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. Using 2000-2018 county level data on nonemployer establishments, I identify differing effects by labor market competitiveness and the availability of the online gig economy. Using two-way fixed effect models and generalized synthetic control designs, I find that increases in the minimum wage produce positive effects on the extensive margin, through increased participation in exempt work among competitive counties with low barrier marketplaces. Less competitive counties experience a reduction in the supply of exempt labor on the intensive margin. Both of these effects are driven by the expansion of the online gig economy, measured by the geographic rollout of Uber. I estimate that an increase in the federal minimum wage to $10, $13, and $15 dollars would result in an additional 113,856 (0.4%), 650,287 (2.5%), and 1,007,907 (3.9%) transportation and warehousing services, respectively.

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Introduction

While a robust literature exists on the effects of minimum wages, work exempted from the Fair Labor standards Act (FLSA), and exempt from minimum wages, has not been the focus. Due to the nature of exempted work, it is often assumed that its exclusion or inclusion will not bias results of minimum wage analyses.[1] 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 in the workplace, miss-classification, and labor market protections for nonstandard work arrangements, 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 if this effect varies across more or less competitive labor markets and the availability of low-barrier marketplaces associated 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 inter-

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[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.

nationally,[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). 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).

Unfortunately, little can be said on how valid theoretical and empirical findings of the minimum wage literature are to the exempt labor market. While the barriers to comparing traditional self-employment and hourly W-2 work are clear, independent contracting also presents hurdles to generalization. Independent contractors and employees within the same firm can differ substantially in access to labor protections and fringe benefits like health insurance and retirement contributions (Harris and Krueger, 2015; Hyman, 2018), both of which may interact with minimum wage increases. A growing interest has been shown at the local, state and federal level in the regulation of independent contracting work and online gig workers.[3] This interest has been primarily on the topics of gaps in the protections supplied to independent contractors due to their 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).

[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.

[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.

The differences in both the type of work and policy environment of employees and independent contractors create substantial hurdles to generalizing findings from the nonexempt market to the exempt market. 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, it is possible that changes to the minimum wage will impact both hiring and job seeking in the exempt labor market.

I use data on nonemployer establishments to test the degree to which changes in the minimum wage impact 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, I construct a measure of the labor market competitiveness to test for differences in effect across more and less competitive counties. I also use Uber deployment at the county level to test how the effect may vary 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 changes in the minimum wage relate to the exempt market by using a two-way fixed effect model in aggregate, and at the industry level, and a two-way fixed effect first difference model when comparing traditional exempt work to the online gig economy. I support these findings using a generalized synthetic control design on local minimum wage changes.

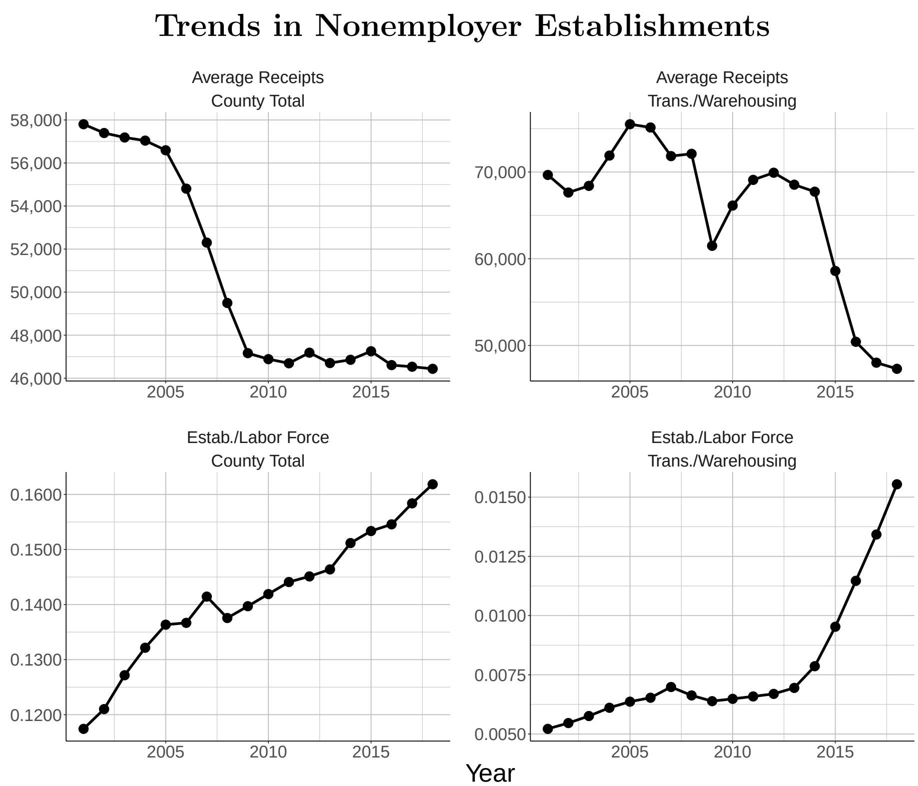

Figure 1. : These figures show the trend in Nonemployer establishments for the aggregated total of all nonemployer establishments on the left and for transportation and warehousing services (NAICS 48-49) on the right.

I find that increases in the minimum wage lead to heterogeneous effects across both the competitiveness of labor markets and in relation to the availability of Uber. Among transportation and warehousing services, competitive labor markets hold a significant positive relationship between the participation in exempt work and changes in the minimum wage. Less competitive markets hold a significant negative relationship between the average receipts of establishments and changes in the minimum wage. These findings are most pronounced following the availability of the Uber marketplace. It is likely that the availability of the Uber marketplace is acting as both an indicator for online gig work among drivers and the spread of gig work generally, as discussed in the results section of this analysis. Due to the relative size of transportation and warehousing services as a share of exempt work, these findings are less pronounced among all nonemployer establishments.

The heterogeneity in effect size and direction across counties and the availability of Uber lends support for the literature on variation in the competitiveness of local labor markets. The predominant positive effect of the minimum wage in competitive labor markets when interacted with Uber highlights the mechanism outlined in this paper, the transition between nonexempt and exempt marketplaces becoming easier as a result of low-barrier marketplaces. The presence of significant effects as well as differing effect estimates linked to Uber deployment is a justification of further research into the interaction between the exempt and nonexempt labor market, and the policies that divide the two.

