The Minimum Wage, Self-Employment, and the Online Gig Economy*

By Benjamin Glasner†

This paper estimates the impact of the real minimum wage on work exempted from the Fair Labor Standards Act, including the self-employed and independent contractors. I use data on nonemployer establishments to test the degree to which the minimum wage impacts the propensity of workers to engage in the exempt labor market, and the average receipts taken in while participating. Using two-way fixed effect models, recently developed difference-in-difference methods from Callaway and Sant'Anna (2019) and de Chaisemartin and d'Haultfoeuille (2019), and a generalized synthetic control design on local minimum wage changes, I find that increases in the minimum wage result in increased participation in work exempted from the minimum wage. For a $1 increase in the minimum wage between 2010 and 2018, the number of nonemployer establishments per member of the labor force increases by 0.0029, or 1.96% of the total stock of nonemployer establishments. This positive relationship is driven by counties with low labor market concentration, as measured by county level HHI, and the presence of an example online gig economy marketplace, Uber. Counties with more concentrated labor markets, and that lack low-barrier marketplaces for exempt labor are shown to be less responsive to the minimum wage, or have a negative relationship. I estimate that a shift to a $15 federal dollar minimum wage in 2018 would have resulted in an additional 2,995,842 nonemployer establishments.

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Introduction

While a robust literature exists on the effects of minimum wages on employment, the distinction between which types of work are or are not exempted from the Fair Labor standards Act (FLSA) and the minimum wage has been shown to carry implications beyond

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† University of Washington, bglasner@uw.edu.

just the level of compensation (Derenoncourt and Montialoux, 2018). Due to the nature of exempted work, it is often assumed that its exclusion or inclusion will not bias results of analyses of minimum wage changes,[1] but this ignores how both the exempt and nonexempt marketplace may be systematically different. Access to Employer supplied health insurance, disability insurance, paid sick leave, retirement benefits, unemployment insurance, tax withholding, and more all differ along the same or similar axis as the minimum wage (Harris and Krueger, 2015; Hyman, 2018), and this creates a substantial difference between the experience of working in the exempt and the nonexempt market. It is for this reason that understanding how the minimum wage impacts the exempt market is necessary. Movement between the exempt and the nonexempt labor market carries a greater impact than the application of a minimum wage alone. While the literature on minimum wages is far from a consensus, inconsistency in the inclusion or exclusion of exempted workers in the analysis appears to be a little focused on design decision. Given the increasing attention to issues of fissuring and misclassification of workers as independent contractors (Weil, 2014) as well as labor market protections for nonstandard work arrangements and the online gig economy (Berg, 2015; Harris and Krueger, 2015; Srnicek, 2017; Schor and Attwood-Charles, 2017), a reevaluation of how the exempt labor market interacts with our current labor policies appears necessary. This paper tests whether changes to the minimum wage impact exempted work, and how this effect interacts with the online gig economy.

Numerous authors have added to the literature on minimum wages, and a number of summaries of this literature have covered a breadth of results. Neumark and Wascher (2007) and Belman and Wolfson (2014) have summarized estimates of both local and aggregate effects of minimum wage changes on employment, earnings, and a variety of related outcomes. Both note the heterogeneity in results across studies, but a tendency toward small negative effects and null results. With the increased attention to the minimum wage both within the U.S. at the local level and internationally,[2] the negative employment effects hypothesis continues to be challenged with findings of no significant employment losses in aggregate (Dube, Lester and Reich, 2010; Lester, 2011; Caliendo et al., 2018; Cengiz et al., 2019; Dube, 2019). In parallel, others have explored how the effect varies across competitive or noncompetitive labor markets, showing substantial variation in both the direction and size of effects across types of work and regions (Bhaskar, Manning and To, 2002; Alan, 2011; Dube et al., 2018; Sokolova and Sorensen, 2018; Caldwell and Oehlsen, 2018; Pörtner and Hassairi, 2018; Azar et al., 2019).

What the literature summarizing the effect of minimum wages historically, as well as the more recent literature on the heterogeneity of the effect of the minimum wage, has missed is the role of classification of workers, and transition in work between the exempt and nonexempt market. Increasing the minimum wage in the nonexempt market, creates an

[1]Common data sources for minimum wage analyses which include exempt workers are the Current Population Survey, the American Community Survey, the Quarterly Census of Employment and Wages, Longitudinal Employer-Household Dynamics, and County Business Patterns. One of the primary sources of data on exclusively nonexempt workers are state level Unemployment Insurance data sets.

[2]This can be seen in the recent vote by the U.S. House of Representatives for a $15 minimum wage and the introduction of the minimum wage in Germany in 2015.

incentive to either substitute current employment arrangements for exempt independent contractors, or misclassify future workers as independent contractors when fulfilling the role of employees. This movement of work arrangements between the exempt and nonexempt market would align with the literature on the legal classification, and the regular hiring, or miss-classification, of workers as independent contractors to avoid costly regulations applied to standard employees (Gramm and Schnell, 2001; Autor, 2003; Weil, 2014; Liu, 2015). While the "Fight for 15"'s impact on local and state minimum wages has emerged at the federal level, an interest has also been shown for the regulation and support of independent contracting work and online gig workers.[3] The overlap between the two sites directly at a problem for minimum wage analyses which attempt to estimate aggregate welfare effects.

Previous ventures into the effects of the minimum wage on the exempt labor market have estimated a negative relationship between higher minimum wages and participating in traditional self-employment (Blau, 1987; Bruce and Mohsin, 2006), but these studies did little to differentiate between types of self-employment and occurred before an expansion in the availability of the low-barrier independent contracting opportunities offered by the online gig economy. Given the identified relationship between nonstandard employment and the regulation of the standard labor market (Gramm and Schnell, 2001; Autor, 2003; Weil, 2014; Liu, 2015), it is possible that changes to the minimum wage will impact both hiring and job seeking in the exempt labor market.

Using data on nonemployer establishments, I test the degree to which the minimum wage impacts the propensity of workers to engage in the exempt labor market, and the average receipts taken in while participating. Nonemployer establishments are businesses that do not have paid employees, primarily composed of the unincorporated self-employed and independent contractors. Using data on nonexempt employment from the publicly available County Business Patterns data, I construct an approximate Herfindahl-Hirschman Index (HHI) to measure county level labor market concentration and test for differences in the effect of the minimum wage. Using Uber deployment at the county level I test how the effect varies when a low-barrier exempt labor market is active. I will discuss how using the deployment of Uber allows for a comparison between the exempt labor market broadly, traditional transportation and warehousing services, and a representative online gig economy marketplace.

As can be seen in Figure 1, while nonemployer establishments in aggregate have been growing consistently since 2000, transportation and warehousing services have increased exponentially since 2013. This is attributed to the introduction of firms like Uber and Lyft. I test how the minimum wage relates to the exempt market by using traditional two-way fixed effect models, recently developed difference-in-difference methods from Callaway and Sant'Anna (2019) and de Chaisemartin and d'Haultfoeuille (2019), and a generalized

[3]For example, California has passed AB 5 with the intent to reduce miss-classification of workers. New York City introduced a minimum pay rate for drivers on Uber and Lyft. Seattle introduced legislation requiring premium payment for food delivery and transportation gig workers in relation to the hazards of operating amid the COVID-19 civil emergency. The passing of the CARES act included Pandemic Unemployment Assistance (PUA) which supported workers who otherwise would not have had access to unemployment benefits.

synthetic control design on local minimum wage changes. I also use a two-way fixed effect first difference model when comparing traditional exempt work to the online gig economy.

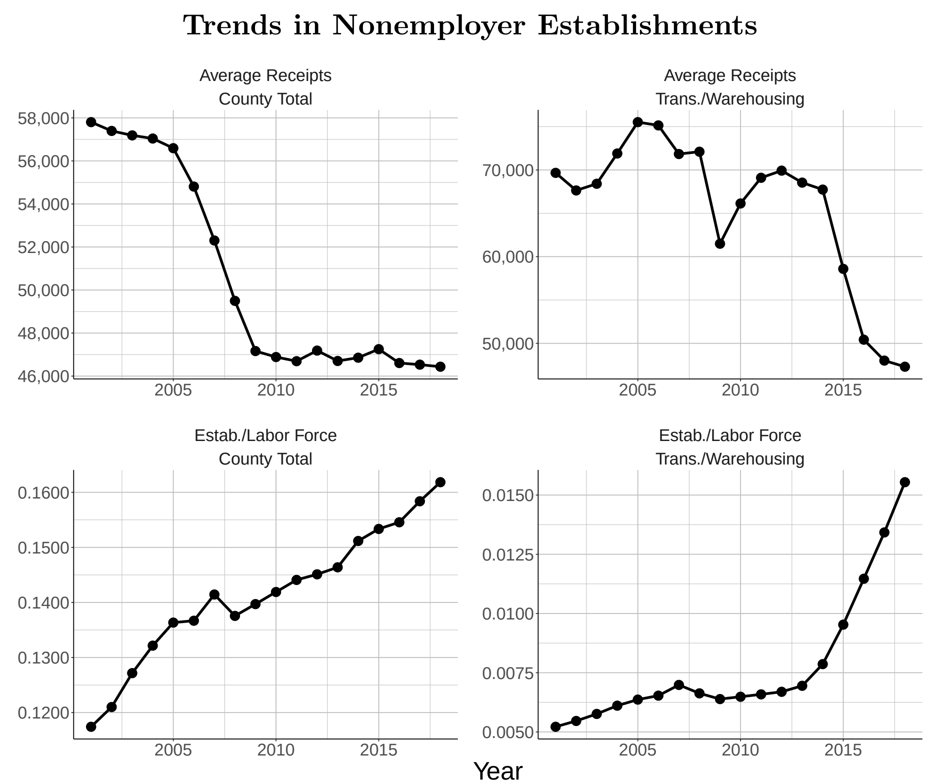

Figure 1. : These figures show the trend in Nonemployer establishments for the aggregated total of all nonemployer establishments on the left and for transportation and warehousing services (NAICS 48-49) on the right.

I find that increases in the minimum wage lead to increases in the number of nonemployer establishments in aggregate. For a \$1 increase in the minimum wage between 2010 and 2018, the number of nonemployer establishments per member of the labor force increases by 0.0029, or 1.7%. I find evidence in support of the conclusion that this positive relationship is a recent development, attributed to the expansion in low barrier nonstandard work opportunities including the online gig economy. I also find evidence of heterogeneous effects across labor market concentration. Counties with low levels of labor market concentration drive the positive effect, while highly concentrated labor markets exhibit a negative relationship between the minimum wage and nonemployer establishments. No significant relationship between the minimum wage and average receipts are found in aggregate.

The recency of the predominant positive effect of the minimum wage, as well as the identified dependence of it on the expansion of the online gig economy, support the conclusion that transition between nonexempt and exempt work has becoming easier. Policies which operate on the same, or similar, classification structures as the minimum wage are likely to see greater spillover in effects between work classifications as the online gig economy, and low-barrier exempt work arrangements, become more prevalent. While the aggregate effect for a $1 increase in the minimum wage is an increase of 1.7%, the effect among transportation and warehousing services is a 6.4% increase.

Literature Review

Previous work has explored how the minimum wage relates to surpluses of workers or work hours, higher prices for goods and services, an increase in the prevalence of training programs, more selective hiring, an increase in mechanization and automation, an intensifying of selling efforts, rising incomes among those employed, and aggregate demand and organizational arrangements shift (Lester, 1941; Stigler, 1946; Cullen, 1961; Grossman, 1978; Rottenberg, 1981; Card and Krueger, 1995; Waltman, 2008). Analysis of the aggregate effect of the minimum wage has pointed toward a negative relationship with employment (Neumark and Wascher, 2007; Belman and Wolfson, 2014), but it is far from a consensus. A substantial amount of work has been done which identifies both null effects on employment and heterogeneous effects across individual workers and regions (Dube, Lester and Reich, 2010; Lester, 2011; Jardim et al., 2018; Caliendo et al., 2018; Cengiz et al., 2019).

While the aggregate effect of the minimum wage has largely been focused on shifts in employment on the extensive margin, explorations into the number of hours worked, take home pay, and effects on new entrants have shown a wide range of potentially important effects. Assessment of both local minimum wages and international minimum wages have identified greater barriers to new entrants (Jardim et al., 2018; Bossler and Gerner, 2016) as well as negative effects on hours worked (Jardim et al., 2017). When considering potential avenues for effects of the minimum wage on the exempt labor market, a loss in employment is not necessarily required. Increased search times and lost hours may be just as important as full loss in employment for capturing entrance into the exempt labor market.

To understand how workers may interact with the minimum wage in the exempt and nonexempt market, I view both through a commodity pricing model, similar to that used by Stigler and Sherwin (1985). Increases in the minimum wage may induce changes in behavior, as workers transition between markets, or shift labor allocations across the two markets. This dynamic depends on the effect minimum wages have on both the demand for exempt and nonexempt labor and the compensation of work across both markets.

Worker allocation of time between these markets is reliant on factors at the individual and market level. Barriers to entry and exit between the exempt and nonexempt market are likely to impact an individual's capacity to transition beyond their individual preferences. These barriers may be in the form of significant differences in skill requirements, geographic overlap, market access, certifications and licensing, and government regulation. Figure A2 depicts the theoretical model of impact between the exempt and nonexempt labor market as an extension of the competitive model of the minimum wage.

