The Affordable Care Act and Gig Employment

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Abstract

The gig economy allows consumers to purchase goods and services with ease, and allows workers to provide goods and services to consumers, on their own schedules. The Affordable Care Act extended the age at which younger individuals can remain on their parent's insurance from 19 to 26 and allowed individuals to purchase their own health insurance. This paper looks at the impact of the Affordable Care Act on a younger individual's probability to partake in gig work, using Uber as a proxy. I find that younger individuals are 0.04% less likely to work in the gig economy, post Uber deployment.

1 Introduction

The gig economy has experienced consistent growth over the past 15 years. An article on Forbes reports gig workers represent around 35 percent of the US workforce in 2020, which has increased from between 14 and 20 percent in 2014 Henderson (2020). Companies such as Uber allow consumers to pay someone to drive them from one location to another without having to hire a taxi from a firm. Driving for Uber allows potential workers to work a flexible schedule on their own time. This paper sets out to look at how a major policy change, specifically the Affordable Care Act (ACA), affects participation in the gig economy for younger individuals. This is important because the Affordable Care Act increased the age that younger individuals can remain on their parent's health insurance. This alleviates pressure for younger individuals to look for a job in order to obtain health insurance. The gig economy provides the perfect opportunity for younger individuals to make additional income, all while not having to worry about purchasing health insurance. This paper is one of the first paper's to look at how a major policy change might affect outcomes in gig economy employment.

This paper pulls it data from the American Community Survey portion of Integrated Public Use Microdata Series and deployment data from Uber. I link the Uber deployment data to the ACS data using state and county fips codes. I then analyze with my data how the deployment of Uber impacts a younger individual's likelihood of partaking in gig work, post the Affordable Care Act mandate. This paper answers this question with a difference in differences in differences model with staggered treatment. I leverage both a two-way fixed effects model for difference in differences in differences with staggered treatment, and the imputation method created by Borusyak et al. (2022). I show why the imputation method is needed in my analysis to correct for the issues with staggered treatment timing outlined by Goodman-Bacon (2018).

To start, I look at how the deployment of Uber within a CBSA affects the probability of an individual within that CBSA of working for Uber. This model uses a difference in differences estimator with staggered treatment timing, specifically using two-way fixed effects and then the imputation method. I again show here why the imputation method is needed in my analysis. From the imputation method, I find a statistically significant increase, of roughly 0.05 percent, in an individual's, who I classify as working for Uber, probability to work for Uber after Uber is deployed within the respective individual's CBSA. I then extend my previous model to control for age and look to see how the Affordable Care Act impacted a younger individual's likelihood to work for Uber. Looking at the years post the ACA mandate, I find a statistically significant decrease, of about 0.04 percent, in a younger individual's likelihood to work for Uber, after Uber is deployed within their CBSA. This paper contributes to the literature because the literature has yet to look at how a major policy change would affect gig economy employment. In Benjamin Glasner's paper titled "The Minimum Wage, Self-Employment, and the Online Gig Economy", he discusses the next steps in researching the gig economy at the end of the paper. Glasner (2020) emphasizes the necessity of assessing how welfare policies may interact with the online gig economy, and how this effect varies across space in the United States at the end of his paper. More importantly, the gig economy is still fairly new and has yet to have much research published in this field.

2 Literature Review

Benjamin Glasner's paper titled "The Minimum Wage, Self-Employment, and the Online Gig Economy" analyzes how minimum wage changes affects gig economy participation, specifically in the transportation and warehousing services industries. Glasner uses the Nonemployer Statistics and County Business Patterns for his data and a two way fixed effects model in his analysis. His model includes a Herfindalh-Hirschamn Index to measure labor market concentration, changes to minimum wage, as well as the deployment of Uber. Glasner also uses the difference in difference methodology constructed by Callaway and Sant'Anna (2020) to analyze the group-time difference. Glasner (2020) finds that with a 10% increase in the minimum wage, the number of non-employer establishments classified as transportation and warehousing services increases by 3.9%. Glasner's paper is relevant to what this paper does because the model in this paper includes the deployment of Uber as a part of the variation. This paper also leverages difference in differences model with staggered timing treatment methodology.

A paper written by James Bailey titled "Health insurance and the supply of entrepreneurs: new evidence from the affordable care act" helped me to formulate my empirical strategy. Bailey looks at changes to self employment as a result of the Affordable Care Act. The author uses difference-in-differences methodology where the first difference is the mandate being passed and the second difference is age group. The treatment group for this paper is 23-25 year old individuals while the control group is 27-29 year old individuals. The dependent coverage mandate increased self-employment among disabled young adults by 19-23%, but had no impact on self-employment among young adults overall Bailey (2017). This paper is relevant to my research because I am extending the model used by changing the differences and adding a third difference. The model in this paper also differs from Bailey's model by looking at gig economy participation post the mandate. Uber started to deploy in the later months of 2010 after congress passed the Affordable Care Act, hence why I must analyze post mandate.

Another paper written by Benjamin Glasner, titled "Tax Evasion Among the Self-Employed: Medicaid Expansion", analyzes how the expansion of Medicaid in 2013 after the introduction of the Affordable Care Act affected reported self employment. Glasner uses Nonemployer Statistics in his analysis. Glasner once again leverages the difference in differences estimator created by Callaway and Sant'Anna (2020) to circumvent the weaknesses of the two way fixed effects model. He runs his model for three outcome variables. First, the log of the number of nonemployer establishments in county c in year t. Second, the log of total report receipts of nonemployer establishments at the county, industry, and year level. Third, the average receipts of nonemployer establishments, which equals the log number of receipts divided by the log number of nonemployer establishments. His model includes the Uber interaction effect with Medicaid expansion, controls for shocks at the national level, and year fixed effects. Glasner (2021) finds 2.17% fewer declared nonemployer establishments in states that expanded Medicaid and states that did not expand Medicaid saw a reduction in total declared receipts of 1.43%. This paper is relevant to my research because it looks at changes in self employment, using the gig economy as a proxy, following a major policy change.