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 A1 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 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).

[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.

[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).

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 changes to the minimum wage may vary in their effect across more or less competitive counties.

One of the difficulties of identifying a relationship between minimum wage changes

[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.

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.[9] 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 A2 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).

[9]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.

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.[10] 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 Uber is expanded to include the core-based statistical areas (CBSAs) in which a county is a member.[11] 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.

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.

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

[11] 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).

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 competitiveness.

I define a variable for 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:

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

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, I use a dummy 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, I construct a measure of the labor market competitiveness of each county, defined as the HHI quantile across the full sample of my data using the CBP. 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.[12] I assume 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.[13] 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 competitiveness.[14]. I include interaction effects between the HHI quantile and changes in 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.

[12]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.

[13]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.

[14]Results are robust to the use of raw HHI, as well as the logged HHI as shown in Tables A6 and A7 but quantiles are my preferred measure to account for the right tailed nature of the data. This can be seen in Figure A3

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

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

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

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

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. ΔM_{ct} identifies the change in 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.

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

[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 and urban bias due to demographic trends. Results are also presented with clustered standard errors at the county level in Tables A2 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 A4 and A5.

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 competitiveness 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 competitiveness.

Equation (2) identifies how changes in the minimum wage relate to the presence of a low-barrier marketplace, Uber. 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 competitiveness and the change in the minimum wage. By including an interaction effect, I am testing the degree to which more or less competitive 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. Competitive counties are expected to show a positive relationship between the minimum wage and the number of establishments per labor market participant. The effect 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 competitiveness and the low-barrier marketplace indicated by Uber. This equation will identify how the low-barrier hypothesis might vary across more or less competitive labor markets, after interacting labor market competitiveness with the presence or absence of Uber.

Previous work has been done to demonstrate that two-way fixed effect models may misestimate the counterfactual employment levels in minimum wage analyses (Allegretto et al., 2017; Cengiz et al., 2019). As such, I use a generalized synthetic control design on local minimum wage changes to support the conclusions drawn from state and local changes in general.[17] The incorporation of a generalized synthetic control follows 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. I also use the work of Gobillon and Magnac (2016) which outlines a method for the application of synthetic control designs for regional policy evaluation. I apply the generalized synthetic control methodology outlined by Bai (2009) and Xu (2017) to local minimum wage changes by defining the adoption of local minimum wage increases at the county or metropolitan level as the treatment. This creates a compatible design with the generalized synthetic control methodology and reduces overlap with previous state and federal minimum wage changes.

This generalized synthetic control is reported by matching in the pre-treatment

[17]Previously, versions of this analysis have also included an event study design but these have been removed following the results of Abraham and Sun (2018), which highlights the bias of event study designs when we expect variation in treatment timing across units.

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. Table A1 identifies which counties adopted local minimum wage changes and when they adopted them within this data set.

III. Results

Figure 2 describes the relationship of both e_{cit} and r_{cit} with the change in the real minimum wage, split between counties which have Uber active and those which do not. A positive relationship can be seen between e_{cit} and the 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

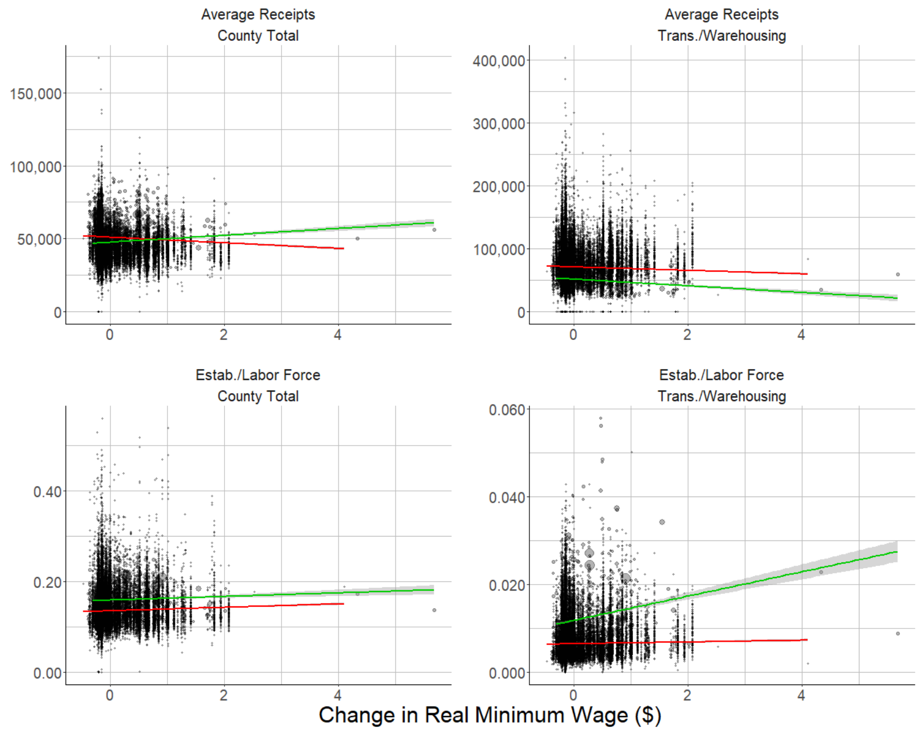

Figure 2. : These figures show the relationship between the average receipts of nonemployer establishments and the change in the real minimum wage, and the number of nonemployer establishments per member of the labor force and the change in the real minimum wage. Each dot is a county-year, scaled to represent the county labor force. The green line plots the linear relationship between the two variables for county-years where Uber is active, while the red line shows the relationship for county-years where Uber is not active.

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 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.[18]

Figure 3 demonstrates the relationship between the size of the county labor force and the HHI quantile, the measure of labor market competitiveness. We can see that counties with larger labor markets tend to have increased labor market competition as measured by the HHI, and that the largest share of the labor market nationally is operating in the lowest HHI quantiles.[19] This is important to consider when addressing the results of the regression analysis as a greater aggregate effect on the national composition of the labor market will occur among low HHI quantile counties.

I begin the analysis be exploring how changes in the minimum wage relate to the most likely competitive and low barrier marketplace in my sample, transportation and warehousing services. Table 1 presents the results using equations (1) through (4), for transportation and warehousing nonemployers. Column one in Table 1 high-

[18]It is clear from these figures just how uncommon changes in the real minimum wage greater than $2 are. The largest change in the 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 minimum wage changes greater than $2.50.