The potential price differential between exempted labor and nonexempt labor can be viewed as an indication of some "transaction cost" resulting from the differing characteristics of work in the two markets. As noted by Bracha and Burke (2016), independent contractors tend to earn higher wages than their nonexempt counterparts, lending support to the use of a commodity pricing model. This is further supported by Hyman (2018), who describes an increasing commodification of work as a result of the organizational structure of independent contracting and the online gig economy.

By using a commodity framework, we can explore how the two overlapping markets may interact as a result of changing the regulatory framework of one or both, the barriers to interacting between them, and the market characteristics of each independently. The introduction of the minimum wage is assumed to not impact the characteristics of work which cause the price differential in any way other than modifying the price floor of the nonexempt labor market.

The competitive model of the minimum wage would argue that as we increase the price of labor in the nonexempt market, we can expect a reduction in employment on the extensive or intensive margin. We can expect then that a portion of those workers who are hurt by this effect may seek out alternative sources of income including exempt work, resulting in a positive relationship between the minimum wage and employment in the exempt market. Alternatively, the monopsony model of the minimum wage would argue that smaller increases in the minimum wage should produce no negative employment effect, and instead result in increases in the earnings of employees. We can imagine that if the return to work increases in the nonexempt market, then this may incentivize some to substitute away from the exempt labor market. The greater the barriers to entry and exit across the exempt and nonexempt market, the smaller the anticipated effect in either market.

The exempt labor market is a diverse set of work arrangements with a wide range of barriers to entry and exit. One of the most talked about subsets of the exempt labor market today is the "online gig economy," which is composed of numerous low-barrier marketplaces, including Uber, Lyft, Airbnb, TaskRabbit, Etsy, and Upwork. These marketplaces may vary in their own level of barriers but generally are easier to enter and exit than their traditional counterparts. Driving for Uber is easier than becoming a driver for Yellow Cab in New York City, and Airbnb makes it easier to rent out a room than trying to build your own website and attract guests. As a result, I will use this portion of the exempt labor market to test the low barrier mechanism.

The online gig economy is a relatively small share of the total exempt labor market which includes all independent contractors, the self-employed, spot-market workers, and other nonstandard work arrangements (U.S. Department of Labor, 2016; Katz and Krueger, 2016; Current Population Survey Staff, 2018; Katz and Krueger, 2019), which can make detecting changes in the online gig economy difficult to detect among the larger aggregate market. The legal separation and categorization of these work arrangements and within the FLSA do serve a purpose though in the applicability and ease of policy enforcement across types of work (Harris and Krueger, 2015). Policy tools like the minimum wage are not designed for the self-employed, workers who are operating simultaneously under multiple employers at a single point in time (e.g. an individual driving for both Uber and Lyft simultaneously), or for workers whose hours are prohibitively difficult to track.

New hybrid organizational structures have emerged that walk the line between exempt and nonexempt workers as well as traditional and alternative work arrangements (Simon, 1991; Malone, Yates and Benjamin, 1994; Sundararajan, 2016). These hybrid organizations have further reduced the barriers for transition between markets, and often utilize a work force of independent contractors. This includes online gig firms, but appears to have been a long-run trend beginning with sub-contracting firms in the post war period and accelerating more recently (Hyman, 2018).

The modern model of these firms is one which create a marketplace to match buyers and sellers and utilizes new methods of lowering the cost of payment coordination, communication across buyers and sellers, and information sharing between consumers. This creates what we experience today as the online gig economy. Included in this process of market creation is a streamlined system for buyers and sellers to participate in the internally organized marketplace. Firms have an incentive to reduce barriers to entry into their marketplace and attract a larger share of both the market supply and demand in their given industry.

As work commodifies, the hypothesized effect of changes in the minimum wage increases, making effects easier to see in low-barrier markets, as workers find it easier to enter and exit exempt work. Studying the minimum wage also serves as a way of gaining insight into how other policies which operate on similar legal divisions in the classification of work may be impacting the labor market broadly.

I. Data

I use Nonemployer Statistics (NES) data provided by the Census Bureau to estimate the size and composition of the exempt labor market. The NES collects annual data on nonemployer establishments and reports the count of establishments by geographic level and industry. Most nonemployer establishments are self-employed individuals running small unincorporated businesses, which includes independent contractors.[4] This analysis uses the aggregate of all NAICS industries, as well as the county-industry level data at the two-digit NAICS code level. Since the NES is a count of establishments, I am unable to directly measure an individual's intensity of engagement in this type of work, but the NES does include data on the total receipts taken in by establishments. Using the count of establishments and the total receipts taken in, a measure of the average receipts per establishment can be made.

Previous work on nonstandard work arrangements has leveraged the Current Population Survey's Contingent Worker Supplement (CWS) due to its identification of contingent

[4]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 income restriction means that I will miss any shift in Uber drivers or other workers earning less than 1,000 dollars.

workers, independent contractors, on-call workers, temporary help agency workers, and workers provided by a contract firm. This paper, however, will favor the NES as it is less restrictive in the set of workers it captures and allows for county level geographic information.[5] If the primary use of the online gig economy is to act as an income smoothing mechanism or to cover transitory periods and unexpected shocks, then it is likely that the NES will capture effects which are unobservable in surveys which only capture primary sources of income, such as the CWS. Data which only captures primary sources of income are likely to under estimate nonstandard work given the conclusions that the online gig economy is linked to part-time income smoothing mechanisms (Brainard, 2016; Farrell and Greig, 2016; Hall and Krueger, 2018; Katz and Krueger, 2019).

I use NES data from 2000 to 2018 and create a balanced panel of counties throughout the sample.[6] 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.[7] 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 appear to be structural zeros, never appearing to have nonemployer establishments in some industries.

Similar to the NES, I use publicly available County Business Patterns (CBP) data from 2000 to 2018 to construct a measure of the nonexempt labor market concentration in each county. The CBP includes counts of the number of establishments in the nonexempt labor market, and the number of employees working at these establishments. While the public data does not allow for a linking of employees directly to nonexempt establishments, it does identify employment counts in firm size categories. I use this to construct a Herfindahl-Hirschman Index (HHI).[8] The HHI is a measure of labor market concentration, and can offer insights into the distribution of labor market power across the US (Rinz et al., 2018). This allows for the testing of how the effect of the minimum wage may vary across more or less concentrated counties.

Due to the censored nature of the CBP data, the nonexempt establishment counts are broken into groups based on the number of employees they have.[9] This is done by assuming

[5] The restrictive nature of the CWS, specifically the focus on primary sources of income, is one explanation for why the percent of workers in alternative work arrangements and the exempt marketplace has seemed to remain stable since 1995, which is in contrast to administrative data sources like NES (Abraham et al., 2018; Katz and Krueger, 2019).

[6] When using the full data at the county-industry-year level, the panel is balanced for each county-industry, this data is used to create industry subsets. When using the aggregated data for the total count of nonemployer establishments in each county, the panel is balanced for each county.

[7] 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.

[8] The Herfindahl-Hirschman Index is calculated by squaring the market share of each firm competing in the market and then summing the resulting numbers. The HHI will approach zero with a greater level of competition, and has a maximum of 10,000. The U.S. Department of Justice uses the HHI, and specifically changes in the HHI, as a flag for problematic firms and mergers.

[9] The CBP breaks the establishments up into groups of firms that have 1 to 4 employees, 5 to 9, 10 to 19, 20 to 49, 50 to 99, 100 to 249, 250 to 499, 500 to 999, 1,000 to 1,499, 1,500 to 2,499, 2,500 to 4,999, and firms greater than 5,000 employees.

that each establishment in the employee group has the minimum number of employees, and use this to create a measure of the labor market concentration in each county every year.[10] By assuming that each firm employs the minimum number of employees in their group, I estimate the number of employees for each of these firms and can calculate the HHI across each group. I then sum each group HHI to get the county HHI. With the full range of HHI calculated, I then compute 100 quantiles and use the HHI quantile as a measure labor market concentration.[11].

One of the difficulties of identifying a relationship between minimum wage changes within NES data is the annual nature of the NES and the non-uniform nature of minimum wage policy implementation, with deployment times varying throughout the year. I code the minimum wage of a county as the highest minimum wage active on January 1st in a county each year. This is inclusive of federal, state, and local minimum wages. The results of this analysis were robust to a coding of the minimum wage on December 31st and the average across months.[12] Minimum wage data at the federal, state, and local level is compiled from U.S. Department of Labor (1938), Vaghul and Zipperer (2016), and UC Berkeley Labor Center (2018).

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 A3 shows this deployment strategy in action at the county level within the U.S. 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.[13] By linking Uber deployment locations to FIPS state-county codes the presence or absence of Uber's marketplace is established for a given year. This coding for the treatment of

[10] I have repeated the analysis using both the minimum, midpoint, and maximum of the range for each group and found the results were consistent. Beginning in 2017, the process of censorship extends to any cell with fewer than three establishments. I extend any value from 2016 to both 2017 and 2018. Results are consistent in a sample excluding 2017 and 2018.

[11] Results are robust to the use of raw HHI, as well as the logged HHI as shown in Tables A8 and A7 but quantiles are my preferred measure to account for the right tailed nature of the data. This can be seen in Figure A4

[12] The variation in minimum wage policy implementation may produce leading effects which appear as a violation of parallel trends. If the minimum wage increases in February, then the nonexempt market may respond before the minimum wage change has been recognized in the following year.

[13] This deployment data was supplied by Uber upon request.

Uber is expanded to include the core-based statistical areas (CBSAs) in which a county is a member.[14] 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 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.

Table 1—: Descriptive Statistics of All Nonemployer Establishments, 2000-2018

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Establishments	7,091	26,264	2	789	4,373	1,107,080
Establishments/Labor Force	0.141	0.037	0.0004	0.116	0.159	0.560
Receipts ($2016)	360,263	1,465,678	0.000	31,060	196,500	58,688,161
Receipts/Establishments ($2016)	43,467	9,047	0.000	37,562	47,968	174,030
Minimum Wage ($2016)	7.35	0.838	5.97	6.70	7.88	15.24
Δ Minimum Wage ($2016)	0.028	0.370	−0.475	−0.155	0.000	5.684
HHI	814.3	260.5	199.8	658.3	898.2	7,307.7
Labor Force	49,995	159,028	232	5,539	32,853	5,095,504

II. Methodology

The primary empirical challenge in this analysis is to create a reasonable counterfactual of how many nonemployer establishments would operate in a county-year in the absence of some change to the minimum wage, and the receipts taken in by these establishments. By exploiting county level variation in the minimum wage from 2000 to 2018, I estimate the effect of the minimum wage on nonemployer establishments. I also test both the low-barrier hypothesis with variation in the deployment timing and location of Uber and use county HHI to explore how this relationship differs by labor market concentration, intended to proxy the "competitiveness" of different counties.

I define a variable in order to measure the extensive marginal effect of minimum wages on the nonexempt labor market by measuring the number of nonemployer establishments per labor market participant in a county in a given NAICS industry. This creates a proxy measure for the likelihood that an individual will engage in the exempt labor market in a given county, defined as:

[14]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).

$$e_{cit} = \frac{E_{cit}}{L_{ct}}$$

where E_{cit} is the number of nonemployer establishments in county c, industry i, and year t, and L_{ct} is county c's total labor force estimate in year t. Using the receipts data included in the NES, I also construct a measure of both the intensive marginal effect and return to work by calculating the average receipts of the establishments in the county. Treating R_{cit} as the total receipts taken in by nonemployer establishments in county c, industry i, and year t, the average receipts are defined as:

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

Figure 2 plots e_{cit} and r_{cit} by the change in the real minimum wage, adjusted to 2016 dollars. The size of each observation is scaled to the county population, and the line is the relationship between the change in the minimum wage and e_{cit}, weighted by the counties average labor force size across the panel.

To account for confounding factors, this analysis leverages a two-way fixed effect model, at the county-year level, on a balanced panel of counties to identify if changes in the minimum wage have an impact on the exempt labor market. A total of 3,008 counties are used across 18 years, 2001-2018. The model is expanded through two primary additions. First, the use of an indicator variable for if Uber is active in a county-year. This is necessary as any observed relationship between Uber, the minimum wage, and nonemployer establishments, as seen in Figure 2, could be capturing a time specific characteristic rather than an actual Uber effect. It is also possible that Uber is only deploying in specific types of counties, and we are just seeing a selection effect. Second, a measure of the labor market concentration of each county, defined as the HHI quantile across the full sample of my data using the CBP, is included.