In their paper titled “Measuring the Gig Economy: Current Knowledge and Open Issues”, Katharine Abraham, John Haltiwanger, Kristin Sandusky, and James Spletzer discuss how to measure and capture gig economy activity in existing data sets. They discuss various datasets that one can use to measure gig economy activity, such as the Consumer Population Survey (CPS) and the American Community Survey (ACS). The authors discuss how Contingent Worker Supplement (CWS) to the CPS includes questions both about alternative work arrangements and whether the individual has an explicit or implicit contract for continued employmentAbraham et al. (2018). The alternate work arrangements include whether or not the respondents main form of employment was a worker at a contract firm, temporary agency worker, independent contractor, or on-call work. I looked into using the CWS in the CPS; however, the data is collected too infrequently and is not usable for my analysis. This paper helped me figure out which data set to use in my analysis.

John Barrios, Yal Hochberg, and Hanyi Yi, the authors of “Launching with a Parachute, the Gig Economy and New Business Formation”, analyze the effect of the gig economy on new business formation by providing a conceptual framework. The authors look at the staggered rollout of ridehailing in US cities in their analysis of the gig economy. Barrios et al. (2020) state the gig economy acts as insurance against entrepreneurial-related income volatility and as a way to supplement income. Their data set consists of incorporated “places” from the Census Bureau, with a population of at least 10,000 in 2010, in the United States. The incorporated places include all self-governing villages, boroughs, towns, and cities. The authors also include the deployment of Uber and Lyft in their analysis. They use a standard generalized difference in differences approach in their empirical analysis. The authors run their model for three outcome variables including new business launches, small business loans to new businesses, and increased interest in entrepreneurship by looking at internet search terms related to starting new businesses. Their model includes city and quarter-year fixed effects, time varying, city specific control variables all lagged one quarter, and a city specific time trend. The introduction of gig opportunities leads to about a 5% increase in the number of new business registrations in the local area, and an increase in the small business lending to newly registered businesses of about the same size Barrios et al. (2020). They also find about a 7% increase in internet searches for relevant entrepreneurial related keywords. This paper is relevant to my analysis as the authors included the deployment of ride share companies in their analysis as well as helping to motivate my analysis.

In their paper titled “The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015”, Lawrence Katz and Alan Krueger set out to analyze trends in alternative work arrangements from 1995 to 2015. The authors administrated a version of the Contingent Worker Survey included in the RAND American Life Panel in 2015. Their survey closely followed the BLS' CWS to collect information about alternative work arrangements for each respondent's main form of employment. The authors reports three key findings. Firstly, the percentage of workers who partake in alternative work arrangements rose from 4.1 percentage points from February 2005 to late 2015. Second, there was a 1.7 percentage point increase in the percentage of workers hired out through contract companies. Third, workers who provide services through online platforms accounted for 0.5 percent of all workers in 2015 Katz and Krueger (2016). The findings of this paper help to motivate my research, as well as giving insight on what data sets to look into when conducting my analysis.

3 Background

The Affordable Care Act was passed in March of 2010. The Affordable Care Act brought about sweeping changes in the availability for individuals to obtain health insurance. One of the major changes in this policy changed the age at which younger individuals can stay on their parent's health insurance from 19 to 26 at the national level. The Affordable Care Act also allowed individuals to purchase their own health insurance in the market, as opposed to having to be insured from an employer. Uber, the largest ride share company in the gig economy, began operating in October 2010. Uber's deployment was a gradual roll out over the counties in the United States, rather than being available everywhere at once. Other ride share companies, such as Lyft, began to operate with hopes to compete with Uber, but my analysis will focus on Uber.

4 Empirical Strategy

I start by using a difference in differences estimator, with staggered treatment, to show how the introduction of Uber in a core base statistical area (CBSA) affects an individual's likelihood, within that CBSA, to drive for Uber. I use both a two-way fixed effects model and the imputation approach as discussed by Borusyak, Jaravel, and Spiess. The first difference being core based statistical areas before and after Uber launches within the CBSA. The second difference being CBSA's that have access to Uber at some point in time in the data compared to CBSA's that never have access to Uber. This acts as a sanity check before I move into my main analysis. See equation 1 below.

$$Y_{ct} = \beta_1 UberNow_{ct} + \alpha_c + \alpha_t + \epsilon_{ct} \tag{1}$$

The coefficient of interest in this equation is β_1. Subscript c for CBSA and subscript t for time. The outcome variable Y is whether or not an individual partook in gig work in CBSA c at time t. Y has a value of 1 if I classify them as working for Uber, 0 otherwise.