[19]This is further supported by the geographic plotting of HHI quantile and labor market size shown in Figure A4.

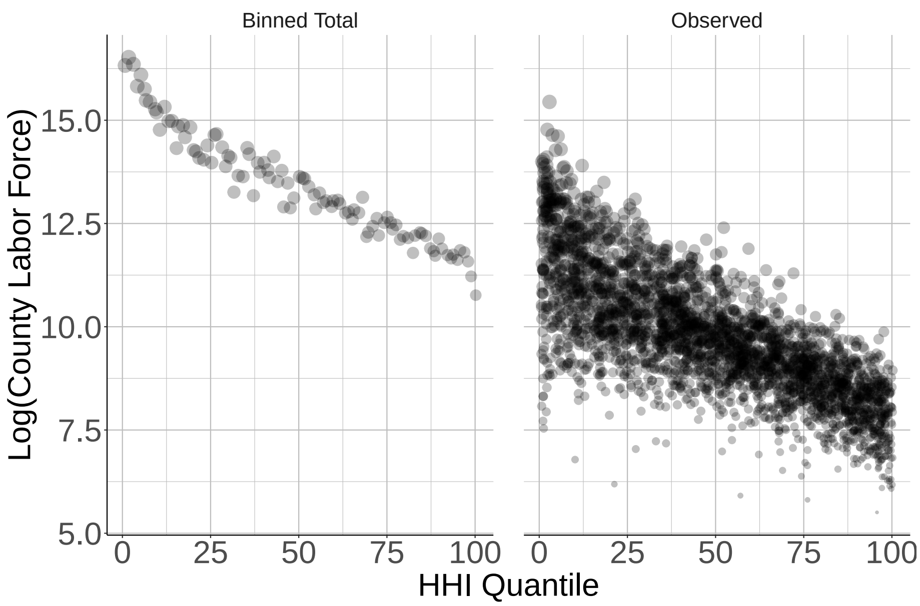

Figure 3. : This figure plots the relationship between the log of the county labor force and the HHI quantile for both the binned sum of the labor force and the observed labor force in each county in 2018.

Table 1—: Transportation and Warehousing

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Δ M	0.001***	−0.0002***	0.001***	−0.0002***
	(0.0002)	(0.0001)	(0.0003)	(0.0001)
Δ M∗Uber Active		0.002***		0.003**
		(0.001)		(0.001)
Δ M∗HHI Quantile			−0.00002**	0.00000
			(0.00001)	(0.00000)
Δ M∗HHI Quantile∗Uber Active				−0.0001*
				(0.00004)
Observations	54,054	54,054	54,054	54,054
R^2	0.809	0.816	0.810	0.841
Adjusted R^2	0.798	0.805	0.799	0.831
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Δ M	−1,207.5	−127.9	−1,445.4	−363.0
	(728.6)	(335.1)	(870.5)	(400.3)
Δ M∗Uber Active		−2,939.4		−1,597.7
		(1,780.1)		(1,844.4)
Δ M∗HHI Quantile			16.9	13.2
			(14.8)	(9.1)
Δ M∗HHI Quantile∗Uber Active				−121.0**
				(47.5)
Observations	54,054	54,054	54,054	54,054
R^2	0.823	0.824	0.823	0.825
Adjusted R^2	0.813	0.813	0.813	0.815
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	

lights that the aggregate effect of changes to the minimum wage is significant for e_{cit} and insignificant for r_{cit}. A \$1 increase in the minimum wage translates to significant 0.001 increase in the number of establishments per member of the labor force and an insignificant decrease in the average receipts of nonemployer establishments by \$1,207.50. This implies that while a significant increase in the propensity to engage in exempt work is occurring among transportation and warehousing services, it is not significantly impacting the average receipts taken in by exempt establishments.

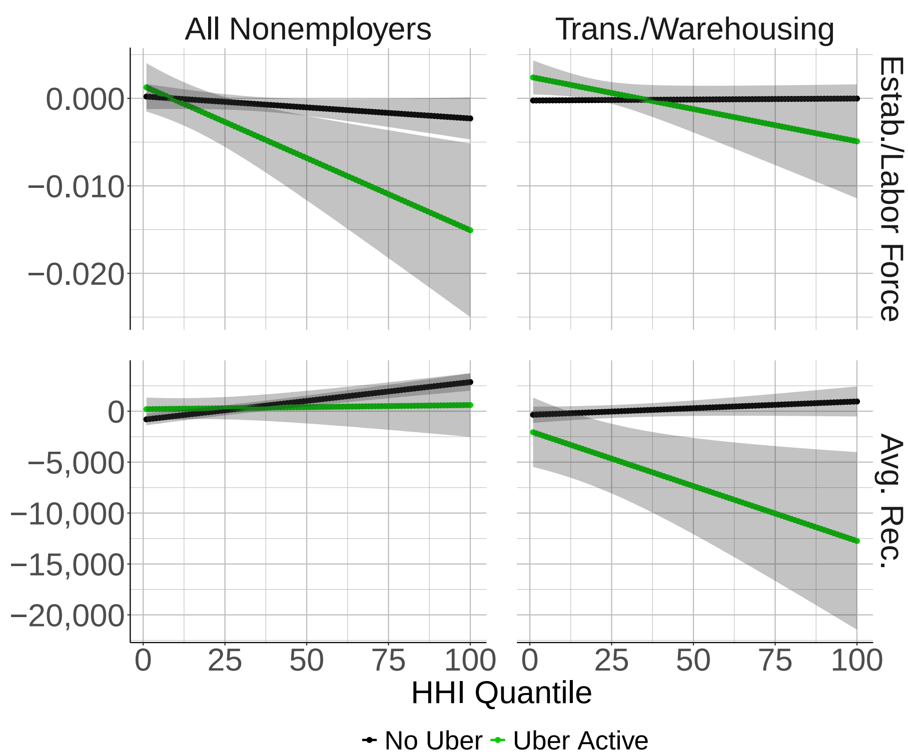

Figure 4. : This figure plots the marginal effect of a \$1 increase in the minimum wage across HHI quantiles and counties with and without Uber active using column four from Tables 1 and 2.