The primary advantage of the two-way fixed effect model in this case is the ability to include interaction effects between the HHI quantile, Uber being active, and the minimum wage. These specifications are described in equations (1) through (4). I repeat all of these equations for both e_{cit} and r_{cit}, but will use Y_{cit} to represent both.

$$Y_{cit} = \beta_0 + \beta_1 M_{ct} + \beta_2 U_{ct} + \beta_3 \mathrm{HHI}_{ct} + \alpha_{ci} + \tau_t + \mu_{cit} \tag{1}$$

$$Y_{cit} = \beta_0 + \beta_1 M_{ct} + \beta_2 \mathrm{U}_{ct} + \beta_3 \mathrm{HHI}_{ct} + \beta_4 (\mathrm{U}_{ct} * M_{ct}) + \alpha_c + \tau_t + \mu_{ct} \tag{2}$$

$$Y_{cit} = \beta_0 + \beta_1 M_{ct} + +\beta_2 \mathrm{U}_{ct} + \beta_3 \mathrm{HHI}_{ct} + \beta_4 (\mathrm{HHI}_{ct} * M_{ct}) + \alpha_c + \tau_t + \mu_{ct} \tag{3}$$

$$\begin{aligned} Y_{cit} = \beta_0 + \beta_1 M_{ct} + \beta_2 \mathrm{U}_{ct} + \beta_3 \mathrm{HHI}_{ct} + \beta_4 (\mathrm{U}_{ct} * M_{ct}) + \beta_5 (\mathrm{HHI}_{ct} * M_{ct}) \\ + \beta_6 (U_{ct} * \mathrm{HHI}_{ct}) + \beta_7 (\mathrm{HHI}_{ct} * U_{ct} * M_{ct}) + \\ \alpha_c + \tau_t + \mu_{ct} \end{aligned} \tag{4}$$

Equations (1) through (4) are estimated using OLS with clustered standard errors at the state level, and regressions are weighted by the average county labor force.[15] Similar to previous work on the minimum wage, these models control for time invariant geographic characteristics, and year fixed effects. M_{ct} identifies the the real minimum wage at the county level, defined as the difference in the real minimum wage in year t and $t-1$. U_{ct} identifies if Uber is active at any time in county c in year t. HHI_{ct} is county c's HHI quantile in year t. A lower quantile means a less concentrated labor market, and is then thought to be a more competitive county.

The time invariant geographic characteristics, α_{ci}, are preferred at the county industry level given the inclusion of local minimum wage changes, local Uber treatment, and local labor force estimates.[16] These time invariant factors may influence the nature of exempt labor markets which form in a county and their long run behavior, and may have led Uber to select some counties over others in the timing of deployment. Year fixed effects, τ_t, control for shocks which occurred nationally. When utilizing τ_t the analysis is testing the effect of state and local minimum wage changes together.

Equation (1) includes controls for the labor market concentration of a county, and whether Uber is or is not active in the county year, but does not allow for interactions between these terms. It presents the average effect of state and local minimum wage changes on the number of nonemployer establishments per person, conditional on county fixed effects, year fixed effects, the availability of Uber, and relative local labor market concentration.

Equation (2) identifies how the presence of Uber interacts with the relationship between the minimum wage and the exempt labor market. After controlling for county characteristics, I treat Uber as a conditionally random treatment of a homogeneous exempt labor market. This allows for a test of if workers have an increased propensity to engage in the exempt labor market as a result of higher minimum wages, and if this effect is related to the barriers between the exempt and nonexempt labor market. By using a two-way fixed effect model in addition to variation in the deployment of Uber, estimates of the effect of the minimum wage on the number of nonemployer establishments can be found across NAICS industry, both generally and in an identified low-barrier market for transportation and warehousing services.

Equation (3) includes an interaction effect between labor market concentration and the change in the minimum wage. By including an interaction effect, I am testing the degree to which more or less concentrated labor markets may influence the observed relationship. Counties with a greater HHI quantile are expected to show either no effect or negative effects on the number of establishments per labor market participant and the minimum wage. Low concentration counties are expected to show a positive relationship between the minimum wage and the number of establishments per labor market participant. The effect

[15] Weighting by the county population or observed labor force size as appose to county averages across the sample, skews the estimate toward a recency bias due to demographic trends. Results are also presented with clustered standard errors at the county level in Tables A4 and A3.

[16] For the purposes of this analysis, data is subset by NAICS code, hence the inclusion of the industry subscript. Results using state fixed effects are also presented in Tables A6 and A5.

on average receipts is unclear due to potential income and substitution effects between the exempt and nonexempt labor market, as effects on the intensive margin may be biased by selection effects on new entrants or exits from the exempt labor market.

Equation (4) combines the information on labor market concentration and the low-barrier marketplace indicated by Uber. This equation identifies how the low-barrier hypothesis might vary across more or less concentrated labor markets, after interacting labor market concentration with the presence or absence of Uber.

A. *Alternatives to the Two-Way Fixed Effect Models*

Previous work has been done to demonstrate that two-way fixed effect models may misestimate the counterfactual employment levels in minimum wage analyses specifically (Allegretto et al., 2017; Cengiz et al., 2019; Callaway and Sant'Anna, 2019). This is in combination with a growing literature on the weaknesses of two-way fixed effect models, including the use of negative weights, failure to validate parallel trends, and a nonconformity with the event study design (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). As such, three alternative designs are utilized to estimate the average treatment effect of the minimum wage on the number of nonemployer establishments per member of the labor force, and the average receipts of establishments.

The first alternative specification comes from de Chaisemartin and d'Haultfoeuille (2019), who demonstrate that two-way fixed effect models can produce negative weights, resulting in biased average treatment effect estimates. A linear regression coefficient may produce a negative result even if all of the average treatment estimates are positive. In order to make a comparable design which can be used within the de Chaisemartin and d'Haultfoeuille (2019) framework, I redefine the treatment as the unadjusted minimum wage. This is because in a staggered adoption design a steady control group needs to be identifiable in each period when a treatment (a minimum wage increase) occurs. Using the real minimum wage prevents a steady counterfactual from being identified due to annual inflation adjustments.[17]

In addition to this, I utilise the difference-in-difference methodology outlined by Callaway and Sant'Anna (2019). This method does not support repeated increases in a treatment, and is instead an event study design on an indicator for when treatment is first introduced. As such, I alter my treatment to be a variable for when the first minimum wage increase occurs for a given county in two different samples split by the federal minimum wage increases between 2007 and 2009. This method will not be as effective at estimating the average treatment effect of the minimum but it is included to support the parallel trends assumption of the two-way fixed effect model.

[17]To avoid a conflation between the transition from the real minimum wage to the unadjusted minimum wage and a change in methodology, I also present the results of the unadjusted minimum wage from equation (1) in Figures A10 and A11.

The final design intended as a robustness check is a generalized synthetic control design on local minimum wage changes. This addition is following the work of Dube and Zipperer (2015) and Powell (2017) in the application of synthetic control designs for the analysis of minimum wage policies across many treated units with varying treatment size, Gobillon and Magnac (2016) which outlines a method for the application of synthetic control designs for regional policy evaluation, and the generalized synthetic control methodology outlined by Bai (2009) and Xu (2017). To conform with the generalized synthetic control design, the treatment is defined as the adoption of local minimum wage increases at the county or metropolitan level.[18] Table A1 identifies which counties adopted local minimum wage changes and when they adopted them within this data set.

III. Results

Figure 2 describes both the average receipts of nonemployer establishments and the number of nonemployer establishments per member of the labor force's relationship with the real minimum wage, split between counties which have Uber active and those which do not. Note that the lines plot the linear relationship between the x and y, weighted by the county average labor force throughout the period. A positive relationship can be seen between the number of nonemployer establishments per member of the labor force and the real minimum wage when looking at the total set of nonemployer establishments, on the left side of the figure. When splitting between counties where Uber is and is not active, no substantial difference in the slope appears. Across all NAICS industries, Uber appears to shift the level of e_{cit}, and is not related to the relationship between the minimum wage and establishments per person, without accounting for either year or county level fixed effects. The relationship between r_{cit} and the minimum wage appears to split between counties with and without Uber active. Counties without Uber active appear to have a slight negative relationship, but counties with Uber active appear to have a positive relationship.

The right side of Figure 2 describes the same relationship, but for the subset of transportation and warehousing services. This industry is chosen as it represent the set of exempt workers likely to be engaging in a low-barrier marketplace for exempt work after the expansion of Uber and Lyft. It offers a comparison between traditional transportation and warehousing services and the online gig economy. For counties with Uber, e_{cit} appears to be positively related to increases in the minimum wage in contrast to counties without Uber, which appear to have a similar relationship to the total count. This conforms with the expectations of the competitive model of the minimum wage with and without a low-barrier marketplace. Changes in the minimum wage appear to match the total relationship without Uber for r_{cit} among transportation and warehousing services. Counties with and without Uber active show a negative relationship, though Uber active counties do appear to have a greater negative slope, in contrast to the observed relationship across

[18]This generalized synthetic control is reported by matching in the pre-treatment period on the number of establishments per member of the labor force or average receipts, the county unemployment rate, the county population, the county labor force, the county HHI, the state minimum wage, previous changes in the minimum wage, and if Uber is active.

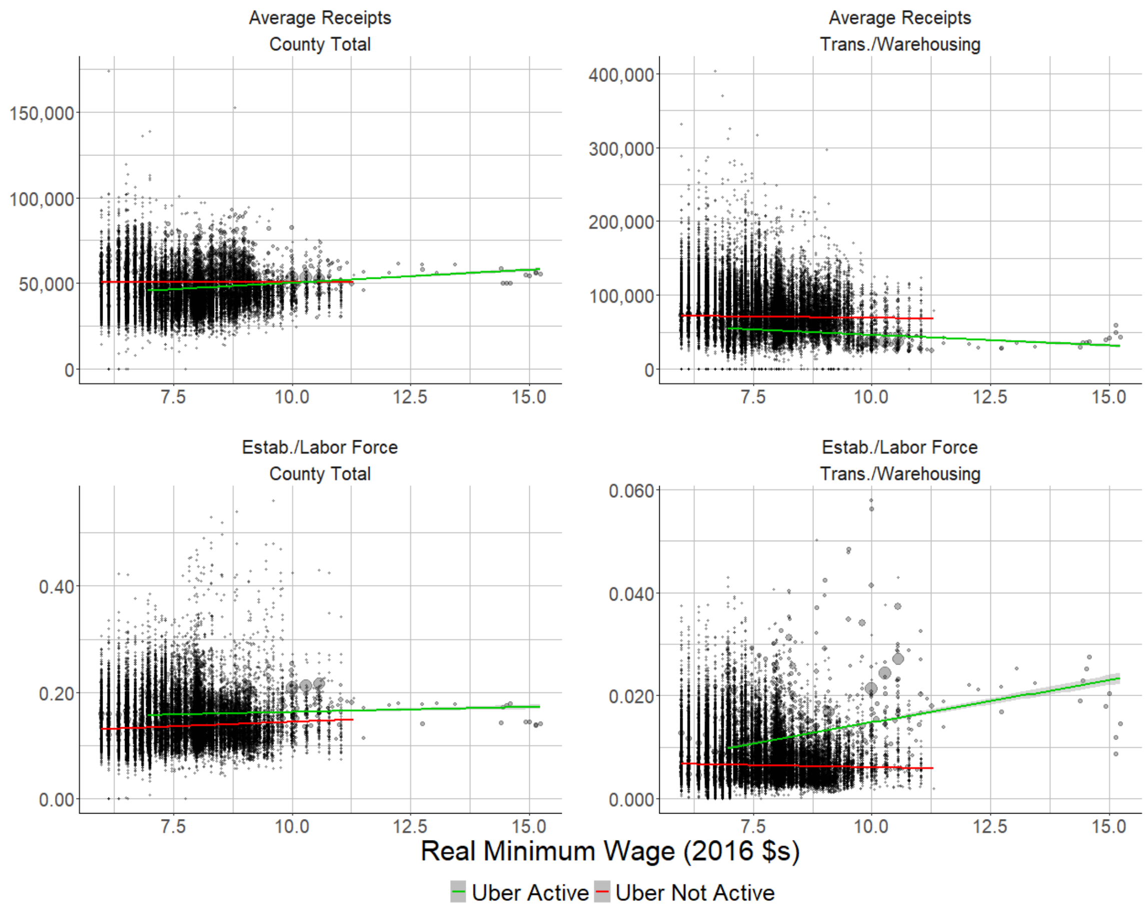

Figure 2. : These figures show both the average receipts of nonemployer establishments and the number of nonemployer establishments per member of the labor force's relationship with the real minimum wage. Each dot is a county-year with the radius scaled to the county labor force.

all nonemployer establishments.

One potential bias on the results in Figure 2 is that Uber did not begin expanding until 2011. The observed positive relationship is vulnerable to bias given the timing and location of Uber. Figure 2 is not controlling for the timing of minimum wage increases, timing of Uber deployment, or local county characteristics.[19]

Table 2—: Average Treatment Effects, All Nonemployer Establishments

		Dependent variable:		
		Establishments/Labor Force, e_{cit}		
Method	Treatment	(Pre 2007)	(Full)	(Post 2009)
Two-Way	Real Min. Wage	0.0000	0.0005	0.0007
		(0.0008)	(0.0006)	(0.0007)
Two-Way	Unadjusted Min. Wage	0.0000	0.0004	0.0007
		(0.0011)	(0.0008)	(0.0006)
de Chaisemartin and d'Haultfoeuille (2019)	Unadjusted Min. Wage	-0.0003	0.0011*	0.0029**
		(0.0006)	(.0006)	(0.0014)
Callaway and Sant'Anna (2019)‡	Year of the First Min. Wage increase	-0.0011	-	0.0021***
		(0.0007)	-	(0.0005)
		Average Receipts, r_{cit}		
Two-Way	Real Min. Wage	-227.0	-29.2	31.0
		(261.7)	(152.9)	(155.8)
Two-Way	Unadjusted Min. Wage	-284.0	-70.7	24.3
		(310.4)	(173.2)	(149.2)
de Chaisemartin and d'Haultfoeuille (2019)	Unadjusted Min. Wage	-136.3	14.8	84.0
		(233.6)	(236.1)	(388.0)
Callaway and Sant'Anna (2019)‡	Year of the First Min. Wage increase	-440.2	-	136.5
		(324.1)	-	(168.6)

*p<0.1; **p<0.05; ***p<0.01

Note:

‡The Callaway and Sant'Anna (2019) method presents the first year's treatment effect while using an event study design with both pre and post treatment effect estimates, as shown in Figure 3. The reported ATE is for period zero, the year when the treatment is first introduced.