UberNow is a dummy equal to 1 if Uber is running in that CBSA at time t, 0 otherwise. I consider a CBSA as treated once at least one county within the CBSA has access to Uber. α_c represents CBSA fixed effects, α_t represents time fixed effects, and ε is the error term. I also use an event study approach to analyze the treatment effect across time both before and after exposure to Uber. See equation 2 below.

$$Y_{ct} = \sum_{k=-4}^{4} \beta_k(\mathbf{1})\{t - t^*(c) = k\}UberEver_c + \alpha_c + \alpha_t + \epsilon_{ct} \tag{2}$$

Where t*(c) equals the year that Uber deployed within CBSA c. k equals the amount of years either before or after treatment. UberEver equals 1 if a CBSA gets access to Uber at some point in time in my data set, 0 otherwise. The rest of the variables are the same as they are in equation 1. I then use a difference in differences in differences, with staggered treatment timing, approach for my main analysis. I once again use a two-way fixed effects model and the imputation approach as discussed by Borusyak, Jaravel, and Spiess. The first difference for this model is the age group. The second difference compares CBSA's before and after Uber becomes available within the CBSA. The third difference being core based statistical areas that have access to Uber at some point in time in the data versus CBSA's that do not have access to Uber at any time. See equation 3 below.

$$Y_{ict} = \beta_1(Young_i * UberNow_{c(i),t(i)}) + \gamma Young_i + \alpha_{ct} + \Gamma X_{i,c(i),t(i)} + \epsilon_{ict} \tag{3}$$

The coefficient of interest in this equation is β_1. Subscript i for individual where c(i) is individual i's CBSA and t(i) is the year that individual i was surveyed. The treatment group consists of individuals 22-25 years old while the control group consists of individuals 27-30 years old. I chose these age ranges because Uber requires individuals to have at least three years of driving experience if they are under 25 years old. See Uber's website under the requirements section for more details. So I simply added the three years to 19 to start the treatment group at 22 years old. I remove 26 year old individuals from the regression because they can be considered both treated and untreated. α_{ct} represents CBSA by time fixed effects and ε is the error term. The outcome variable Y is whether or not an individual i partook in gig work in county c at time t. Young is a dummy equal to 1 if an individual is 22-25 years old, 0 otherwise. UberNow is a dummy equal to 1 if Uber is running in that CBSA at time t, 0 otherwise. Once again, I consider a CBSA as treated as soon as at least one county within the CBSA has access to Uber. X contains individual level controls such as highest level of education completed, race, gender, and metropolitan status. I also use an event study approach to analyze the treatment effect across time both before and after exposure to Uber for individuals who are 22 to 25 years old compared to 27 to 30 year old individuals. See equation 4 below.

$$Y_{ict} = \sum_{k=-4}^{4} \beta_k \mathbf{(1)}\{t - t^*(c) = k\}(Young_i * UberEver_{c(i)}) + \gamma Young_i + \alpha_{ct} + \Gamma X_{i,c(i),t(i)} + \epsilon_{ict} \quad (4)$$

Where t*(c) equals the year that Uber deployed within CBSA c go that Uber deployed within a CBSA. k equals the amount of years either before or after treatment. UberEver equals 1 if a CBSA gets access to Uber at some point in time in my data set, 0 otherwise. The rest of the variables are the same as they are in equation 3.

5 Data

The data set I use is the American Community Survey (ACS) portion of Integrated Public Use Microdata Series (IPUMS). With this data set, I am classifying a gig worker as a self employed taxi driver, in the taxi and limousine service industry, working for an unincorporated business. These gig workers have a Y value of 1. All other observations in my data set have a value of 0 for Y. Some important variables include occupation, classification of worker, industry, age, highest level of education completed, race, metropolitan status, gender, and state/county FIPS code. I list summary statistics below for the outcome variable and control variables.

Table 1: Summary Statistics for Outcome(Y)

Y	Frequency	Percent	Cumulative
0	1,542,163	99.95	99.95
1	799	0.05	100.00
Total	1,542,962	100.00	

Note:
Y=1 represents individuals who are a self employed taxi driver, in the taxi and limousine service industry, working for an unincorporated business. These are the individuals I classify as working for Uber. Y=0 are the remaining individuals in my sample who I do not classify as working for Uber.

Table 2: Summary Statistics for Outcome(Y) Split by Age Group

Y	Frequency	Percent	Cumulative
0 for age < 26	748,773	48.53	48.53
1 for age <26	290	0.02	48.55
0 for age > 26	793,390	51.42	99.97
1 for age >26	509	0.03	100.00
Total	1,542,962	100.00	

Note:
Y=1 represents individuals who are a self employed taxi driver, in the taxi and limousine service industry, working for an unincorporated business. These are the individuals I classify as working for Uber. Y=0 are the remaining individuals in my sample who I do not classify as working for Uber.

Table 3: Gender Summary Statistics by Outcome(Y)

Gender	Y=0	Y=1	Total
Male	794,383	685	795,068
Female	747,780	114	747,894
Total	1,542,163	799	1,542,962

Note:
Y=1 represents individuals who are a self employed taxi driver, in the taxi and limousine service industry, working for an unincorporated business. These are the individuals I classify as working for Uber. Y=0 are the remaining individuals in my sample who I do not classify as working for Uber.

Table 4: Education Summary Statistics by Outcome(Y)

Educational Attainment	Y=0	Y=1	Total
N/A or No Schooling	8,667	9	8,676
Nursery School to Grade 4	3,287	1	3,288
Grade 5, 6, 7, or 8	17,816	8	17,824
Grade 9	12,881	9	12,890
Grade 10	14,610	11	14,621
Grade 11	22,361	19	22,380
Grade 12	436,016	305	436,321
1 Year of College	293,651	176	293,827
2 Years of College	131,996	84	132,080
4 Years of College	462,504	152	462,656
5+ Years of College	138,374	25	138,399
Total	1,542,163	799	1,542,962

Note:
Y=1 represents individuals who are a self employed taxi driver, in the taxi and limousine service industry, working for an unincorporated business. These are the individuals I classify as working for Uber. Y=0 are the remaining individuals in my sample who I do not classify as working for Uber.