Column two shows that when applying an Uber interaction effect, the effect of the minimum wage on e_{cit} is positive in the low-barrier marketplace, but negative without it, and statistically significant for both. While the relationship is insignificant for r_{cit}, the difference in effect sizes are similar to what could be expected, with the low barrier marketplace having a substantially larger effect, as new entrants find it easier to enter, bringing the average receipts down.

When utilizing the measure of labor market competitiveness, in column three, the minimum wage is shown to have significant differences in effect across more and less competitive counties in relation to e_{cit}. The effect of changes in the minimum wage is positively related to e_{cit} in highly competitive labor markets, but as market competition decreases, so does the relationship between ΔM_{ct} and e_{cit}. The effect on r_{cit} in column three is not significant, but indicates a tendency for less competitive labor markets to smaller effects on average receipts than more competitive labor markets. Columns one, two, and three all imply that effects on the extensive margin are more easily observed than the intensive margin given the data available in the NES. This aligns with the descriptive results in Figure 2.

In column four, Uber being active is interacted with labor market competitiveness and I find evidence that the bulk of the positive effect on e_{cit} comes from competitive counties where Uber is active. Less competitive labor markets and markets where Uber is not active show no significant effect on the propensity to engage in exempted work. This follows the results of the first three columns. In contrast to this, the relationship between ΔM_{ct} and r_{cit} shows a significant difference when including the interaction between Uber being active and labor market competitiveness. I find that in low competition labor markets, where Uber is active, there is a significant reduction in the average receipts of nonemployer establishments. This, paired with the lack of a significant negative effect on the intensive margin in competitive markets, implies that increases in the minimum wage in less competitive markets results in a shift away from labor in the exempt marketplace. Paired with the lack of a significant effect on the extensive margin, this is likely a reduction in hours worked in the exempt market. The marginal effect of a $1 increase in the minimum wage are plotted in Figure 4 and contrasted between transportation and warehousing services and the aggregate of all nonemployer establishments.

Table 2—: All Nonemployer Establishments

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Δ M	0.0002	−0.0002	0.001	0.0002
	(0.0004)	(0.0005)	(0.001)	(0.001)
Δ M∗Uber Active		0.001		0.001
		(0.002)		(0.002)
Δ M∗HHI Quantile			−0.00004***	−0.00003
			(0.00001)	(0.00002)
Δ M∗HHI Quantile∗Uber Active				−0.0001**
				(0.0001)
Observations	54,144	54,144	54,144	54,144
R^2	0.927	0.927	0.927	0.930
Adjusted R^2	0.923	0.923	0.923	0.925
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Δ M	−80.0	−171.9	−491.7**	−835.1***
	(172.1)	(258.5)	(193.3)	(289.3)
Δ M∗Uber Active		250.2		1,028.5
		(739.0)		(799.1)
Δ M∗HHI Quantile			29.2***	37.0***
			(4.9)	(4.9)
Δ M∗HHI Quantile∗Uber Active				−32.8*
				(18.6)
Observations	54,144	54,144	54,144	54,144
R^2	0.916	0.916	0.916	0.917
Adjusted R^2	0.911	0.911	0.911	0.913
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		

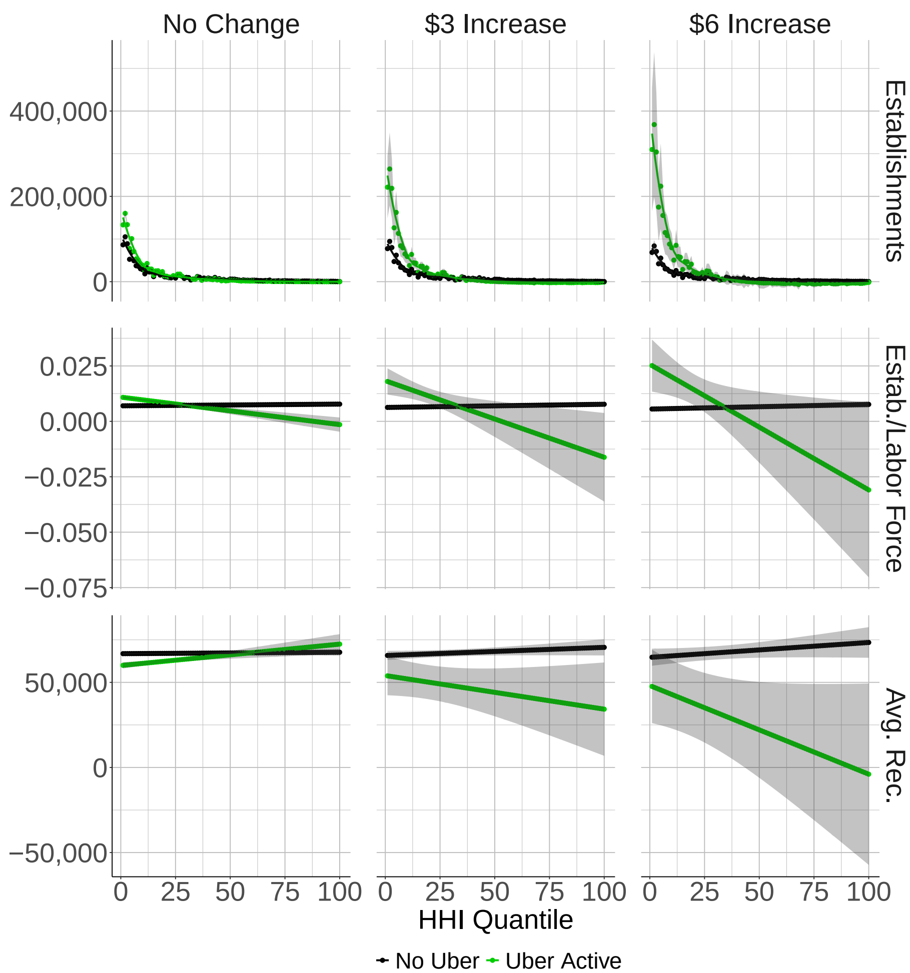

Figure 5. : This figure plots the predicted number of nonemployer establishments, establishments per member of the labor force, and the average receipts across HHI quantile and if Uber is or is not active for transportation and warehousing services using column four of Table 1.

