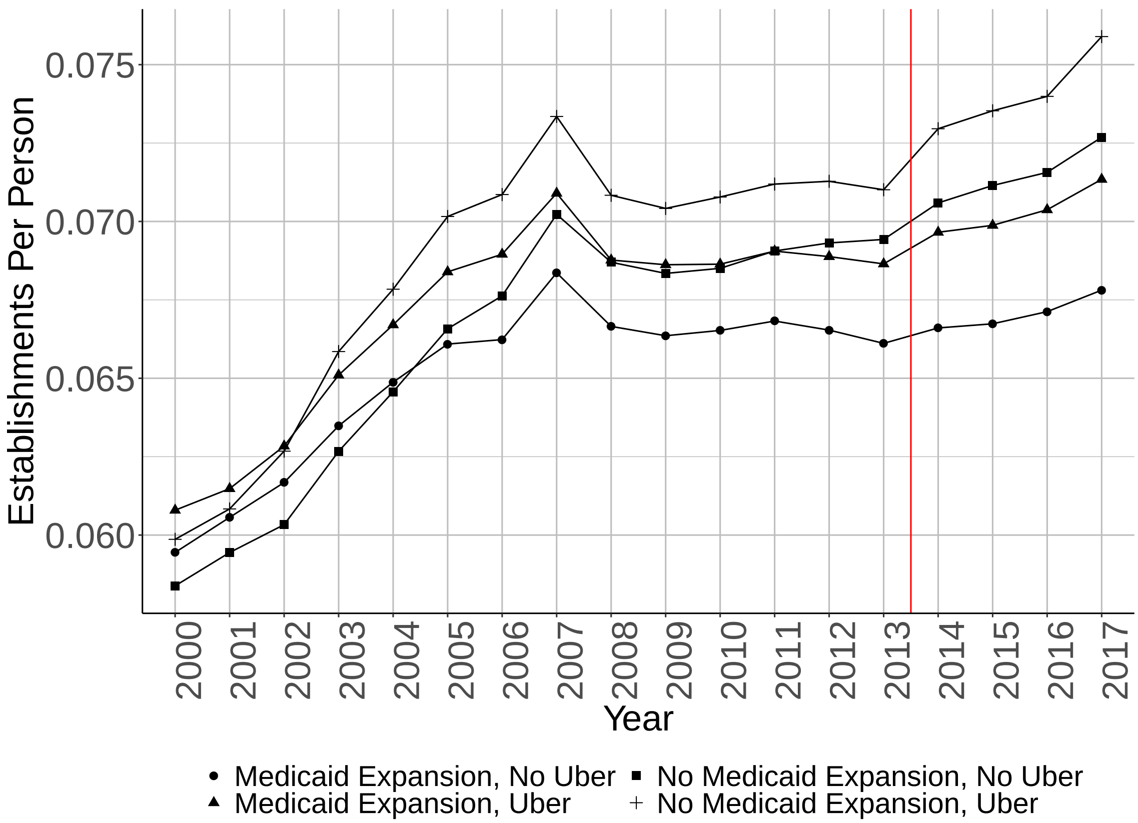
Year
Medicaid Expansion
No Medicaid Expansion

Figure A3.



Establishments Per Person
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2000
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Medicaid Expansion, No Uber
No Medicaid Expansion, No Uber
Medicaid Expansion, Uber
No Medicaid Expansion, Uber

Figure A4.