Table 5: Race Summary Statistics by Outcome(Y)

Race	Y=0	Y=1	Total
White	1,080,230	324	1,080,554
Black/African American	171,356	159	171,515
American Indian or Alaska Native	9,694	2	9,696
Chinese	31,586	17	31,603
Japanese	3,509	2	3,511
Other Asian or Pacific Islander	87,147	161	87,308
Other Race	100,824	81	100,905
Two Major Races	50,691	47	50,738
Three or More Major Races	7,126	6	7,132
Total	1,542,163	799	1,542,962

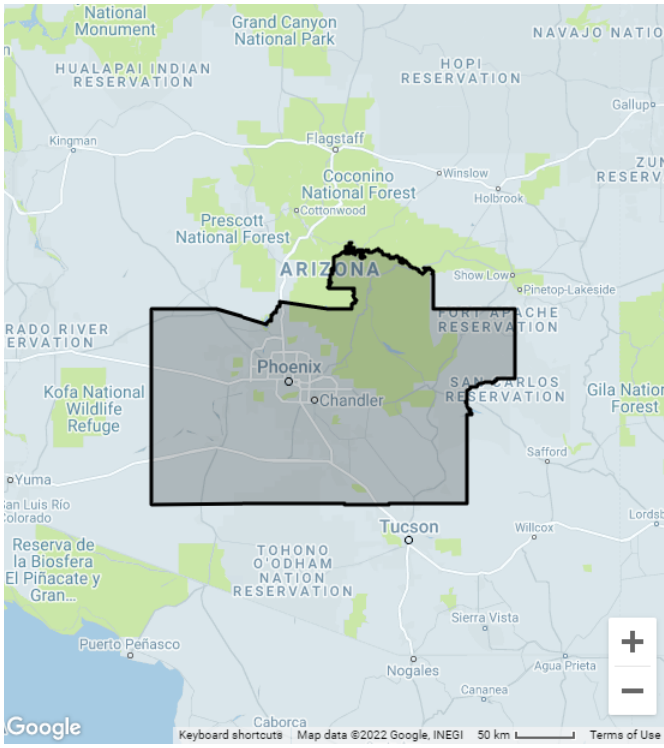
Note:
Y=1 represents individuals who are a self employed taxi driver, in the taxi and limousine service industry, working for an unincorporated business. These are the individuals I classify as working for Uber. Y=0 are the remaining individuals in my sample who I do not classify as working for Uber.

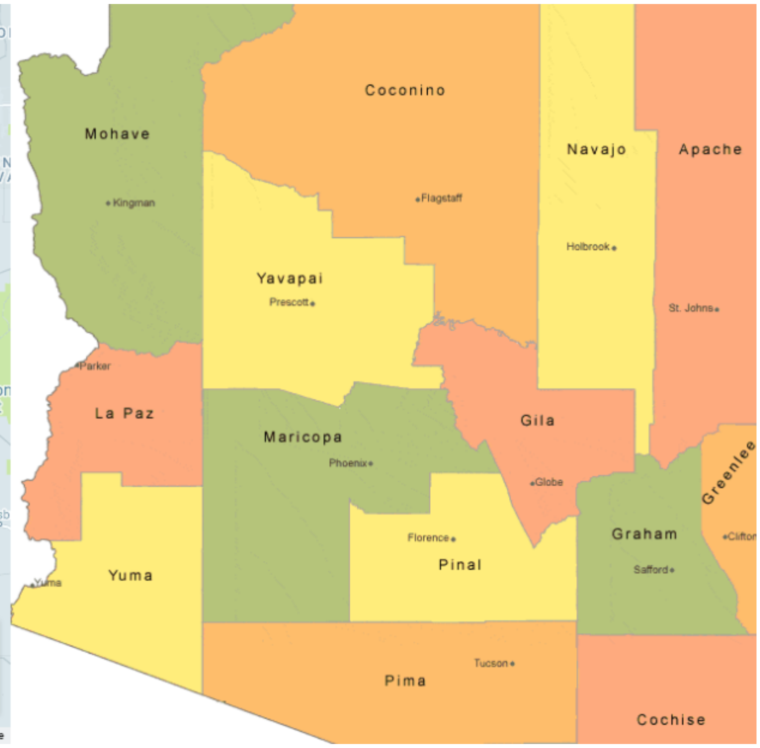
Table 6: Metropolitan Status Summary Statistics by Outcome(Y)

Race	Y=0	Y=1	Total
Metropolitan Status Indeterminable	1,958	0	1,958
Not in Metropolitan Area	15,450	7	15,457
In Metropolitan Area: in Central/Principal City	365,313	388	365,701
In Metropolitan Area: Not in Central/Principal City	502,299	174	502,473
In Metropolitan Area: Central/Principal City Status Indeterminable	657,143	230	657,373
Total	1,542,163	799	1,542,962

Note:
Y=1 represents individuals who are a self employed taxi driver, in the taxi and limousine service industry, working for an unincorporated business. These are the individuals I classify as working for Uber. Y=0 are the remaining individuals in my sample who I do not classify as working for Uber.

I then reached out to a data scientist from Uber for a data set that specifies that deployment locations of Uber for each month over the years 2010 to 2017. See the appendix for a map that shows the rollout of Uber over the years 2010 to 2017. Uber's website displays a map of the counties that have access to Uber in each deployment region. I use an image of a county map to trace over the Uber deployment region to find what counties each specific deployment region includes. Look at the deployment region of Phoenix, Arizona for example. This deployment region includes the counties of Maricopa, Gila, and Pinal. The map on the left side of the image comes from Uber's website and the map on the right side of the image is a simple county map for Arizona. See the image below for reference.