Due to the significant effects identified among transportation and warehousing services, but the relatively small share of the labor market that this industry represent, I contrast these results with the aggregate of all nonemployer establishments. Table 2 presents the same results as Table 1 but for sum of all NAICS industries, including transportation and warehousing services. Since this is an aggregation, a direct comparison between the coefficient sizes can be made across the tables. Across all nonemployer establishments, I find that the relationship between ΔM_{ct} and e_{cit} is positive, but insignificant, and the relationship between ΔM_{ct} and r_{cit} is negative, but insignificant, in aggregate. I also plot column four from this table in Figure 4 and it is clear that while the relationship between minimum wage and the propensity to engage in exempt work is negative among counties with Uber active, it is only significant among smaller and less competitive labor markets. It is not significantly different among counties where Uber is not active. In contrast with transportation and warehousing services, Uber being active or not does not significantly impact the average receipts of establishments. While increases in the minimum wage are shown to decrease the average receipts in competitive markets, they increase receipts among less competitive markets. This could be reflecting an increase in economic activity resulting from the minimum wage increase or a selection effect regarding more active establishments remaining in the market and less active leaving, since their is a slight reduction in e_{cit} among less competitive counties where Uber is not active.

In total, it appears that the positive effect between ΔM_{ct} and e_{cit} observed among transportation and warehousing services accounts for the majority of any positive effect identified across all nonemployer establishments, but the market is too small to overcome the noise in aggregate. In fact, it appears that across all nonemployer establishments a small negative relationship exists among less competitive counties, which aligns with the findings of Blau (1987) and Bruce and Mohsin (2006). While the difference in the measured effect on average receipts between the aggregate total of all nonemployer establishments and transportation and warehousing services is more easily explained by the small share of work in this industry, the significant negative relationship observed ΔM_{ct} and e_{cit} is less clear. It is possible that if Uber is acting as an indicator for other types of work in the online gig economy, then individual workers leaving due to the rising minimum wage, will appear to be leaving "Uber" in greater numbers then would be observed in just transportation and warehousing services.

When considering the aggregate effects of changes in the minimum wage, the relationship between HHI and the size of the labor market is key. Given the spread of Uber and the increased size of the labor market among lower HHI quantiles, the effect of e_{cit} and r_{cit} are most pronounced among competitive urban counties where the online gig economy is active. While the shift in average receipts is relatively easy to understand as it relates to the earnings among those participating in exempt work, it is more difficult to visualize the shift in the number of establishments per member of the labor market. I use the HHI quantiles to create bins and calculate the average size of the labor market in each HHI quantile across the sample. I then use these labor market bins to predict the number of nonemployer establishments in each bin given different changes in the minimum wage. Since a push to a \$15 dollar federal minimum wage falls outside of the range of observed changes, I estimate the effect of roughly the maximum increase in the minimum wage observed in my sample, and use this as an approximation for making the change to a \$15 minimum wage.[20] Figures 5 and 6 plot the predicted values of the number of establishments as well as e_{cit}, and r_{cit} for three different situations, no change in the minimum wage, a \$3

[20]An increase of this size is a clear outlier within the data, as the largest single year increase in the real minimum wage is in King County, WA in 2014 at \$5.68. This speaks to the significance of an single year increase to \$15.

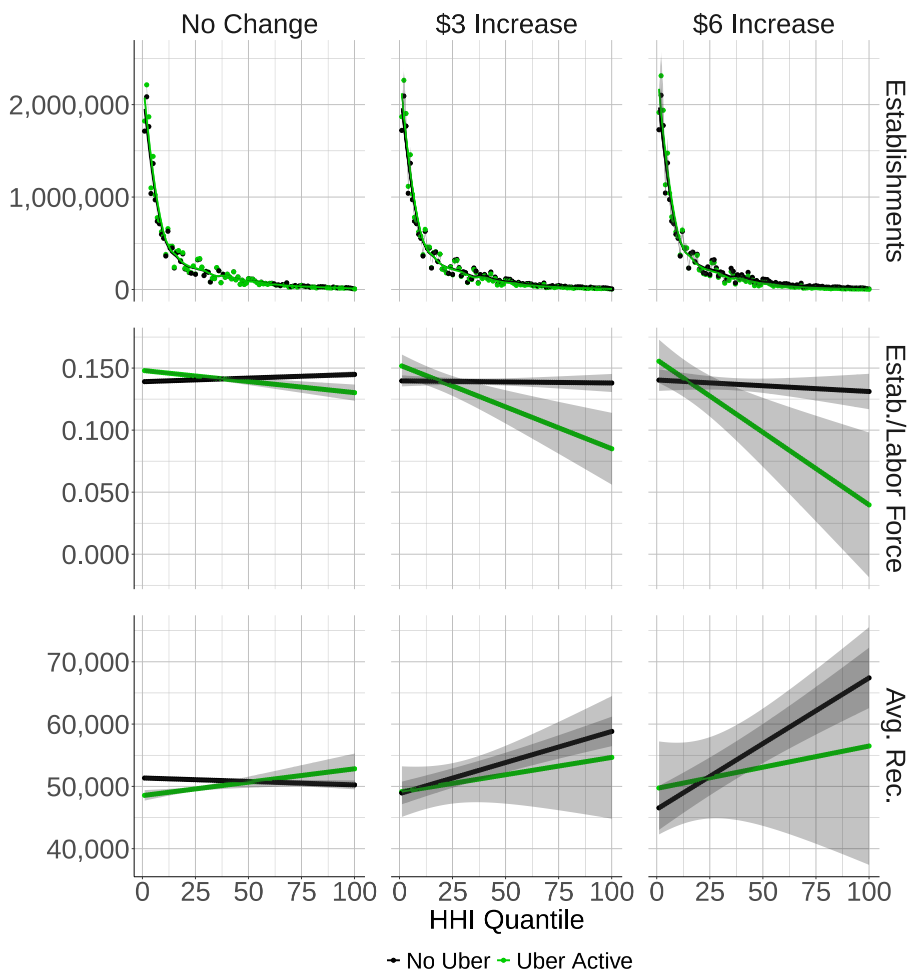

Figure 6. : This figure plots the predicted number of nonemployer establishments, establishments per member of the labor force, and the average receipts across HHI quantile and if Uber is or is not active for all nonemployer establishments using column four of Table 2.

increase, and a \$6 increase.