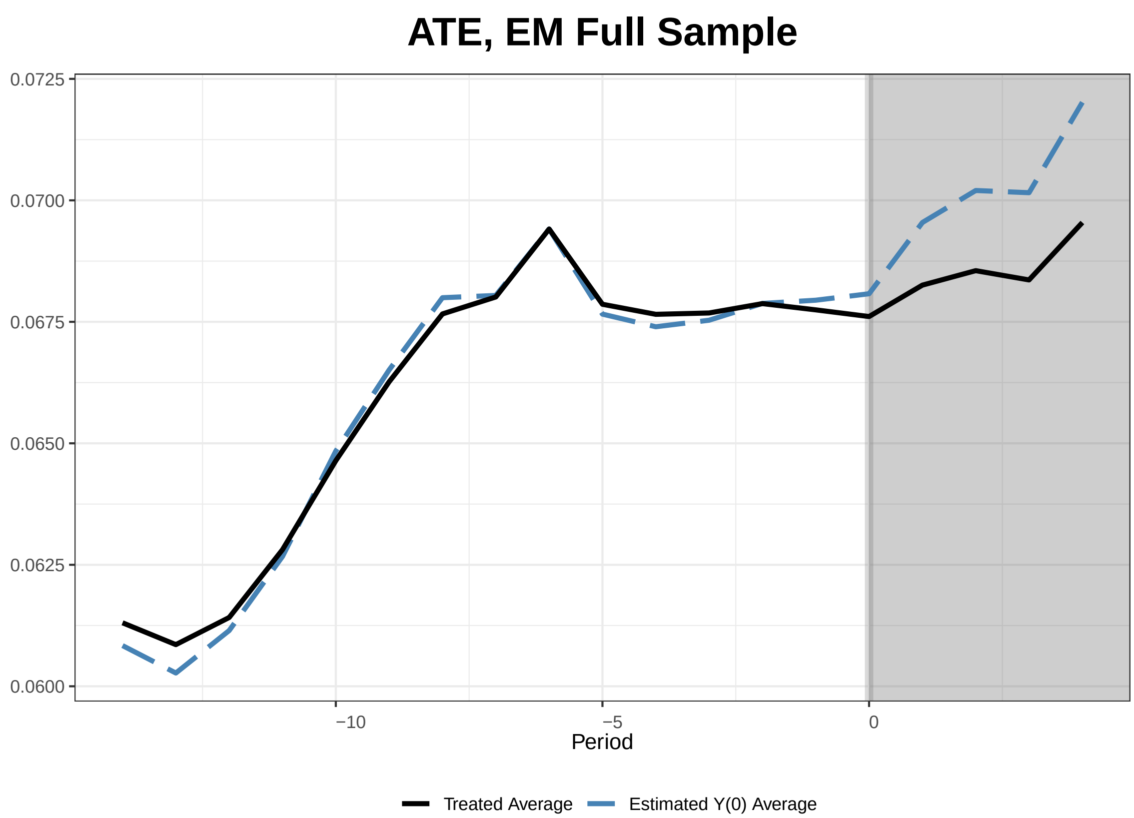
ATE, EM Full Sample
0.0725
0.0700
0.0675
0.0650
0.0625
0.0600
−10
−5
0
Period
Treated Average
Estimated Y(0) Average

Figure A5.

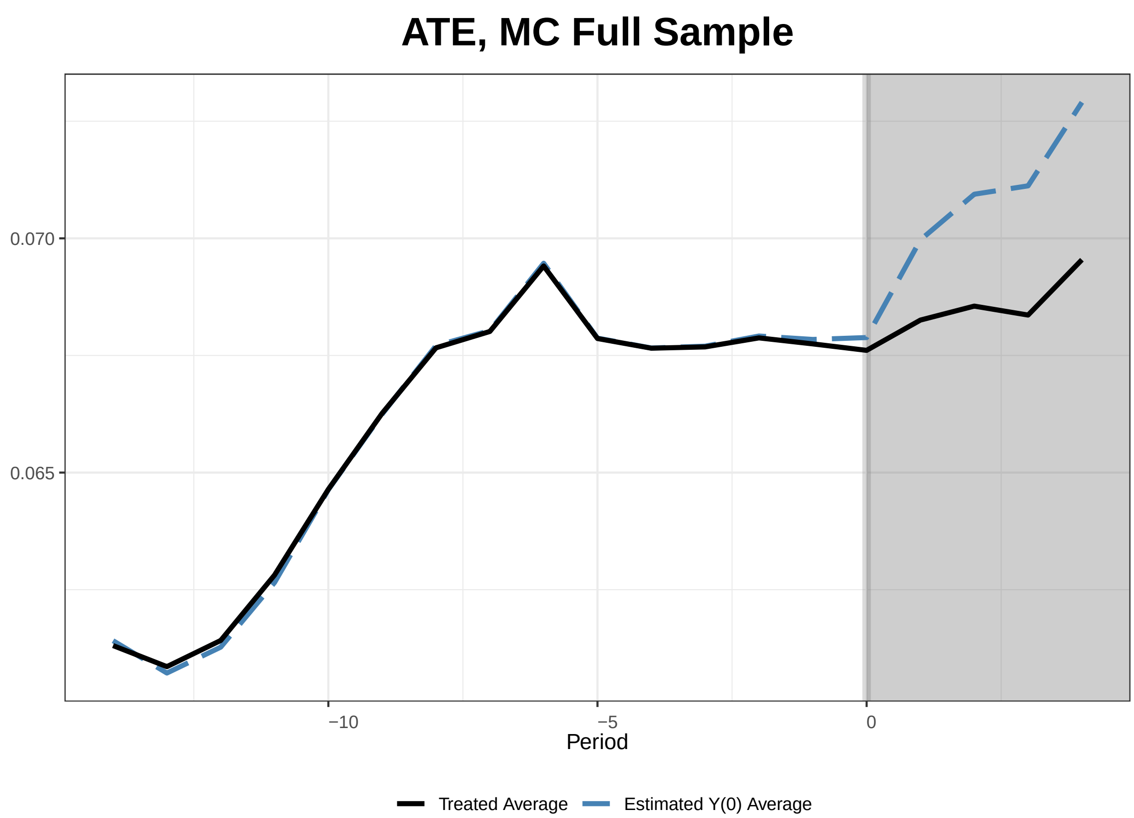
ATE, MC Full Sample
0.070
0.065
−10
−5
0
Period
Treated Average
Estimated Y(0) Average

Figure A6.