I then link the deployment times at each county to my data set using county and state FIPS codes. I then cluster the counties by core based statistical area using a simple cross-walk. Core based statistical areas are counties that are economically linked. Glasner (2020) emphasizes how the use of CBSA's reduce 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. In the end, my data set consists of around 1.54 million observations.

6 Results

First, I look at the introduction of Uber in a CBSA and how that affects the likelihood that an individual, within that CBSA, drives for Uber. I use difference in differences with staggered treatment timing methodology, with a two-way fixed effects model. See Table 7 below.

Table 7: Equation 1 Non Imputation Results

	(1)
	Y
β_1 for UberNow = 1	-0.000474***
	(0.000145)
N	1542962
adj. R^2	0.001

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note:
I am controlling for level of education, gender, metropolitan status, and race. To keep the table clear, I do not report the coefficients of the controls.

Table 7 reports a 0.05 percent decrease in the probability an individual drives for Uber within their CBSA post uber deployment. This result is statistically significant at the 1 percent level. This result goes against my prior belief that after Uber releases within a CBSA, the probability that an individual works for Uber should increase. I now move towards using the imputation method with equation 1. Again, I am using difference in differences with staggered treatment timing. Table 8 also corresponds to equation 1. See table 8 below.

Table 8: Equation 1 Results with Imputation

	(1)
	y
β_1	0.000460***
	(0.000114)
N	1480296
adj. R^2	

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note:
The sample size is different then my total sample size. The imputation method drops the observations when the fixed effects of the respective observations cannot be imputed. See Borusyak et al. (2022) for reference.

Table 8 shows the average treatment effect of an individual's probability to drive for Uber after Uber deploys within their CBSA. The probability an individual drives for Uber, after deployment within their CBSA, increases by 0.05 percentage. This result is statistically significant at the 1 percent level and matches with my prior beliefs. The conflicting result presented by the two-way fixed effects model indicates the issues with staggered treatment in difference in differences outlined by Goodman-Bacon (2018) may be present. The imputation model also corrects for these staggered treatment timing issues. Therefore, I will use the results of the imputation method for my analysis. Now I use an event study approach to look at the treatment effect across time and to test the pretrends assumption. Table 9 and graph 1 come from equation 2 and are displayed below.

Table 9: Equation 2 Results

	(1)
	Y
β_0	-0.000124***
	(0.0000427)
β_1	-0.0000110
	(0.000114)
β_2	0.0000783
	(0.0001000)
β_3	0.000276*
	(0.000152)
β_4	0.000501**
	(0.000204)
β_{-1}	-0.0000476
	(0.000212)
β_{-2}	0.00000428
	(0.000187)
β_{-3}	-0.000128
	(0.000143)
β_{-4}	0.0000181
	(0.0000944)
N	1174388
adj. R^2	
Joint Test F	1.172
P Value	0.324

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note:
The sample size is different then my total sample size. The imputation method drops the observations when the fixed effects of the respective observations cannot be imputed. See Borusyak et al. (2022) for reference. I am controlling for level of education, gender, metropolitan status, and race here.

Graph 1

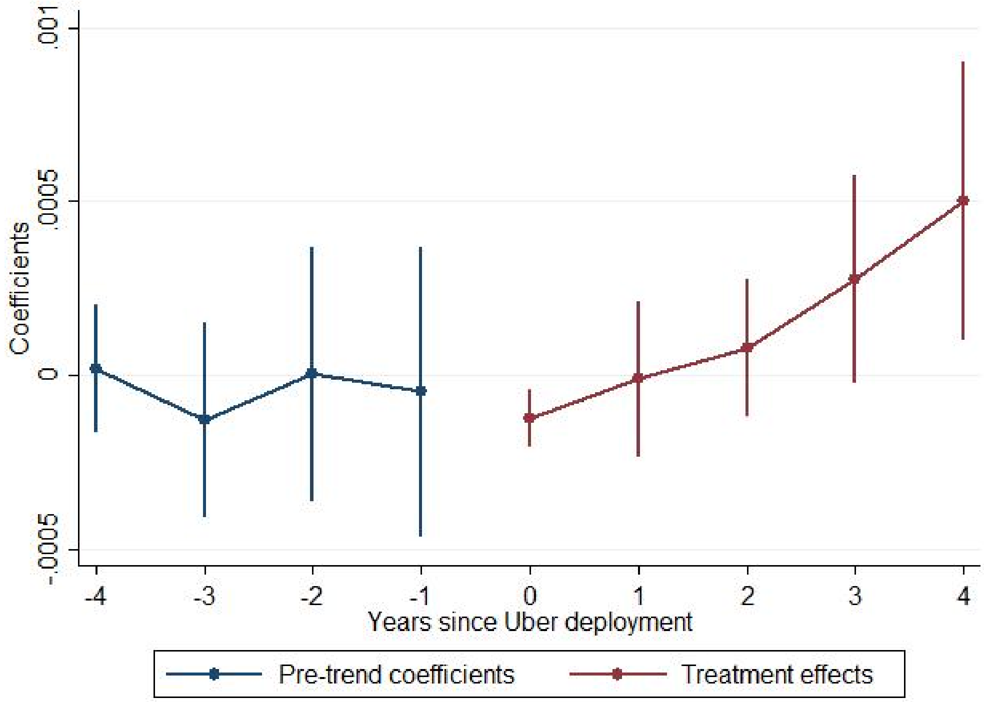


Table 9 shows the treatment effect relative to the year of pre or post treatment exposure and graph 1 illustrates these treatment effects. The treatment effect post Uber deployment on the year of deployment is statistically significant at the 1 percent level. The coefficient for 3and 4 years after uber deployment is statistically significant at the 10 percent level and 5 percent level respectively. Graph 1 shows a nice upward trend in the treatment effect after Uber is deployed within a CBSA. I also preform a joint test on all the pre-period coefficients to make sure the pretrends assumption holds. The resulting joint test produces a p-value of 0.32; therefore, I conclude that the pretrends assumption holds. I again conclude the introduction of Uber in a CBSA increases the likelihood that an individual, within that CBSA, drives for Uber. I now move to the difference in differences in differences analysis, to look out how the deployment of Uber within a CBSA affects a younger individual's probability to drive for Uber within that CBSA.