What these figures miss is the relative starting minimum wage level is not consistent across counties, so changes in the federal minimum wage will impact counties differently. As a result, I calculate the change in the minimum wage for each county given an increase in the federal minimum wage to \$10, \$13, and \$15. Using the observed HHI quantile for a county in 2018, and whether or not Uber is active in the county, I create national predictions for the change in the number of nonemployer establishments in transportation and warehousing services. I estimate that increasing the federal minimum wage to each of these three values would result in an additional 113,856 establishments, 650,287 establishments, and 1,007,907 establishments, respectively. These translate to a 4.6%, 26.4%, and 40.9% increase in the stock of transportation and warehousing services compared to the observed count in 2018. Compared to the stock of all nonemployer establishments these increases would represent a 0.4%, 2.5%, and 3.9% increase.

These findings support the conclusion that the expansion of the online gig economy has resulted in a reduction to barriers to entry and exit, and induced more movement into and out of the exempt labor market. This is a relatively recent shift in the behavior of both the exempt and nonexempt labor market, and the effect would be likely to grow as these work arrangements become more prevalent. The movement into and out of the exempt labor market is likely occurring among secondary or tertiary sources of income. This is because it appears to be substituted away from on the intensive margin in less competitive labor markets, where negative employment shocks are less likely.

In total, these findings show an increase on the extensive margin among more competitive counties, with larger labor forces, and where the online gig economy is active and able to take advantage of large consumer networks. The positive extensive marginal effect does not significantly impact the average receipts taken in though, which is in contrast to the anticipated effect. This is best explained by an increased willingness to purchase services in the exempt labor market, supplied through the online gig economy. While Uber being active has a level effect on the average receipts among competitive counties, the increased number of nonemployer establishments appear to not crowd each other out. 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.

Less competitive 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. I also find a reduction in the average receipts of those establishments which remain. These two results paired together signal either a reduction in the demand for exempt labor or a reduction in the supply on the extensive margin in general, and the intensive margin among transportation and warehousing services. 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 competitive labor markets are likely not experiencing a downward 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, and more a reduction following an income effect.

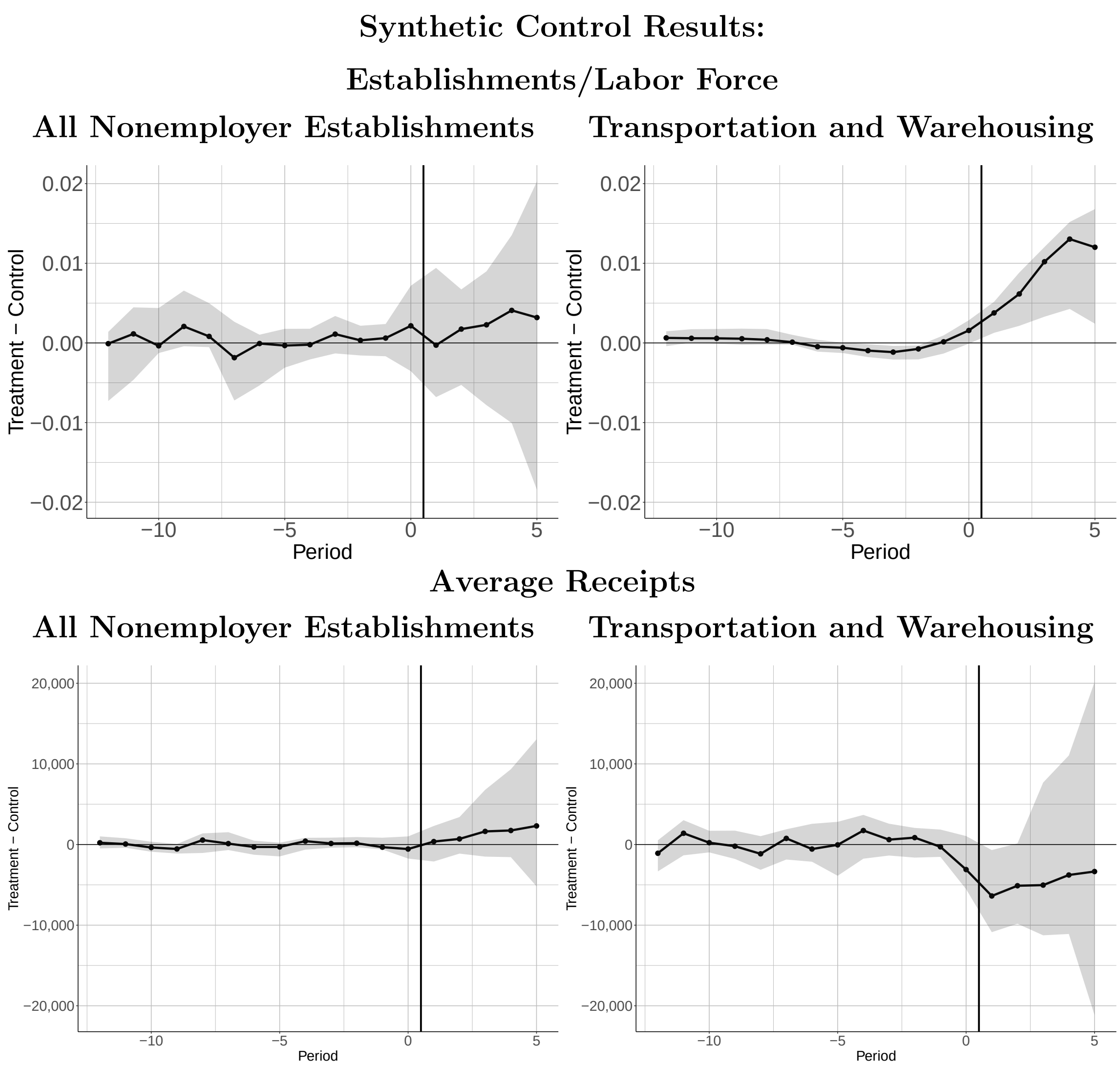

Figure 7. : These figures illustrate the average effect of the treatment on the treated (ATT) for e_{cit} and r_{cit} for both transportation and warehousing services and all nonemployer establishments.