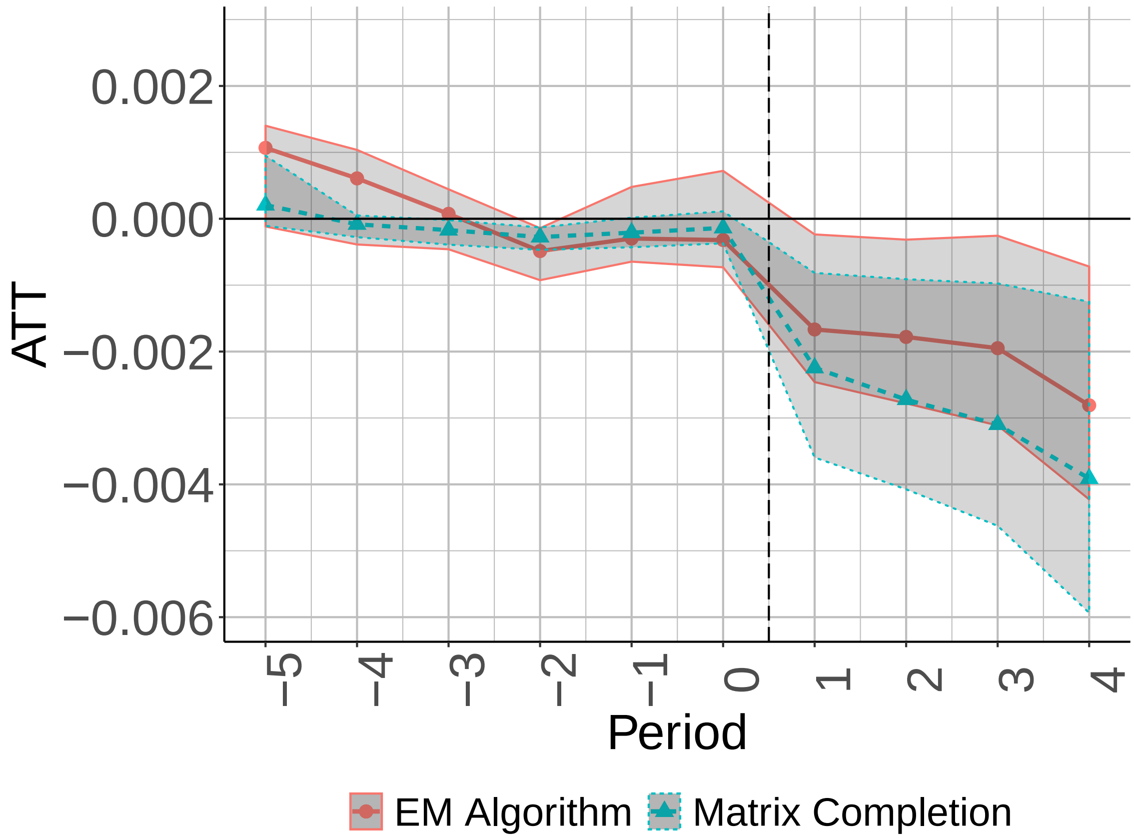

Figure A7. : Comparison between EM and MC synth methods

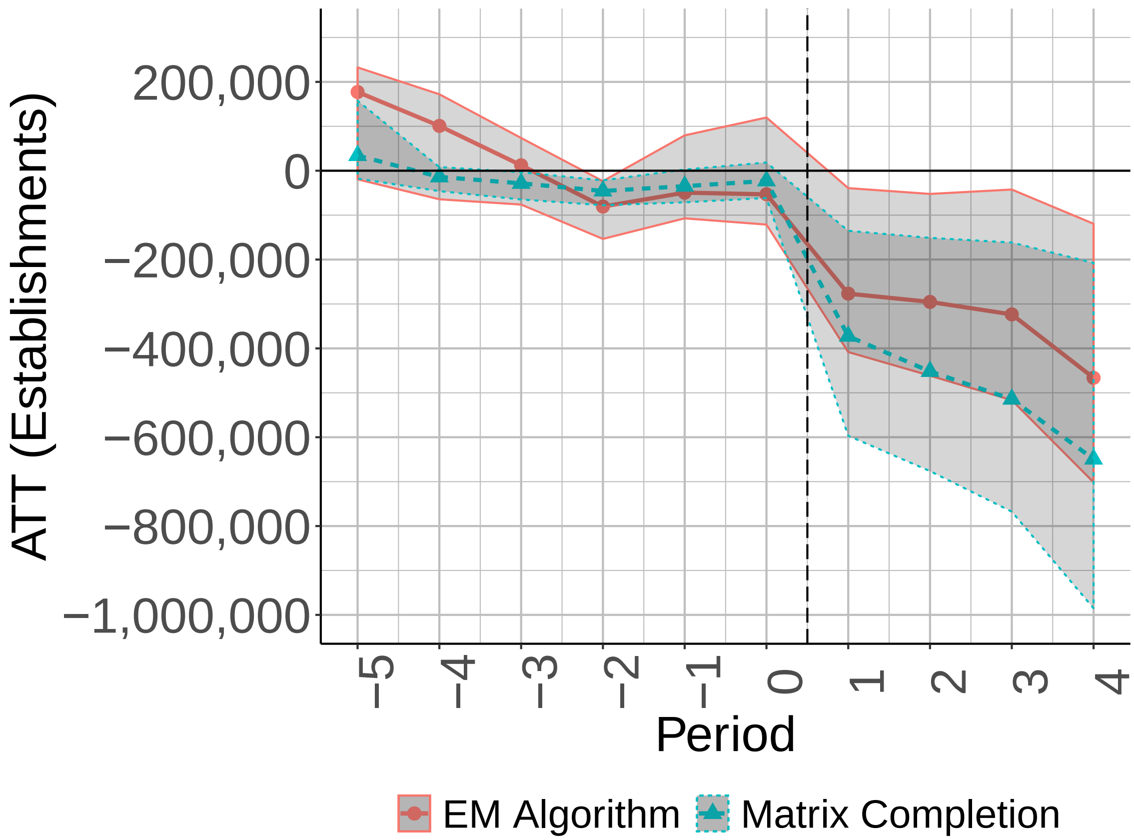

Figure A8. : Comparison between EM and MC synth methods

Table A1—

	Dependent variable:					
	Establishments Per Person					
	Two-Way Fixed Effect		Int. Fixed Effects		EM Synth	MC
Medicaid	-0.00227***	-0.00256***	-0.00089***	-0.00092***	-0.00167***	-0.00225***
	(0.00016)	(0.00018)	(0.00012)	(0.00010)	(0.00054)	(0.00076)
Lag 1	-0.00046**	-0.00058**	-0.00031***	-0.00040***	-0.00178***	-0.00272***
	(0.00021)	(0.00024)	(0.00009)	(0.00009)	(0.00062)	(0.00089)
Lag 2	-0.00065***	-0.00025	-0.00013	-0.00015	-0.00195**	-0.00310***
	(0.00021)	(0.00026)	(0.00010)	(0.00012)	(0.00072)	(0.00100)
Lag 3	-0.00056**	-0.00089***	-0.00060***	-0.00067***	-0.00281**	-0.00391***