I begin the analysis be exploring how the minimum wage relates to both the number of nonemployer establishments per member of the labor force, as well as the average re-

[19]It is clear from these figures just how uncommon real minimum wage values greater than \$10 are. The largest real minimum wage in these plots are in King County, WA in 2014 and Alameda, CA in 2016. The relationship shown in Figure 2 is robust to the exclusion of all real minimum wage values greater than \$11.50

ceipts of those establishments. Using equation (1) as well as the difference-in-difference estimators from de Chaisemartin and d'Haultfoeuille (2019) and Callaway and Sant'Anna (2019), I estimate the ATE for each of their respective treatments, as shown in Tables 2 and A2.[20] When comparing between the two-way fixed effect approach and de Chaisemartin and d'Haultfoeuille (2019)'s difference-in-difference estimator for all nonemployer establishments, the ATE estimate for both the number of nonemployer establishments per member of the labor force and the average receipts of establishments is underestimated by the two-way fixed effect approach. The Callaway and Sant'Anna (2019) methodology results in similar ATE estimates in the first period of a minimum wage increase, but this method does not differentiate between the size of minimum wage increases. Even with the difference in treatment and methodology, all four methods align with the conclusion that the post-2009 period has larger positive effect estimates than the pre-2007 period. the post 2009 sample is driving the positive relationship with the minimum wage observed in Figure 2.

Given the differences in treatment definition, methodology, and sample, I favor the estimates from de Chaisemartin and d'Haultfoeuille (2019) in the post-2009 period. As a result, I find that the ATE on the number of nonemployer establishments per member of the labor force, e_{cit}, of a dollar increase in the minimum wage is 0.0029. The average number of nonemployer establishments per member of the labor force from 2010 to 2018 is 0.148 and so a dollar increase in the minimum wage results in 1.96% increase in the stock of nonemployer establishments, and this result is significant at the 5% level. I do not find a significant relationship between the minimum wage and the average receipts on nonemployer establishments. Given the passage of a $15 federal minimum wage in the House of Representatives and the campaign promises of the Biden campaign in 2020, I estimate the effect a $15 federal minimum wage on aggregate nonemployer establishments. Due to variation in local and state minimum wages, not every county would experience an equal change as a result of a federal increase. After accounting for variation in the applied minimum wage in 2018, and the size of the local labor force, I estimate that a shift to a $15 federal dollar minimum wage in 2018 would have resulted in an additional 2,995,842 nonemployer establishments, an 11.7% increase relative to the 25,679,509 establishments in the sample in 2018.

To support these estimates of the ATE, the parallel trends assumption is tested with an event study design. Callaway and Sant'Anna (2019)'s estimator captures the first minimum wage increase in a given period, and is intended to be a complement, rather than substitute, to the results from de Chaisemartin and d'Haultfoeuille (2019)'s estimator. This also allows for a clear integration into an event study design as shown in Figure 3. I also utilize a series of placebos in relation to de Chaisemartin and d'Haultfoeuille (2019)'s estimator to create a quasi-event study as shown in Figures A7 and A8. I do not find evidence of a significant violation of parallel trends for either the number of nonemployer establishments per member of the labor force or the average receipts of nonemployer establishments using either method.

[20]Figures A10 and A11 illustrate these estimates and their size in relation to the 2018 nonemployer marketplace.

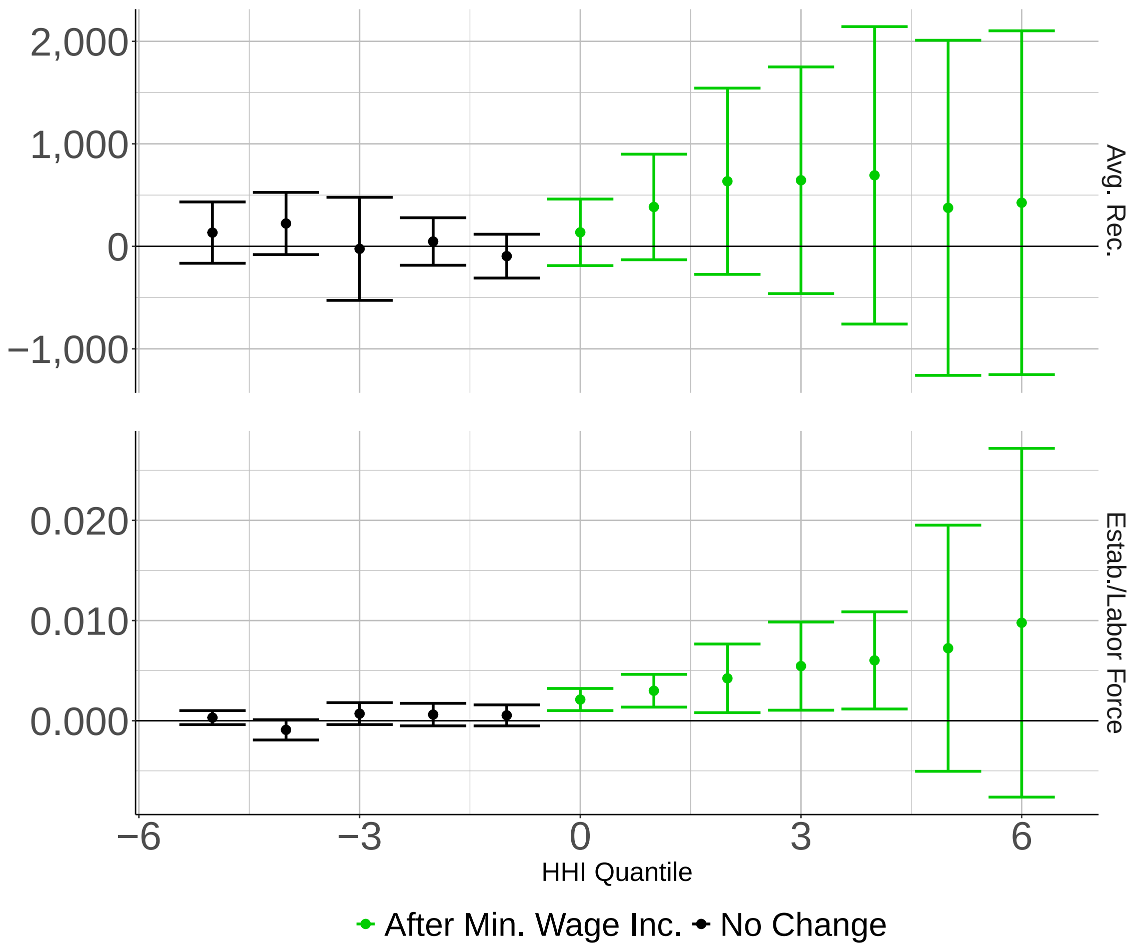

Figure 3. : This figure shows the event study for the Callaway and Sant'Anna (2019) methodology on the sample from 2010 to 2018. The treatment is an indicator variable for the first minimum wage increase in the sample period.

The consistency in sign for the ATE of the minimum wage on the number of nonemployer establishments per member of the labor force, and the validation of the parallel trends hypothesis, supports the competitive model of the minimum wage, but the lack of a significant relationship with the average receipts of nonemployer establishments does not. These results would imply that as minimum wages increase, we find a increasing number of workers participating in the exempt labor market, as independent contractors, gig workers, or the traditional self-employed, but this influx of workers does not result in a crowding out effect. What remains to be seen is if the increase in engagement in exempt work is consistent across labor market concentration as well as what role the online gig economy may play in this relationship. The expansion in online gig work is of interest for two reasons: (1) the significant positive effect is only occurring in more recent years, and (2) the online gig economy offers a lower cost to entry and exit than traditional self-employment, which should allow for a greater share of workers impacted by the minimum wage to transition between the exempt and nonexempt labor market.

A. *The Impact of Labor Market Concentration and the Online Gig Economy*

Table 3—: de Chaisemartin and d'Haultfoeuille (2019) Estimates by Labor Market Concentration, All Nonemployer Establishments

		Dependent variable:		
		Establishments/Labor Force, e_{cit}		
HHI Quantile	Bottom Quartile (Least Concentrated)	2nd Quartile	3rd Quartile	Top Quartile (Most Concentrated)
2010-2018	0.0030**	0.0019	-0.0008	-0.0024
	(0.0015)	(0.0013)	(0.0016)	(0.0030)
Full Sample	0.0014*	-0.0000	-0.0005	-0.0019
	(0.0008)	(0.0006)	(0.0006)	(0.0011)
2001-2007	0.0002	-0.0011**	-0.0004	-0.0018
	(0.0009)	(0.0004)	(0.0007)	(0.0011)
		Average Receipts, r_{cit}		
2010-2018	239.0	95.9	1483.3	683.5
	(280.7)	(552.5)	(971.1)	(1046.0)
Full Sample	90.1	-8.6	47.1	99.5
	(208.5)	(414.2)	(356.4)	(383.3)
2001-2007	-36.3	-270.2	-419.4	-416.9
	(238.1)	(444.7)	(279.5)	(427.1)

One of the limitations of de Chaisemartin and d'Haultfoeuille (2019)'s estimator is an inability to test for interaction effects on the primary treatment. As a result, I explore the relationship between the real minimum wage and both the labor market concentration and the online gig economy using subsets of the data and the two-way fixed effect model. Table

3 uses subsets of the sample split by the average county HHI quantile. While the ATE of the minimum wage on the number of nonemployer establishments per member of the labor force from Table A10 was shown to be 0.0029, Table 3 shows that this effect is driven primarily by the least concentrated counties. Table 4 shows equations (1) and (3) on all nonemployer establishments using the real minimum wage, and supports the conclusions from Table 3. As shown in Table 2, the two-way fixed effect model is underestimating the size and significance of the relationship between the minimum wage and the the average receipts of nonemployer establishments as well as the number of nonemployer establishments per member of the labor market. These results are used to inform the relationship between the real minimum wage and both the labor market concentration and the online gig economy, but it is assumed the the exact size of the ATE may be underestimated.

Table 4—: All Nonemployer Establishments

	Dependent variable:	
	Establishments/Labor Force, e_{cit}	
	(1)	(3)
Real Min. Wage	0.0005	0.0016**
	(0.0006)	(0.0008)
Real Min. Wage∗HHI Quantile		−0.0001***
		(0.00002)
Observations	54,162	54,162
R^2	0.927	0.929
Adjusted R^2	0.923	0.925
	Average Receipts, r_{cit}	
	(1)	(3)
Real Min. Wage	−29.2	−417.6*
	(152.9)	(234.6)
Real Min. Wage∗HHI Quantile		33.9***
		(8.3)
Observations	54,162	54,162
R^2	0.916	0.918
Adjusted R^2	0.911	0.913
Uber Active	Yes	Yes
HHI Quantile	Yes	Yes
HHI Quantile∗Uber Active	-	-
County FE	Yes	Yes
Year FE	Yes	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01	

Column (1) of Table 4 shows the ATE of the real minimum wage on the number of nonemployer establishments per member of the labor force and the average receipts of nonemployer establishments across the full sample of counties and years. These results are the same as shown in Table 2, and the effect is reported as insignificant for both dependent variables. The second column shows the results of equation (3), where an interaction is included between the real minimum wage and the measure of labor market concentration, with lower quantiles identifying lower levels of market concentration. The inclusion of this interaction highlights the hypothesized difference between the competitive model of the minimum wage and the monopsonistic model. Without the inclusion of the interaction term, the effect of the minimum wage on the number of nonemployer establishments per member of the labor force is positive, but this effect diminishes as the labor market becomes more concentrated. The inverse relationship is shown in the measure of average receipts, as the real minimum wage increases, the average receipts of nonemployer establishments fall, but the negative effect diminishes as markets become more concentrated. After accounting for variation in local labor market competitiveness both the competitive and monopsonistic models of the minimum wage are supported.

Table 5—: de Chaisemartin and d'Haultfoeuille (2019) Estimates by Labor Market Concentration, Transportation and Warehousing Services (NAICS 48-49)

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
HHI Quantile	x ≤ 25	25 < x ≤ 50	50 < x ≤ 75	75 < x
2010-2018	0.00078*	0.00015	0.00024	0.00000
	(0.00046)	(0.00026)	(0.00047)	(0.00045)
Full Sample	0.00037*	0.00000	0.00003	-0.00011
	(0.00022)	(0.00009)	(0.00014)	(0.00021)
2001-2007	0.00005	-0.00006	0.00003	-0.00022
	(0.00010)	(0.00004)	(0.00008)	(0.00024)
	Average Receipts, r_{cit}			
2010-2018	1330.6	-3730.8	1587.5	81.7
	(1827.8)	(9171.56)	(3941.9)	(3304.1)
Full Sample	-314.4	-637.2	337.3	755.9
	(841.5)	(1073.7)	(1318.6)	(1898.4)
2001-2007	-1356.4	1177.2	632.5	-399.4
	(866.4)	(1027.1)	(979.2)	(1393.7)

Across the aggregate of all nonemployer establishments, a significant relationship is found between the minimum wage and the exempt labor market, but the online gig economy represents a particular sliver of the much broader exempt market. To test the effect of the expansion of online gig work on this relationship I use a subset of the full nonemployer establishment data on transportation and warehousing services. Testing the degree to which labor market concentration interacts with the minimum wage in this industry, I replicate Table 3 in Table 5. I find that transportation and warehousing services replicate the relationship found across all nonemployer establishments.[21] Table 6 shows the results of equations (1) through (4) on this subset. Column one presents the ATE for this subset. Similar to the effect in aggregate, a significant positive relationship is found between the minimum wage and the number of nonemployer establishments per member of the labor force, and an insignificant negative relationship is shown for the average receipts of nonemployer establishments.