I will now again show why the imputation model produces better results than a two-way fixed effects model. First I use a two-way fixed effects model. See Table 10 below for the findings of the model of equation 3, using difference in differences in differences methodology with staggered treatment timing.

Table 10: Equation 3 Non-Imputation Results

	(1)
	Y
β_1 for UberNow = 1 and Young = 1	-0.000161
	(0.000123)
γ for Young = 1	-0.000215***
	(0.0000484)
N	1542962
adj. R^2	0.001

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note:
I am controlling for level of education, gender, metropolitan status, and race. To keep the table clear, I do not report the coefficients of the controls.

This model finds a 0.02 percent decrease on a 22 to 25 year old individual's likelihood in partaking in gig economy employment post Uber deployment within a CBSA, and post ACA as well. This result is not statistically significant. γ reports that an individual between the ages 22 to 25 years old is about 0.02 percent less likely to be classified as driving in the gig economy pre Uber deployment. I then move to running equation 3 with the imputation method. See Table 11 below.

Table 11: Equation 3 Results with Imputation

	(1)	(2)	(3)	(4)	(5)	(6)
	Y	Y	Y	Y	Y	Y
β_1	-0.000294***	-0.000371***	-0.000359***	-0.000268***	-0.000360***	-0.000351***
	(0.0000580)	(0.0000669)	(0.0000642)	(0.0000628)	(0.0000667)	(0.0000646)
N	1542962	1542962	1542962	1542962	1542962	1542962
adj. R^2						

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note:
Column 1 has no controls. Column 2 has level of education, race, and metropolitan status as controls. Column 3 has level of education, gender, and metropolitan status as controls. Column 4 has race, gender, and metropolitan status as controls. Column 5 has level of education, race, and gender as controls. Column 6 has level of education, gender, race, and metropolitan status as controls.

Table 11 shows the resulting coefficient for various sets of controls. Column 6, the column with the most controls, reports a 0.04 percent decrease in the probability a younger individual drives for Uber after Uber deployment within their CBSA. All of the coefficients in Table 11 are statistically significant at the 1 percent level. γ, the coefficient for Young, cannot be imputed as it is not as age is not staggered treatment. Also individuals go from being classified as treated when they are 22 to 25 years old to being classified as not treated when they are 27 to 30 years old. The two-way fixed effects model produces statistically insignificant results while the imputation model produces statistically significant results. I believe the issues with staggered treatment timing presented by Goodman-Bacon (2018) are present yet again. I once again will use the results of the imputation method for my analysis. Now I use an event study approach for my triple difference imputation model. The results tied to equation 4 are displayed in table 12. Graph 2 displays the coefficients of column 4, the model with metropolitan status, gender, and race controls, below. I explain why I graph that column below.