	(0.00024)	(0.00031)	(0.00012)	(0.00015)	(0.00089)	(0.00133)
Medicaid*Uber	-	0.00131***	-	0.00013	-	-
	-	(0.00034)	-	(0.00017)	-	-
Lag 1*Uber	-	0.00021	-	0.00031***	-	-
	-	(0.00042)	-	(0.00012)	-	-
Lag 2*Uber	-	-0.00136***	-	-0.00005	-	-
	-	(0.00040)	-	(0.00015)	-	-
Lag 3*Uber	-	0.00058	-	0.00004	-	-
	-	(0.00040)	-	(0.00018)	-	-
Impact	-655,103	-711,588	-320,979	-356,580	-466,292	-649,274
(%)	(-35.8)	(-38.8)	(-17.5)	(-19.5)	(-25.4)	(-35.4)
Impact (With Uber)	-	-589,868	-	-283,835	-	-
(%)	-	(-32.2)	-	(-15.5)	-	-
Uber Active	-	Yes	-	Yes	Matched	Matched
County GDP	Yes	Yes	Yes	Yes	Matched	Matched
GDP Per Person	Yes	Yes	Yes	Yes	Matched	Matched
Establishments	-	-	-	-	Matched	Matched
Population	-	-	-	-	Matched	Matched
County Fixed Effects	Yes	Yes	Yes	Yes	-	-
Year Fixed Effects	Yes	Yes	Yes	Yes	-	-

Note: *p<0.1; **p<0.05; ***p<0.01