Table 6—: Transportation and Warehousing

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Real Min. Wage	0.0012***	0.0002	0.0017***	0.0005***
	(0.0003)	(0.0001)	(0.0003)	(0.0002)
Real Min. Wage∗Uber Active		0.0014***		0.0014***
		(0.0004)		(0.0005)
Real Min. Wage∗HHI Quantile			−0.00005***	−0.00002***
			(0.00001)	(0.000003)
Real Min. Wage∗HHI Quantile∗Uber Active				−0.00004***
				(0.00001)
Observations	54,072	54,072	54,072	54,072
R^2	0.820	0.831	0.834	0.856
Adjusted R^2	0.809	0.821	0.824	0.848
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Real Min. Wage	−809.3	1,029.0*	−1,271.1*	461.4
	(561.6)	(555.4)	(684.9)	(640.8)
Real Min. Wage∗Uber Active		−2,525.0**		−1,551.5
		(1,155.7)		(1,168.0)
Real Min. Wage∗HHI Quantile			40.3**	27.4**
			(16.1)	(11.0)
Real Min. Wage∗HHI Quantile∗Uber Active				−62.7***
				(17.1)
Observations	54,072	54,072	54,072	54,072
R^2	0.823	0.826	0.824	0.827
Adjusted R^2	0.813	0.816	0.813	0.817
Uber Active	Yes	Yes	Yes	Yes
HHI Quantile	Yes	Yes	Yes	Yes
HHI Quantile∗Uber Active	-	-	-	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01

[21] Effect estimates are expected to be smaller when doing industry subset analysis is each industry is additive in it's relationship to all nonemployer establishment effect estimates.

Column two shows that when applying an Uber interaction effect, the majority of the effect of the minimum wage on the number of nonemployer establishments per member of the labor force, e_{cit}, is driven by counties where the low-barrier marketplace is active. At the same time, the relationship between the average receipts and nonemployer establishments is positive where Uber is inactive, but negative when Uber is active. These results suggest that when a low barrier exempt labor market is available, individuals workers are more likely to take up exempt work than when it is not. In fact, it would appear that the the exempt labor market for transportation and warehousing services is unresponsive to changes in the minimum wage without the presence of Uber in the county. The relationship to the average receipts of nonemployer establishments also implies that those new entrants into the exempt market are taking up fewer receipts, so either a crowding out effect is occurring, and/or individuals who enter are only participating as a supplemental source of income, and taking in fewer receipts as a result.

When utilizing the measure of labor market concentration, in column three, the minimum wage is shown to have significant differences in effect across more and less concentrated counties. The minimum wage is positively related to participation in exempt work in highly concentrated labor markets, but as market concentration decreases, so does the relationship between the minimum wage and exempt work. The effect of the minimum wage on the average receipts of nonemployer establishments aligns with this results. Columns one and three imply a similar story to that seen in the aggregate market, and column two identifies how the effect may be deeply linked to the online gig economy, supporting the descriptive results in Figure 2.

To test the degree to which Uber being active is interacting with local labor market concentration, an interaction effect with labor market concentration and the minimum wage is included. I find evidence that the bulk of the positive effect on the number of nonemployer establishment per member of the labor force comes the Uber interaction with the minimum wage. This positive effect is weakened as labor markets become more concentrated, and it is weakened at a faster rate among counties with Uber active. Less concentrated labor markets with Uber active are therefore the areas most likely to see significant increase in participation in exempt work following minimum wage increases. This follows the results of the first three columns. In contrast to this, the relationship between the real minimum wage and the average receipts of nonemployer establishments highlights that among counties without Uber active and higher levels of labor market concentration, the average receipts of transportation and warehousing services increase. This effect is not present when Uber is active though. I find that in low concentration labor markets, where Uber is active, there is an insignificant reduction in the average receipts of nonemployer establishments. This implies that increases in the minimum wage in less concentrated markets with Uber active result in a shift away from full-time or primary employment in the exempt marketplace, but instead an increase in the share of secondary or supplemental work in the exempt labor market.

Due to the significant effects identified among transportation and warehousing services, but the relatively small share of the exempt labor market that this industry represent, direct comparisons to the aggregate labor market may be limited in the share of the relationship attributed to the expansion of Uber. Naturally, the deployment of a platform taxi service will have a smaller impact on construction than it would on transportation, but the clear increase in effect size within industry is telling. The presence of a low-barrier marketplace increases the observed effect substantially, but primarily among more concentrated labor markets. Among more concentrated labor markets, a small negative relationship exists, which aligns with the findings of Blau (1987) and Bruce and Mohsin (2006), as well as the hypothesized extension of the monopsonistic model of the minimum wage. While the exact ATE may be compromised among the two-way fixed effect results, as outlined earlier, the interactions between the minimum wage and both the labor market concentration and the online gig economy as measured by the deployment of Uber, are telling.

In total, these findings show an increase in the number of workers engaging in exempt work among more concentrated counties, with larger labor forces, and where the online gig economy is active and able to take advantage of large consumer networks. The increase in the supply of labor in the exempt market does not significantly impact the average receipts taken in across all nonemployer establishment, but heterogeneous effects were shown among transportation and warehousing services in more or less concentrated labor markets. This is best explained by an increased willingness to purchase services in the exempt labor market, supplied through the online gig economy. This supports the conclusion that Uber, and other forms of platform work, are able to effectively take up the slack from excess labor supply in the nonexempt labor market resulting from minimum wage increases.

Less concentrated labor markets do not experience the same positive extensive marginal effect. Instead, in both transportation and warehousing services and nonemployer establishments broadly, I find a reduction in establishments per member of the labor force among less concentrated counties. For those establishments which remain, I find that the eaverage receipts increase, which would imply an exit of low earning nonemployer establishments. These two results paired together signal a reduction in the supply of labor on the extensive margin among secondary and supplemental earners. Since this data is unable to track hours worked or identify primary or secondary sources of income among workers, I am unable to determine exactly what the balance is. Following the conclusion of the Seattle minimum wage project Jardim et al. (2018), I am inclined to believe that less concentrated labor markets are likely not experiencing a reduction shift in the demand for exempt labor, and are instead observing individual workers reduce their supply of labor in the exempt market following increasing returns to work in the nonexempt market. Given that low-wage labor is not often on-demand, this is likely less a movement in hours from the exempt market to the nonexempt market, and more a reduction in exempt hours following an income effect.

IV. Conclusion

The minimum wage remains an important component of the policies governing low wage labor in the U.S. Though it is intended as a tool for addressing a minimum standard of living, conclusions on the aggregate effects of the minimum wage remain elusive. Adding to the uncertainty regarding the effects of the minimum wage is the presence of work outside of the scope of federal, state, and local legislation. The division between the exempt and nonexempt market is in part driven by structural differences in work, but also the rules we set and the programs we design.

This analysis intended to address the degree to which changes in the minimum wage impact the propensity of workers to engage in the exempt labor market and finds that, (1) in aggregate increase in the minimum wage result in increased engagement in exempt work, (2) the concentration of local labor markets does significantly impact the effect of the minimum wage, and (3) low-barrier marketplaces and the development of the online gig economy increase this effect substantially. A positive relationship between the minimum wage and engagement in exempt work is found among counties with low levels of labor market concentration. This is paired with negative effects on the average receipts of establishments in less concentrated counties. In aggregate, I find that for a one dollar increase in the minimum wage, the number of nonemployer establishments per member of the labor force increases by 0.0029, or 1.96% of the average number of nonemployer establishments per member of the labor force from 2010 to 2018. This increase in the number of nonemployer establishments would be located primarily among high population and low concentration counties. Highly concentrated counties on the other hand would see a reduction in the supply of labor to the exempt market or no change, as low wage workers experience the benefits of higher minimum wages in the nonexempt labor market.

With the identification of significant effects on exempt labor, and differences in this effect across geography, questions are raised regarding the aggregate effect of minimum wage policies on the labor market. For those studies which utilize data solely on nonexempt work, any negative relationship between minimum wages and the quantity of labor may be overestimated, as the transition of workers between the exempt and nonexempt market may be classified as exit from the labor market. These studies are also unlikely to capture movement on the intensive margin of the exempt labor market, masking what may be important shifts in hours allocation between the exempt and nonexempt labor market. Studies which rely on data sources that capture both the exempt and nonexempt labor market, but fail to distinguish between the two, may underestimate negative consequences of transition. Workers leaving the nonexempt market to take up exempt work may be losing access to a substantial number of policy protections and fringe benefits. Without properly accounting for this shift, the assessment of aggregate welfare effects will be positively biased. Both of these are of particular concern in concentrated metropolitan regions with access to the online gig economy.

Through organizational restructuring, and technological change, portions of the exempt labor market are growing more like traditional work arrangements, and similar types of work exist on either side of divisions in policy. The online gig economy has contributed to the commodification of work, and policy makers are attempting to get a grasp on how to manage it. The continued development of work arrangements which walk the line of labor protections and regulations creates opportunities for research on the effects of labor policy, but it also impacts the lived experiences of individuals within our communities. This analysis hopes to add to the evidence from which policy makers can draw to create and improve legislation. With the growing interest of local policy in addressing minimum wages within the online gig economy, specifically minimum wages for drivers on platforms in New York City and Seattle, understanding these dynamics is crucial.

While this analysis is unable to address the effect on aggregate welfare, the assessment of welfare effects is a next step in this research. This paper also highlights the necessity of assessing how other policies which operate on a similar division in the labor market may interact with the exempt market in general and the online gig economy, and how this effect varies across space in the U.S. These policies include the Affordable Care Act, disability insurance, retirement benefits, paid sick leave, unemployment insurance, tax withholding, and more recently the CARES act.

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APPENDIX

A1. Generalized Synthetic Control on Local Minimum Wage Increases

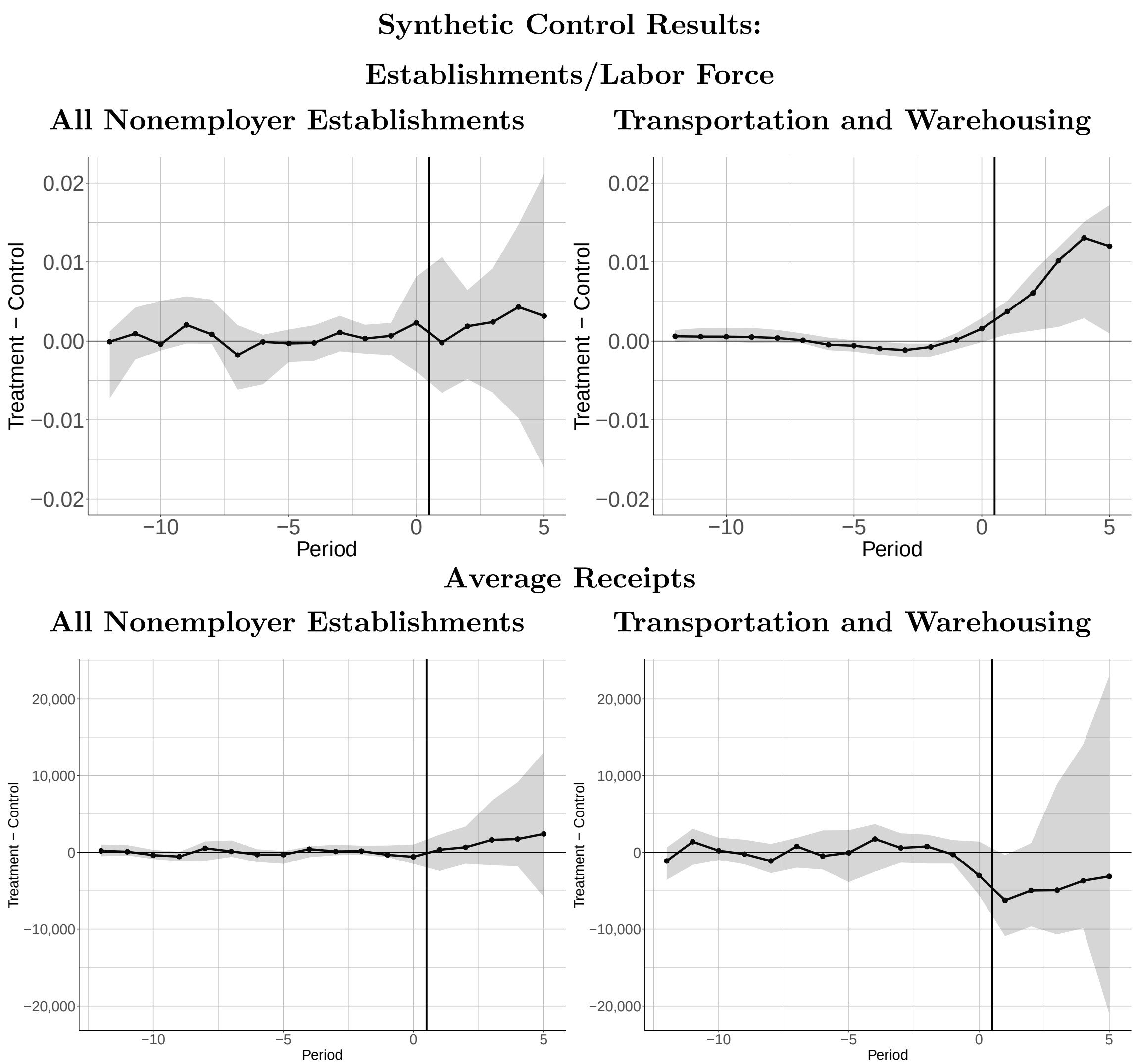

Figure A1. : These figures illustrate the average effect of the treatment on the treated (ATT) for e_{cit} and r_{cit} for both transportation and warehousing services and all nonemployer establishments.