Table 12: Equation 4 Results

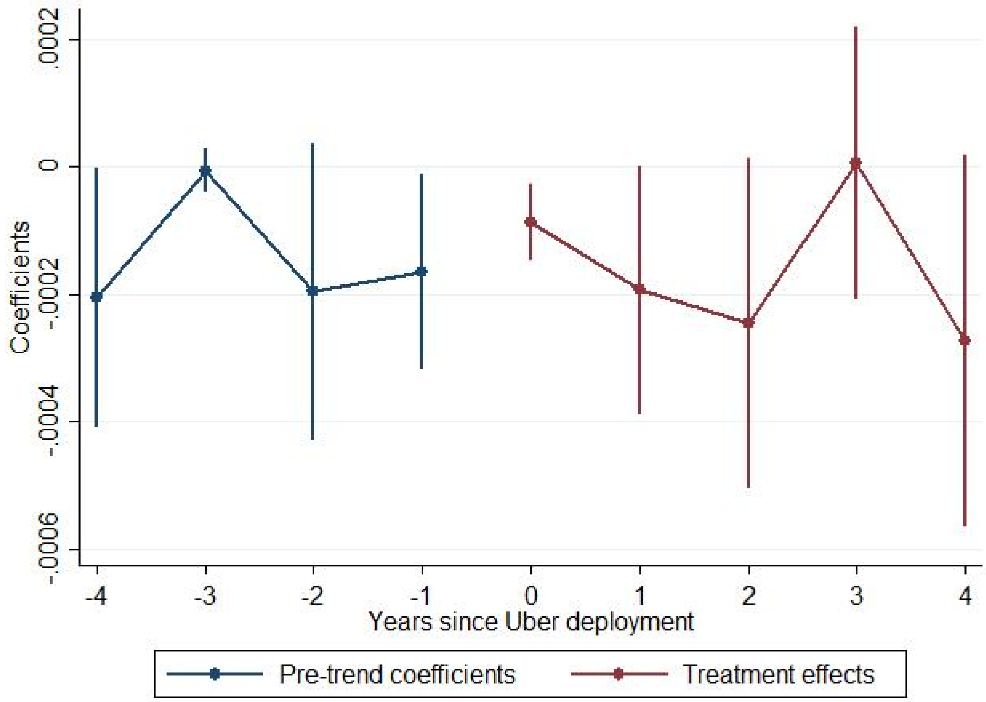
	(1)	(2)	(3)	(4)	(5)	(6)
	Y	Y	Y	Y	Y	Y
β_0	-0.000104***	-0.000188***	-0.000178***	-0.0000877***	-0.000170***	-0.000169***
	(0.0000356)	(0.0000510)	(0.0000524)	(0.0000305)	(0.0000475)	(0.0000476)
β_1	-0.000206**	-0.000298***	-0.000285***	-0.000194*	-0.000280***	-0.000279***
	(0.0000977)	(0.000101)	(0.000101)	(0.0000998)	(0.0000999)	(0.0000995)
β_2	-0.000265**	-0.000343***	-0.000331***	-0.000246*	-0.000331***	-0.000325***
	(0.000119)	(0.000114)	(0.000114)	(0.000132)	(0.000115)	(0.000116)
β_3	-0.0000156	-0.0000979	-0.0000849	0.00000559	-0.0000849	-0.0000780
	(0.000104)	(0.000106)	(0.000104)	(0.000110)	(0.000106)	(0.000105)
β_4	-0.000303**	-0.000377**	-0.000365**	-0.000273*	-0.000364**	-0.000355**
	(0.000154)	(0.000163)	(0.000160)	(0.000149)	(0.000162)	(0.000160)
β_{-1}	-0.000185**	-0.000266***	-0.000261***	-0.000165**	-0.000245***	-0.000248***
	(0.0000757)	(0.0000798)	(0.0000796)	(0.0000777)	(0.0000771)	(0.0000776)
β_{-2}	-0.000212*	-0.000296**	-0.000286**	-0.000197*	-0.000268**	-0.000275**
	(0.000118)	(0.000121)	(0.000120)	(0.000119)	(0.000119)	(0.000119)
β_{-3}	-0.0000134	-0.0000968***	-0.0000883***	-0.00000580	-0.0000701***	-0.0000794***
	(0.0000134)	(0.0000340)	(0.0000302)	(0.0000174)	(0.0000249)	(0.0000298)
β_{-4}	-0.000220**	-0.000297***	-0.000290***	-0.000206**	-0.000268**	-0.000278***
	(0.000103)	(0.000108)	(0.000107)	(0.000104)	(0.000105)	(0.000107)
N	1384839	1384839	1384839	1384839	1384839	1384839
adj. R^2						
Joint Test F	3.914	5.997	6.208	2.867	6.229	5.926
P Value	0.004***	0.0001***	0.0001***	0.0236**	0.0001***	0.0001***

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note:
The sample size is different then my total sample size. The imputation method drops the observations when the fixed effects of the respective observations cannot be imputed. See Borusyak et al. (2022) for reference. Column 1 has no controls. Column 2 has level of education, race, and metropolitan status as controls. Column 3 has level of education, gender, and metropolitan status as controls. Column 4 has race, gender, and metropolitan status as controls. Column 5 has level of education, race, and gender as controls. Column 6 has level of education, gender, race, and metropolitan status as controls.

Graph 2



All of the columns show a statistically significant decrease in a younger individual's probability to drive for Uber, albeit at different levels of significant, in every post period except for 3 years after deployment. The coefficients become more negative over time in the post periods, except for 3 years post Uber deployment being an outlier. Graph 2 shows that 22 to 25 year old individuals are less likely to drive for Uber over time, after Uber deployment within their CBSA. Graph 2 correlates with the coefficients of column 4 in table 12 above as the pretrends assumption weakly holds with this set of controls. I once again preform a joint test on all of the pre period coefficients to test the pretrends assumption. All of the columns, except for the column 4 which does not control for level of education, are statically significant at the 1 percent level. The pretrends assumption fails to hold here because the resulting p values are statistically significant. In the case of column 4, the joint test is only statistically significant at the 5 percent level. I now extend my previous model but add more controls to try to make sure the pretrends assumption holds at a stronger significance. The additional controls include birthplace, marital status, total income, and usual weekly hours worked. I rerun this set of controls, but remove the level of education control because the older age groups are likely to have more years of education which could have an impact on my results. See table 13 and graph 3 below. Graph 3 displays the coefficients in column 2 of table 13 below.