IV. Robustness

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.[21] The use of the generalized synthetic control is to resolve any bias of 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 for a slightly different treatment. In this case, concerns may exist regarding the generalizability of local minimum wage changes to state and federal changes.

Figure 7 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. Both of these results are in line with the two-way fixed effect model.

The results of the synthetic control are not able to show any interaction effect between Uber being active or labor market competitiveness, but they do illustrate

[21]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.

the lagged effect of increases in the minimum wage. We can see that the effect of the minimum wage continues after the first year of treatment in Figure 7. These results support the identified effects of the two-way fixed effects approach.

V. 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) the competitiveness of local labor markets do significantly impact the effect of the minimum wage, and (2) low-barrier marketplaces and the development of the online gig economy increase this effect substantially. I find evidence showing positive effects on engagement in exempt work in competitive counties, and negative effects on the average receipts of establishments in less competitive counties. I estimate that a change in the federal minimum wage to \$10, \$13, and \$15 would result in an additional 113,856, 650,287, and 1,007,907 establishments, respectively. This increased number of establishments would be located among population dense competitive counties, while less competitive counties would likely see a reduction in the supply of labor to the exempt market, as low wage workers experience the benefits of higher minimum wages.

With the identification of significant effects on exempt labor, and differences in this effect across industries, 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 and 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, as well as leisure. 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 competitive 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. Tables

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

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Δ M	0.0007***	−0.0002***	0.0010***	−0.0002***
	(0.0002)	(0.0001)	(0.0003)	(0.0001)
Δ M:Uber Active		0.0025***		0.0027***
		(0.0007)		(0.0010)
Δ M:HHI Quantile:Uber Active				−0.0001**
				(0.00004)
Δ M:HHI Quantile			−0.00002***	0.000002*
			(0.00001)	(0.000001)
Observations	54,054	54,054	54,054	54,054
R^2	0.8092	0.8155	0.8100	0.8406
Adjusted R^2	0.7979	0.8046	0.7987	0.8311
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Δ M	−1,207.533***	−127.885	−1,445.437***	−363.034
	(299.801)	(195.043)	(420.331)	(259.630)
Δ M:Uber Active		−2,939.385***		−1,597.697
		(1,122.582)		(1,274.289)
Δ M:HHI Quantile:Uber Active				−120.986**
				(51.272)
Δ M:HHI Quantile			16.870*	13.218**
			(10.110)	(6.442)
Observations	54,054	54,054	54,054	54,054
R^2	0.823	0.824	0.823	0.825
Adjusted R^2	0.813	0.813	0.813	0.815
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 A3—: All Nonemployer Establishments, clustered at the county level

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Δ M	0.0002	−0.0002	0.0008	0.0002
	(0.0004)	(0.0003)	(0.0005)	(0.0005)
Δ M:Uber Active		0.0011		0.0012
		(0.0013)		(0.0016)
Δ M:HHI Quantile			-0.00004^{***}	-0.00003^{**}
			(0.00001)	(0.00001)
Δ M:HHI Quantile:Uber Active				-0.0001^{**}
				(0.0001)
Observations	54,144	54,144	54,144	54,144
R^2	0.927	0.927	0.927	0.930
Adjusted R^2	0.923	0.923	0.923	0.925
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Δ M	−80.020	−171.928	-491.712^{***}	-835.069^{***}
	(76.096)	(107.018)	(132.058)	(153.790)
Δ M:Uber Active		250.216		$1{,}028.457^{***}$
		(324.846)		(398.055)
Δ M:HHI Quantile			29.221^{***}	36.977^{***}
			(3.692)	(3.635)
Δ M:HHI Quantile:Uber Active				-32.821^{**}
				(13.547)
Observations	54,144	54,144	54,144	54,144
R^2	0.916	0.916	0.916	0.917
Adjusted R^2	0.911	0.911	0.911	0.913
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 A4—: Transportation and Warehousing Services, clustered at the state level with state fixed effects

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Δ M	0.0008***	−0.0003*	0.0013***	−0.0003*
	(0.0003)	(0.0002)	(0.0004)	(0.0002)
Δ M:Uber Active		0.0030***		0.0035**
		(0.0010)		(0.0013)
Δ M:HHI Quantile:Uber Active				−0.0001**
				(0.0001)
Δ M:HHI Quantile			−0.00004***	−0.000001
			(0.00001)	(0.000002)
Observations	54,054	54,054	54,054	54,054
R^2	0.3969	0.4064	0.3993	0.4553
Adjusted R^2	0.3961	0.4056	0.3985	0.4545
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Δ M	−1,583.390*	−148.978	−2,427.139**	−807.580
	(869.684)	(406.037)	(1,201.870)	(525.155)
Δ M:Uber Active		−3,856.961*		−3,097.138
		(1,939.868)		(2,244.373)
Δ M:HHI Quantile:Uber Active				13.275
				(70.223)
Δ M:HHI Quantile			60.297**	36.769***
			(28.626)	(13.696)
Observations	54,054	54,054	54,054	54,054
R^2	0.481	0.482	0.481	0.485
Adjusted R^2	0.480	0.482	0.481	0.484
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 A5—: All Nonemployer Establishments, clustered at the state level with state fixed effects

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(1)	(2)	(3)	(4)
Δ M	0.0004	−0.0005	0.0019*	0.0004
	(0.0008)	(0.0009)	(0.0011)	(0.0011)
Δ M:Uber Active		0.0025		0.0033
		(0.0024)		(0.0030)
Δ M:HHI Quantile:Uber Active				−0.0004*
				(0.0002)
Δ M:HHI Quantile			−0.0001**	−0.0001**
			(0.00004)	(0.00003)
Observations	54,144	54,144	54,144	54,144
R^2	0.3810	0.3812	0.3815	0.3907
Adjusted R^2	0.3802	0.3803	0.3807	0.3899
	Average Receipts, r_{cit}			
	(1)	(2)	(3)	(4)
Δ M	−20.394	−14.925	−217.846	−462.999
	(196.203)	(256.888)	(241.271)	(325.874)
Δ M:Uber Active		−14.706		968.764
		(668.740)		(708.900)
Δ M:HHI Quantile:Uber Active				−79.128***
				(20.732)
Δ M:HHI Quantile			14.124*	24.776***
			(7.930)	(8.120)
Observations	54,144	54,144	54,144	54,144
R^2	0.482	0.482	0.482	0.483
Adjusted R^2	0.481	0.481	0.481	0.482
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 A6—: Transportation and Warehousing Services, Comparing measures of HHI