Using the generalized synthetic control methodology following the work of Bai (2009), Gobillon and Magnac (2016), and Xu (2017), and defining the adoption of local minimum wage increases at the county or metropolitan level as the treatment, I find similar results those already identified among low concentration counties.[22] I use a generalized synthetic control to help resolve bias in the adoption of minimum wage changes in relation to the deployment of Uber and increases among transportation and warehousing establishments. This method does not account for differences in the size of local minimum wage changes or the process of increasing local minimum wages in the following years. By matching on the pre-treatment trends of counties which adopt local minimum wage increases, I am performing a more comprehensive accounting of the parallel trends assumption than the two-way fixed effect model, while using a different treatment. In this case, concerns may exist regarding the generalizability of local minimum wage changes to state and federal changes.

Figure A1 shows the average effect of the treatment on the treated (ATT) for transportation and warehousing services and all nonemployer establishments. A significant increase in the number of nonemployer establishments follows the introduction of a local minimum wage change for transportation and warehousing services. I also find a significant reduction in average receipts at the 95% level in the first year after a local minimum wage change, but this reduction is insignificant in the following years. When estimating the effect for all nonemployer establishments, I find no significant change in establishments per member of the labor force or average receipts.

The results of the synthetic control are not able to show any interaction effect between Uber being active or labor market concentration, but they do illustrate the lagged effect of increases in the minimum wage similar to that found in Figure 3. We can see that the effect of the minimum wage continues after the first year of treatment in Figure A1. These results support the identified effects of the two-way fixed effects approach for transportation and warehousing services, but does not replicate the significant positive effect for all nonemployer establishments.

A2. Tables

[22] The average change in the real minimum wage in the first year of implementation of a local minimum wage in my sample is $1.44. Local minimum wage increases at the county level are shown in Table A1.

Table A1—: Local Minimum Wage Increases

FIPS State - County	County Name, State	Year of Adoption	HHI Quantile
6-1	Alameda, CA	2015	7
6-13	Contra Costa, CA	2015	11
6-73	San Diego, CA	2015	4
6-85	Santa Clara, CA	2014	1
17-31	Cook, IL	2017	2
19-103	Johnson, IA	2016	3
21-111	Jefferson, KY	2016	6
21-67	Fayette, KY	2017	9
23-5 ‘	Cumberland County, ME	2016	10
24-31	Montgomery, MD	2015	6
24-33	Prince Georges, MD	2015	20
35-13	Dona Ana, NM	2015	38
53-33	King, WA	2014	2
53-53	Pierce, WA	2017	9

Table A2—: Average Treatment Effects, Transportation and Warehousing

		Dependent variable:		
		Establishments/Labor Force, e_{cit}		
Method	Treatment	(Pre 2007)	(Full)	(Post 2009)
Two-Way	Real Min. Wage	0.0000	0.0012***	0.0015***
		(0.0001)	(0.0003)	(0.0003)
Two-Way	Unadjusted Min. Wage	0.0000	0.0013***	0.0015***
		(0.0002)	(0.0003)	(0.0003)
de Chaisemartin and d'Haultfoeuille (2019)	Unadjusted Min. Wage	0.00003	0.0003	.0008
		(.00007)	(0.0002)	(.0005)
Callaway and Sant'Anna (2019)	Year of the First Min. Wage increase	-0.0003	-	0.0025***
		(0.0001)	-	(0.0010)
		Average Receipts, r_{cit}		
Two-Way	Real Min. Wage	-988.4	-809.3	-1,095.0
		(566.1)	(561.6)	(886.3)
Two-Way	Unadjusted Min. Wage	-994.7	-1,137.1	-1,092.3
		(667.7)	(708.1)	(840.3)
de Chaisemartin and d'Haultfoeuille (2019)	Unadjusted Min. Wage	-118.2	-247.4	-6.6
		(361.0)	(862.5)	(1,941.8)
Callaway and Sant'Anna (2019)	Year of the First Min. Wage increase	-891.1	-	-644.0
		(641.3)	-	(1,203.7)

Table A3—: All Nonemployer Establishments, clustered at the county level

	Dependent variable:	
	Establishments/Labor Force, e_{cit}	
	(1)	(3)
Real Min. Wage	0.0005	0.0016**
	(0.0005)	(0.0007)
Real Min. Wage∗HHI Quantile		−0.0001***
		(0.00002)
Observations	54,162	54,162
R^2	0.927	0.929
Adjusted R^2	0.923	0.925
	Average Receipts, r_{cit}	
	(1)	(3)
Real Min. Wage	−29.2	−417.6**
	(110.4)	(164.0)
Real Min. Wage∗HHI Quantile		33.9***
		(4.9)
Observations	54,162	54,162
R^2	0.916	0.918
Adjusted R^2	0.911	0.913
Uber Active	Yes	Yes
HHI Quantile	Yes	Yes
HHI Quantile∗Uber Active	-	-
County FE	Yes	Yes
Year FE	Yes	Yes

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

Table A4—: Transportation and Warehousing Services, clustered at the county level

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Real Min. Wage	0.0012***	0.0002	0.0017***	0.0005***
	(0.0002)	(0.0001)	(0.0003)	(0.0001)
Real Min. Wage:Uber Active		0.0014***		0.0014***
		(0.0003)		(0.0004)
Real Min. Wage:HHI Quantile			−0.00005***	−0.00002***
			(0.00001)	(0.000002)
Real Min. Wage:HHI Quantile:Uber Active				−0.00004***
				(0.00001)
Observations	54,072	54,072	54,072	54,072
R^2	0.8201	0.832	0.834	0.856
Adjusted R^2	0.809	0.822	0.824	0.848
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Real Min. Wage	−809.3***	1,029.0***	−1,271.1***	461.4
	(287.5)	(344.4)	(406.9)	(433.3)
Real Min. Wage:Uber Active		−2,525.0***		−1,551.5**
		(607.5)		(755.0)
Real Min. Wage:HHI Quantile			40.3***	27.4***
			(11.3)	(8.5)
Real Min. Wage:HHI Quantile:Uber Active				−62.7***
				(24.0)
Observations	54,072	54,072	54,072	54,072
R^2	0.823	0.826	0.824	0.827
Adjusted R^2	0.813	0.816	0.813	0.817
Uber Active	Yes	Yes	Yes	Yes
HHI Quantile	Yes	Yes	Yes	Yes
HHI Quantile∗Uber Active	-	-	-	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table A5—: All Nonemployer Establishments, clustered at the state level with state fixed effects

	Dependent variable:	
	Establishments/Labor Force, e_{cit}	
	(1)	(3)
Real Min. Wage	0.0015**	0.0026***
	(0.0007)	(0.0009)
Real Min. Wage∗HHI Quantile		−0.0001**
		(0.0001)
Observations	54,162	54,162
R^2	0.3816	0.3855
Adjusted R^2	0.3808	0.3847
	Average Receipts, r_{cit}	
	(1)	(3)
Real Min. Wage	334.462	309.273
	(217.661)	(292.553)
Real Min. Wage∗HHI Quantile		2.631
		(9.914)
Observations	54,162	54,162
R^2	0.482	0.482
Adjusted R^2	0.482	0.482
Uber Active	Yes	Yes
HHI Quantile	Yes	Yes
HHI Quantile∗Uber Active	-	-
State FE	Yes	Yes
Year FE	Yes	Yes
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A6—: Transportation and Warehousing Services, clustered at the state level with state fixed effects

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Real Min. Wage	0.0012***	0.0001	0.0017***	0.0004**
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Real Min. Wage*Uber Active		0.0015***		0.0014***
		(0.0004)		(0.0005)
Real Min. Wage*HHI Quantile			−0.00005***	−0.00002***
			(0.00001)	(0.000004)
Real Min. Wage*HHI Quantile*Uber Active				−0.0001**
				(0.00002)
Observations	54,072	54,072	54,072	54,072
R^2	0.4087	0.4222	0.4346	0.4737
Adjusted R^2	0.4079	0.4214	0.4339	0.4730
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Real Min. Wage	−1,869.0*	−96.2	−2,402.2**	−794.6
	(958.8)	(537.9)	(1,167.3)	(709.2)
Real Min. Wage*Uber Active		−2,402.9**		−1,678.1
		(1,181.1)		(1,048.8)
Real Min. Wage*HHI Quantile			55.7*	36.4
			(29.4)	(26.8)
Real Min. Wage*HHI Quantile*Uber Active				−10.5
				(20.6)
Observations	54,072	54,072	54,072	54,072
R^2	0.483	0.486	0.485	0.488
Adjusted R^2	0.482	0.485	0.485	0.488
Uber Active	Yes	Yes	Yes	Yes
HHI Quantile	Yes	Yes	Yes	Yes
HHI Quantile∗Uber Active	-	-	-	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table A7—: All Nonemployer Establishments, Comparing measures of HHI

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(4)	(4)	(4)	(4)
Real Min. Wage	0.0016**	0.0080***	−0.0027***	0.0621***
	(0.0007)	(0.0025)	(0.0005)	(0.0199)
Real Min. Wage*HHI Quantile	−0.0001***			
	(0.00002)			
Real Min. Wage*HHI		−0.00001***		
		(0.000004)		
Real Min. Wage*HHI Normalized			−0.0034***	
			(0.0009)	
Real Min. Wage*Log(HHI)				−0.0097***
				(0.0031)
Observations	54,162	54,162	54,162	54,162
R^2	0.929	0.928	0.928	0.929
Adjusted R^2	0.925	0.924	0.924	0.924
	Average Receipts, r_{cit}			
Real Min. Wage	0.0016**	0.0080***	−0.0027***	0.0621***
	(0.0007)	(0.0025)	(0.0005)	(0.0199)
Real Min. Wage*HHI Quantile	−0.0001***			
	(0.00002)			
Real Min. Wage*HHI		−0.00001***		
		(0.000004)		
Real Min. Wage*HHI Normalized			−0.0034***	
			(0.0009)	
Real Min. Wage*Log(HHI)				−0.0097***
				(0.0031)
Observations	54,162	54,162	54,162	54,162
R^2	0.918	0.917	0.917	0.917
Adjusted R^2	0.913	0.912	0.912	0.912
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table A8—: Transportation and Warehousing Services, Comparing measures of HHI

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(4)	(4)	(4)	(4)
Real Min. Wage	0.0005***	0.0018***	−0.0003***	0.0138***
	(0.0001)	(0.0004)	(0.0001)	(0.0028)
Real Min. Wage*Uber Active	0.0014***	0.0033*	−0.0001	0.0086
	(0.0004)	(0.0018)	(0.0005)	(0.0115)
Real Min. Wage*HHI Quantile	−0.00002***			
	(0.000002)			
Real Min. Wage*HHI		−0.000003***		
		(0.000000)		
Real Min. Wage*HHI Normalized			−0.0007***	
			(0.0001)	
Real Min. Wage*Log(HHI)				−0.0021***
				(0.0004)
Real Min. Wage*HHI Quantile*Uber Active	−0.00004***			
	(0.00001)			
Real Min. Wage*HHI*Uber Active		−0.000004		
		(0.000003)		
Real Min. Wage*HHI Normalized*Uber Active			−0.0011	
			(0.0007)	
Real Min. Wage*Log(HHI)*Uber Active				−0.0012
				(0.0018)
Observations	54,072	54,072	54,072	54,072
R^2	0.8563	0.8549	0.8549	0.8566
Adjusted R^2	0.8478	0.8463	0.8463	0.8481
	Average Receipts, r_{cit}			
Real Min. Wage	461.4	−1,943.6	1,817.7***	−19,742.0*
	(640.8)	(1,481.0)	(584.7)	(11,290.1)
Real Min. Wage*Uber Active	−1,551.5	5,925.7***	−5,799.7***	60,224.2***
	(1,168.0)	(2,058.9)	(1,275.2)	(11,159.2)
Real Min. Wage*HHI Quantile	27.4**			
	(11.0)			
Real Min. Wage*HHI		4.6**		
		(2.0)		
Real Min. Wage*HHI Normalized			1,171.4**	
			(502.4)	
Real Min. Wage*Log(HHI)				3,219.5*
				(1,736.8)
Real Min. Wage*HHI Quantile*Uber Active	−62.7***			
	(17.1)			
Real Min. Wage*HHI*Uber Active		−14.4***		
		(2.8)		
Real Min. Wage*HHI Normalized*Uber Active			−3,651.7***	
			(704.1)	
Real Min. Wage*Log(HHI)*Uber Active				−9,869.4***
				(1,692.1)
Observations	54,072	54,072	54,072	54,072
R^2	0.827	0.827	0.827	0.827
Adjusted R^2	0.817	0.817	0.817	0.817
Note:			*p<0.1; **p<0.05; ***p<0.01	

A3. Figures

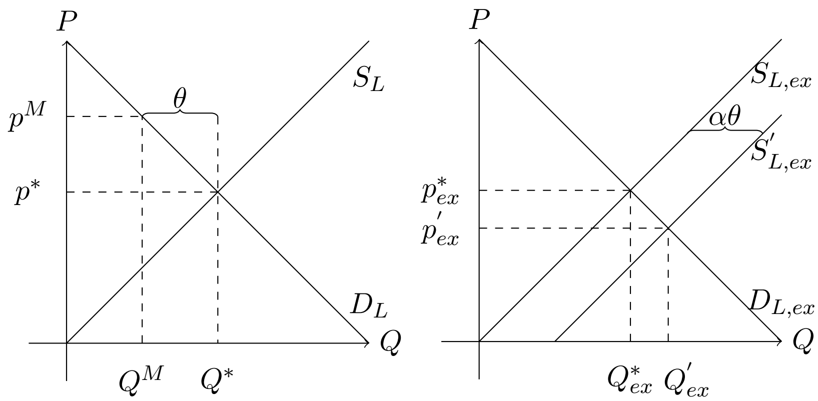

Figure A2. : An illustration of the competitive model of the minimum wage in the nonexempt, on the left, and exempt, on the right, labor market as viewed as commodities. If the minimum wage is set at level P^M, such that $P^M > P^*$, the quantity of labor purchased on the nonexempt labor market falls from Q^* to Q^M. This is a reduction in the quantity of labor purchased of size θ. Here α is the share of labor capable of overcoming the barriers between markets and $\alpha\theta$ is the amount of labor that transitions into the exempt market as a result of the minimum wage.