Table 13: Equation 4 Results with More Controls

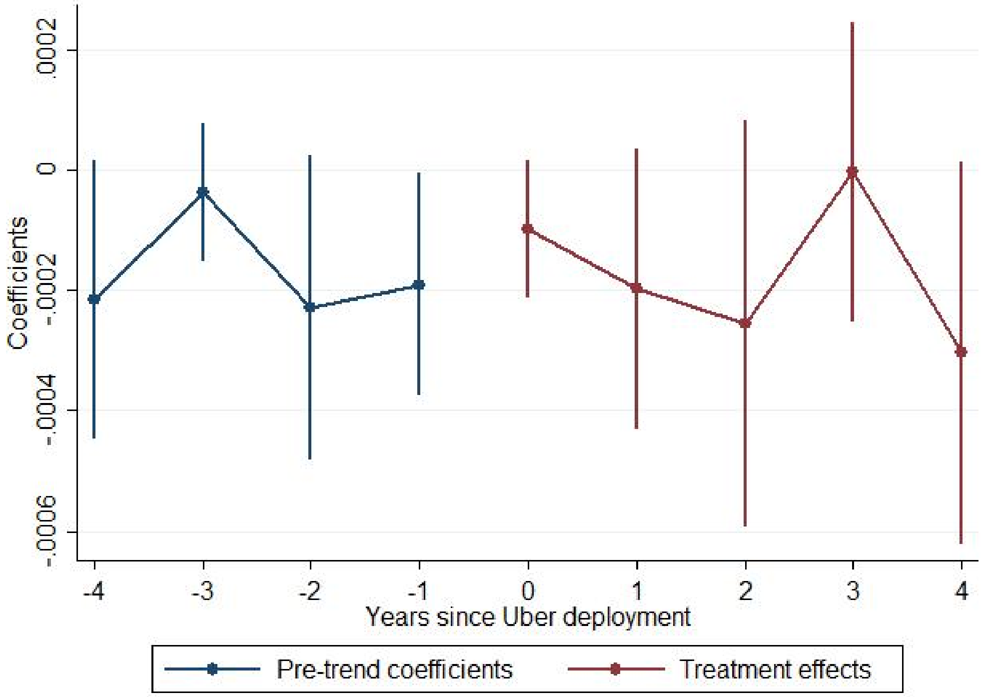
	(1)	(2)
	Y	Y
β_0	-0.000139***	-0.0000988*
	(0.0000488)	(0.0000583)
β_1	-0.000242**	-0.000198*
	(0.000108)	(0.000119)
β_2	-0.000293*	-0.000255
	(0.000159)	(0.000172)
β_3	-0.0000457	-0.00000318
	(0.000115)	(0.000127)
β_4	-0.000343**	-0.000304*
	(0.000163)	(0.000162)
β_{-1}	-0.000234***	-0.000191**
	(0.0000844)	(0.0000944)
β_{-2}	-0.000270**	-0.000229*
	(0.000122)	(0.000129)
β_{-3}	-0.0000747*	-0.0000369
	(0.0000437)	(0.0000585)
β_{-4}	-0.000253**	-0.000216*
	(0.000112)	(0.000118)
Usual Weekly	0.00000949	0.00000862
Hours Worked	(0.00000838)	(0.00000779)
Total Income	-1.23e-08***	-1.44e-08***
	(2.22e-09)	(3.16e-09)
N	1384839	1384839
adj. R^2		
Joint Test F	3.690	2.258
P Value	0.0060	0.0631

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note:
The sample size is different then my total sample size. The imputation method drops the observations when the fixed effects of the respective observations cannot be imputed. See Borusyak et al. (2022) for reference. Column 1 has level of education, gender, race, and metropolitan status, marital status, birthplace, total income, and usual weekly hours worked as controls. Column 2 has all of the same controls except with level of education removed.

Graph 3



The columns of table 13 show very similar results to the columns of table 12. Graph 3 yet again shows the coefficients become more negative over time in the post periods, except for 3 years post Uber deployment being an outlier. Graph 3 also again shows that 22 to 25 year old individuals are less likely to drive for Uber over time, after Uber deployment within their CBSA. Notice in column 2 of table 13 that when additional controls are added and level of education is removed, the joint test is not statistically significant at the 5 percent level. This means the pretrends assumption holds for the set of controls in column 2 of table 13. All of this is at the cost of less statistically significant coefficients in the post periods. For the set of controls for column 2 of table 13, the coefficients in the year of deployment, 1 year after, and 4 years after are statistically significant at the only at the 10 percent level. Overall, I conclude that there is a statistically significant decrease on a younger individual's likelihood to work in the gig economy after Uber deployment, within their CBSA, post the Affordable Care Act mandate.

7 Conclusion

This paper sets out to find how gig economy employment changed for younger individuals after the major policy change in the form of the Affordable Care Act. This paper uses ACS data to analyze the question presented. I received deployment data from an Uber data scientist. I used state and county fips codes to link Uber deployment to the ACS data set. Then, I use a crosswalk to cluster the counties together into their respective core based statistical area.

I start by constructing a difference in differences model to analyze how the deployment of Uber impacted an individual's probability, within a CBSA, to work for Uber post Uber deployment within their respective CBSA. This model is independent of age and necessary to use before moving to the difference in differences in differences model. This model uses a difference in difference estimator with staggered treatment timing. I show why the imputation method created by Borusyak et al. (2022) is superior to a simple two-way fixed effects model here. From the imputation method, I find a statistical significant increase of roughly 0.05 percent in an individual's likelihood to work for Uber after Uber deployment within in a CBSA.

I then use difference in differences in differences methodology to analyze the impact of Uber deployment, by CBSA, on a younger individual's probability of participating in gig work, post ACA mandate. The treatment group for the age difference is 22 to 25 year old individuals. The control group for the age difference is 27 to 30 year old individuals. Again, the deployment of Uber has a staggered treatment timing. I also show the need for using imputation as opposed to using a two-way fixed effects model here. I find that the deployment of Uber within a CBSA causes a decrease, of roughly 0.04 percent, on a younger individual's likelihood in working for Uber. The resulting coefficient is statistically significant at the 1% level.

This paper points to how a good set of gig economy data is hard to find, as previous papers in this field also mention. This data set issue has an impact on why the resulting coefficients are so small. I hope more available data will be accessible in the future. For future work, someone should look at a policy change that occurred a few years after Uber started to see if that had an impact on gig economy employment. The model this paper presents cannot use pre and post period of the ACA mandate because Uber started operating 6 months after the ACA was passed. Overall, I find a statistically significant decrease on a younger individual's probability to work in the gig economy after Uber deployment, within their CBSA, post the Affordable Care Act mandate.

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A Appendix

Uber Deployment map is displayed below. The map does not include Hawaii and Alaska for visual clarity. Uber deployed in Honolulu in 2013, Maui in 2015, and the rest of Hawaii in 2017. Uber is not in Alaska during the time period of my data set.