Figure A3. : The figures above depict the counties in which Uber is operating from 2013-2018. Black counties are areas without Uber, green counties are where Uber is active, and white counties are counties which are structural zeros and are dropped from the analysis. White counties are not in the balanced panel, but all black and green counties are.

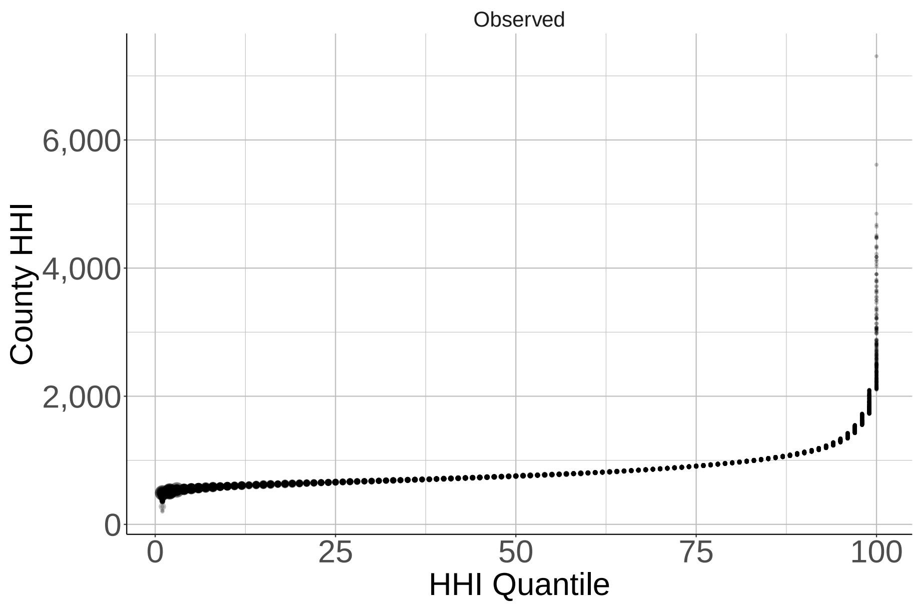

Figure A4. : This figure shows the distribution of HHI values as they are binned into 100 quantiles. The bulk of the quantile trend is linear with some extreme low HHI scores falling into the first quantile and extreme high falling into the last quantile. This highlights the advantage to using the quantile based measure of HHI as appose to the raw continuous value of HHI when including a linear interaction between HHI and the change in the minimum wage.

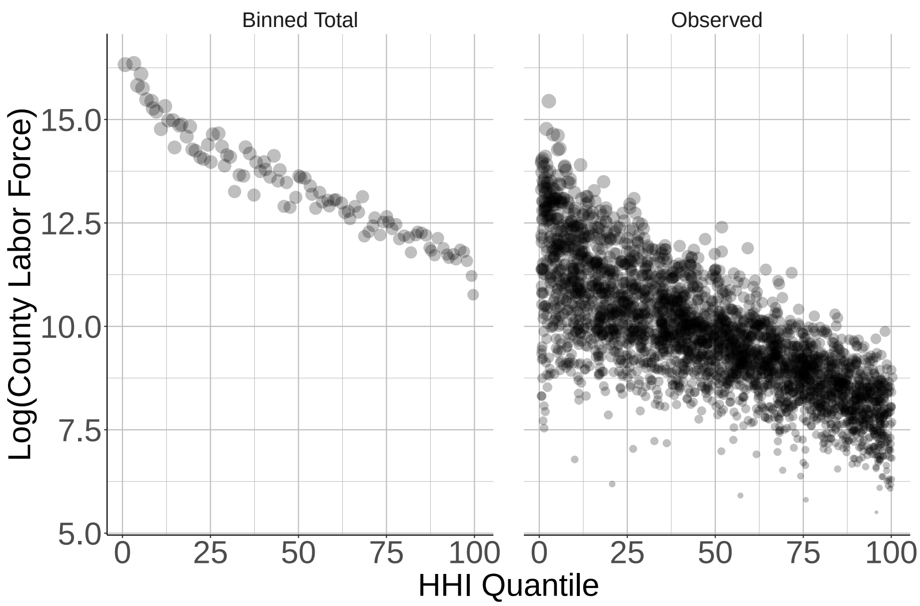

Figure A5. : This figure plots the relationship between the log of the county labor force and the HHI quantile for both the binned sum of the labor force and the observed labor force in each county in 2018.

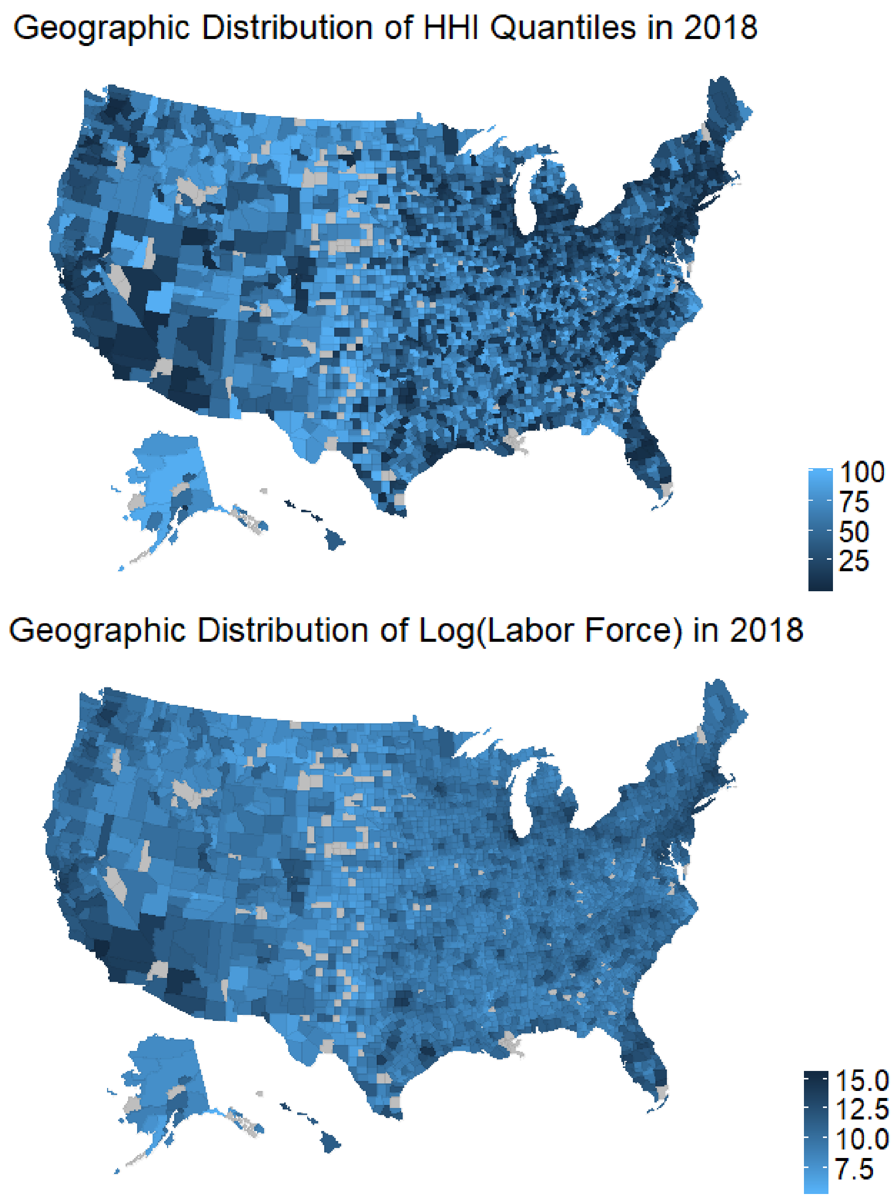

Figure A6. : The figures above depict the geographic distribution of HHI quantiles and the log of the county labor force in 2018. Counties which are not included in the sample are shown in grey.

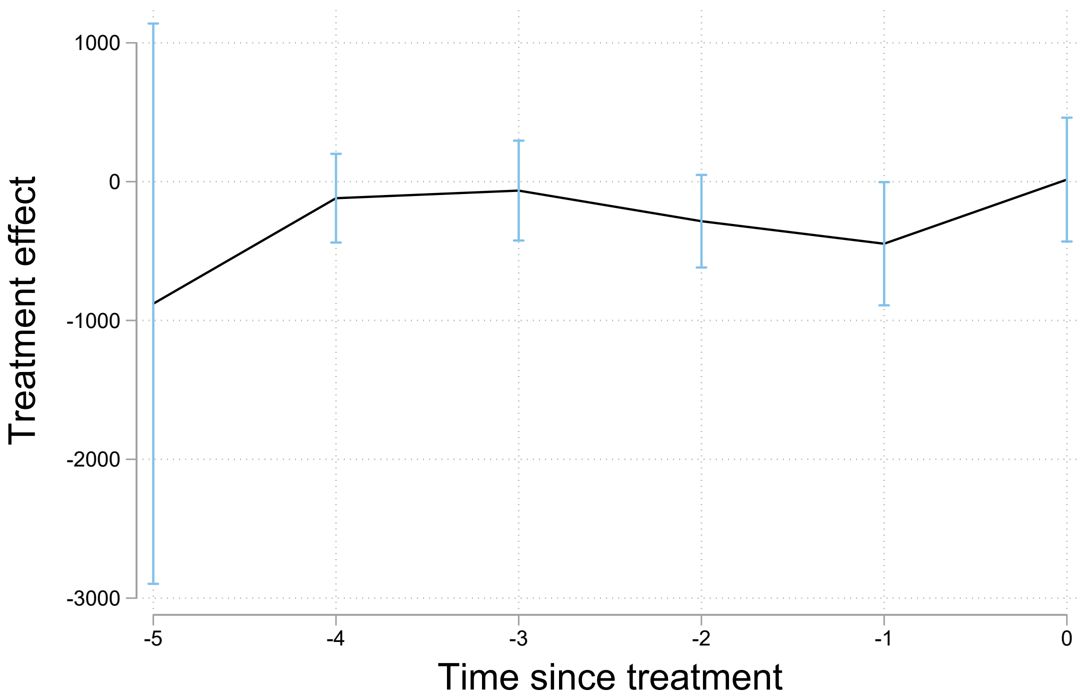

Figure A7. : This figure shows the event study for the de Chaisemartin and d'Haultfoeuille (2019) methodology for the full sample from 2000 to 2018 on the average receipts of nonemployer establishments. Bars show a 95% confidence interval around the point estimate.

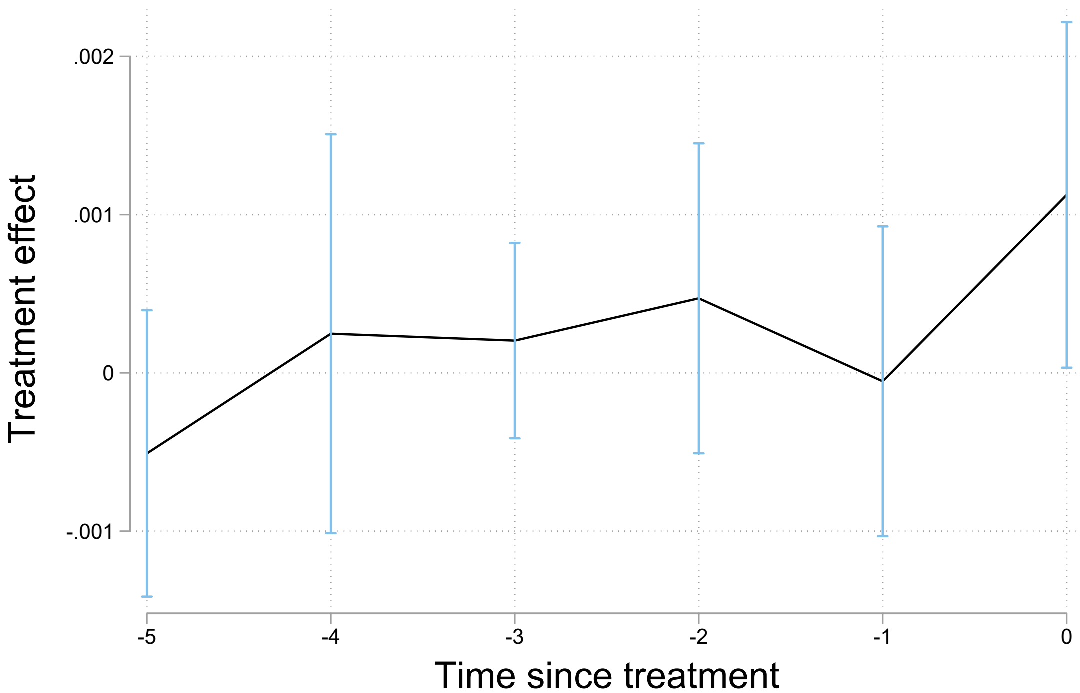

Figure A8. : This figure shows the event study for the de Chaisemartin and d'Haultfoeuille (2019) methodology for the full sample from 2000 to 2018 on the number of nonemployer establishments per member of the labor force. Bars show a 95% confidence interval around the point estimate.

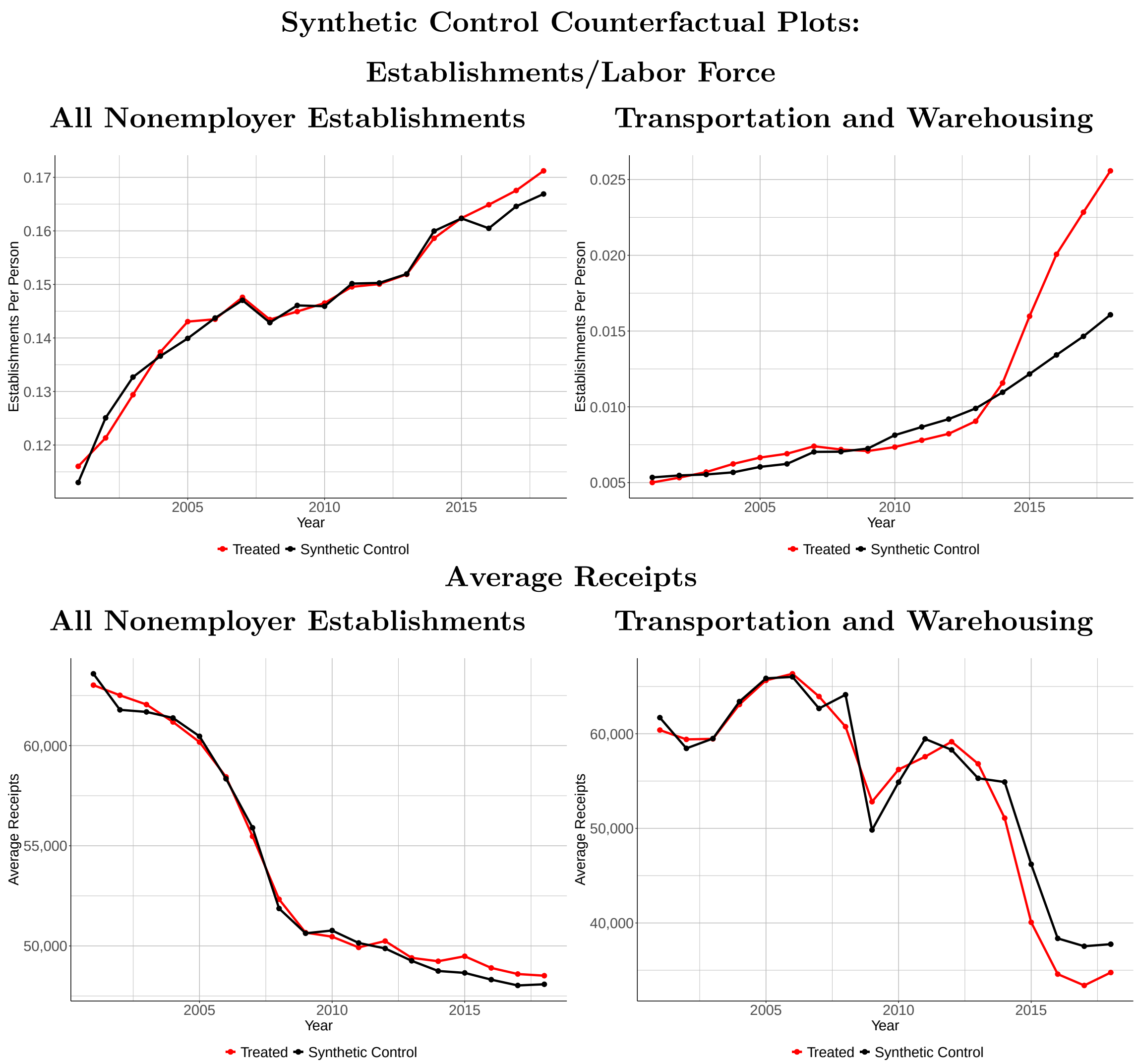

Figure A9. : These figures illustrate the treated and counterfactual group trends in e_{cit} and r_{cit} for both transportation and warehousing services and all nonemployer establishments.

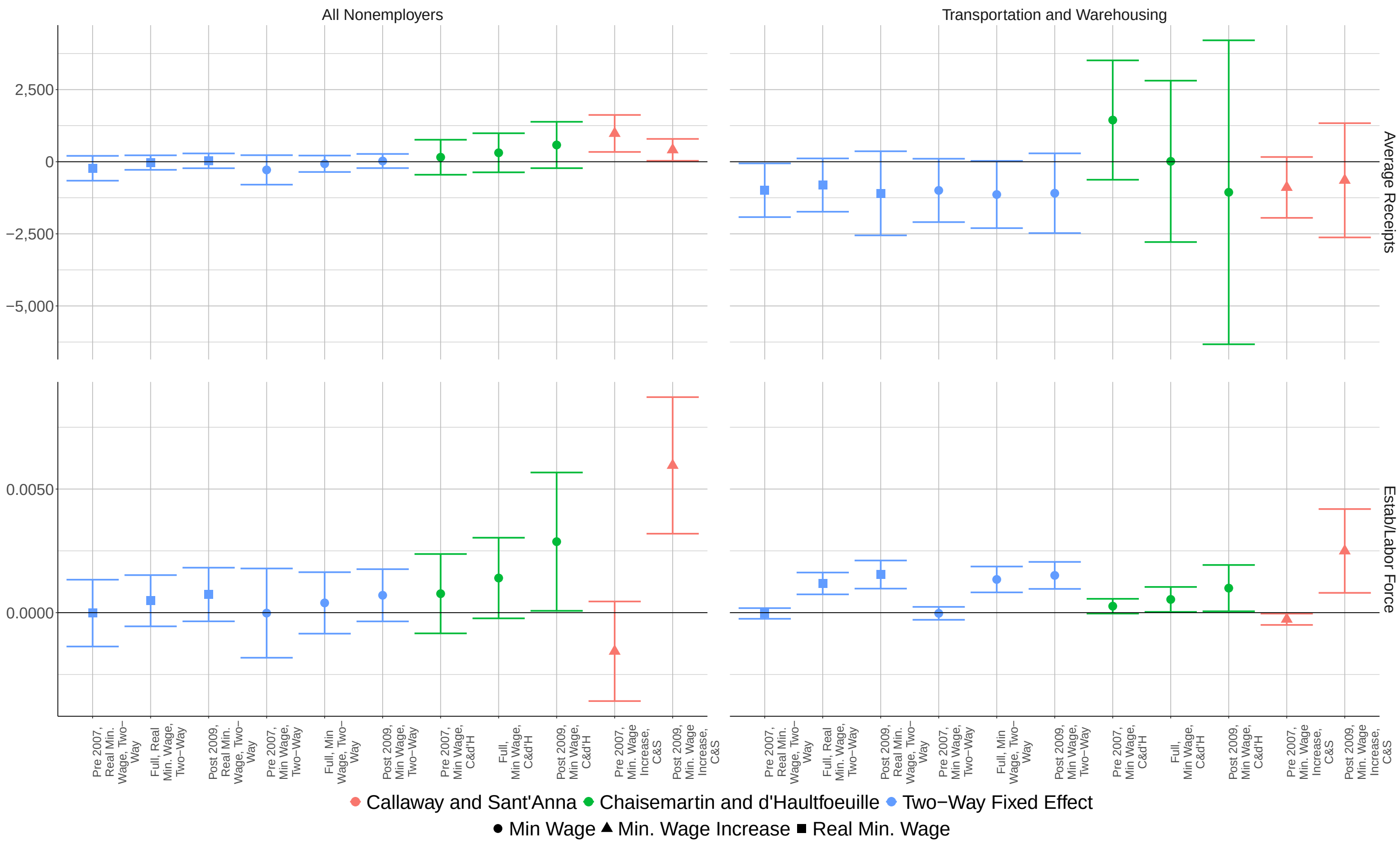

Figure A10. : Comparison between two-way fixed effect models with the treatment being the real minimum wage and the non-inflation adjusted minimum wage, the de Chaisemartin and d'Haultfoeuille (2019) DIDM with the non-inflation adjusted minimum wage, and the Callaway and Sant'Anna (2019) method on the first minimum wage increase in the respective time periods.

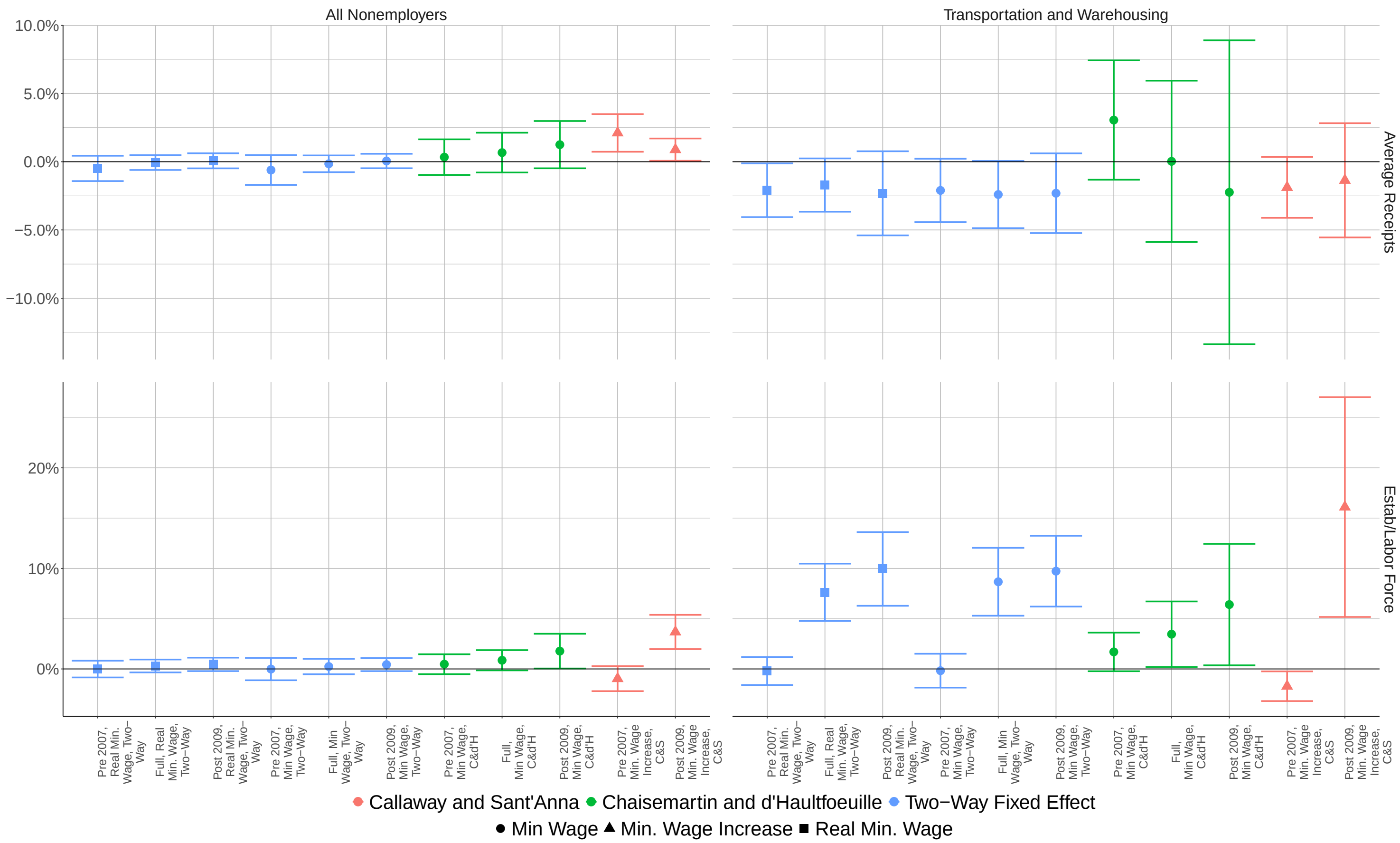

Figure A11. : Comparison between two-way fixed effect models with the treatment being the real minimum wage and the non-inflation adjusted minimum wage, the de Chaisemartin and d'Haultfoeuille (2019) DIDM with the non-inflation adjusted minimum wage, and the Callaway and Sant'Anna (2019) method on the first minimum wage increase in the respective time periods.