	Dependent variable:			
	Establishments/Labor Force, e_{cit}			
	(4)	(4)	(4)	(4)
Δ M	−0.0002***	−0.0005***	−0.0001**	−0.0024**
	(0.0001)	(0.0002)	(0.00004)	(0.0012)
Δ M:Uber Active	0.0027***	0.0065	−0.00002	0.0240
	(0.0010)	(0.0041)	(0.0012)	(0.0258)
Δ M:HHI Quantile	0.000002*			
	(0.000001)			
Δ M:HHI		0.000001**		
		(0.000000)		
Δ M:HHI Normalized			0.0001**	
			(0.0001)	
Δ M:Log(HHI)				0.0003*
				(0.0002)
Δ M:HHI Quantile:Uber Active	−0.0001**			
	(0.00004)			
Δ M:HHI :Uber Active		−0.00001		
		(0.00001)		
Δ M:HHI Normalized :Uber Active			−0.0020	
			(0.0016)	
Δ M:Log(HHI):Uber Active				−0.0035
				(0.0040)
Observations	54,054	54,054	54,054	54,054
R^2	0.8406	0.8410	0.8410	0.8440
Adjusted R^2	0.8311	0.8316	0.8316	0.8348
	Average Receipts, r_{cit}			
Δ M	−363.034	−1,687.866	364.725	−11,113.580
	(400.314)	(1,013.774)	(359.178)	(7,057.575)
Δ M:Uber Active	−1,597.697	11,998.240*	−9,536.456***	108,548.300***
	(1,844.419)	(5,993.218)	(2,324.840)	(37,393.190)
Δ M:HHI Quantile	13.218			
	(9.080)			
Δ M:HHI		2.527*		
		(1.409)		
Δ M:HHI Normalized			637.460*	
			(355.430)	
Δ M:Log(HHI)				1,713.541
				(1,085.335)
Δ M:HHI Quantile:Uber Active	−120.986**			
	(47.533)			
Δ M:HHI :Uber Active		−26.510***		
		(9.361)		
Δ M:HHI Normalized :Uber Active			−6,687.894***	
			(2,361.613)	
Δ M:Log(HHI):Uber Active				−17,636.480***
				(5,807.107)
Observations	54,054	54,054	54,054	54,054
R^2	0.825	0.825	0.825	0.825
Adjusted R^2	0.815	0.814	0.814	0.814
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)
Δ M	0.0002	0.0015	−0.0008***	0.0152
	(0.0005)	(0.0015)	(0.0003)	(0.0113)
Δ M:Uber Active	0.0012	0.0037	−0.0015	−0.0049
	(0.0016)	(0.0076)	(0.0028)	(0.0522)
Δ M:HHI Quantile	−0.00003**			
	(0.00001)			
Δ M:HHI		−0.000003		
		(0.000002)		
Δ M:HHI Normalized			−0.0007	
			(0.0005)	
Δ M:Log(HHI)				−0.0024
				(0.0017)
Δ M:HHI Quantile:Uber Active	−0.0001**			
	(0.0001)			
Δ M:HHI :Uber Active		−0.00001		
		(0.00001)		
Δ M:HHI Normalized :Uber Active			−0.0017	
			(0.0033)	
Δ M:Log(HHI):Uber Active				0.0008
				(0.0082)
Observations	54,144	54,144	54,144	54,144
R^2	0.9296	0.9292	0.9292	0.9294
Adjusted R^2	0.9254	0.9250	0.9250	0.9252
	Average Receipts, r_{cit}			
Δ M	−835.069***	−3,744.014***	965.526***	−29,210.180***
	(289.284)	(597.044)	(259.907)	(4,354.495)
Δ M:Uber Active	1,028.457	5,135.696**	−1,352.904	40,954.180***
	(799.053)	(2,210.065)	(988.772)	(13,679.830)
Δ M:HHI Quantile	36.977***			
	(4.945)			
Δ M:HHI		5.784***		
		(0.779)		
Δ M:HHI Normalized			1,506.939***	
			(202.849)	
Δ M:Log(HHI)				4,529.313***
				(669.196)
Δ M:HHI Quantile:Uber Active	−32.821*			
	(18.566)			
Δ M:HHI :Uber Active		−7.969**		
		(3.435)		
Δ M:HHI Normalized :Uber Active			−2,076.195**	
			(894.952)	
Δ M:Log(HHI):Uber Active				−6,363.312***
				(2,133.241)
Observations	54,144	54,144	54,144	54,144
R^2	0.917	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	

A2. Figures

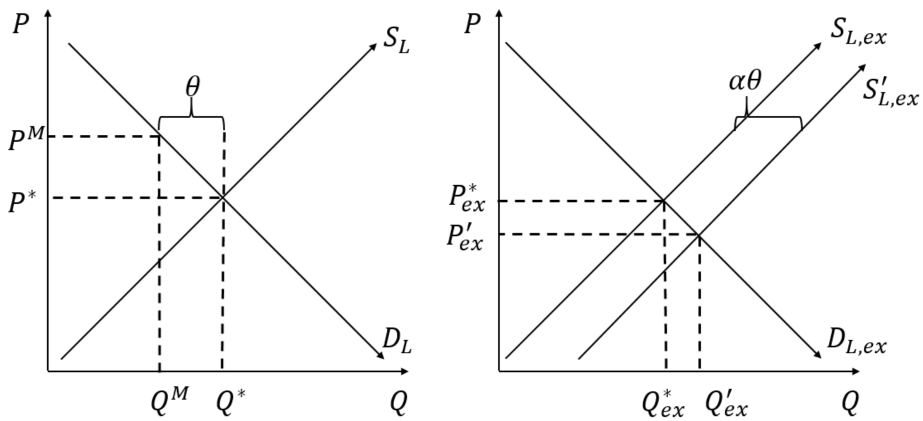


Figure A1. : An illustration of the competitive model of the minimum wage in the nonexempt, on the left, and exempt, on the right, labor market. If the minimum wage is set at level P^M, such that $P^M > P^*$, the quantity of labor purchased on the nonexempt labor market falls from Q^* to Q^M. This is 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 A2. : 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.

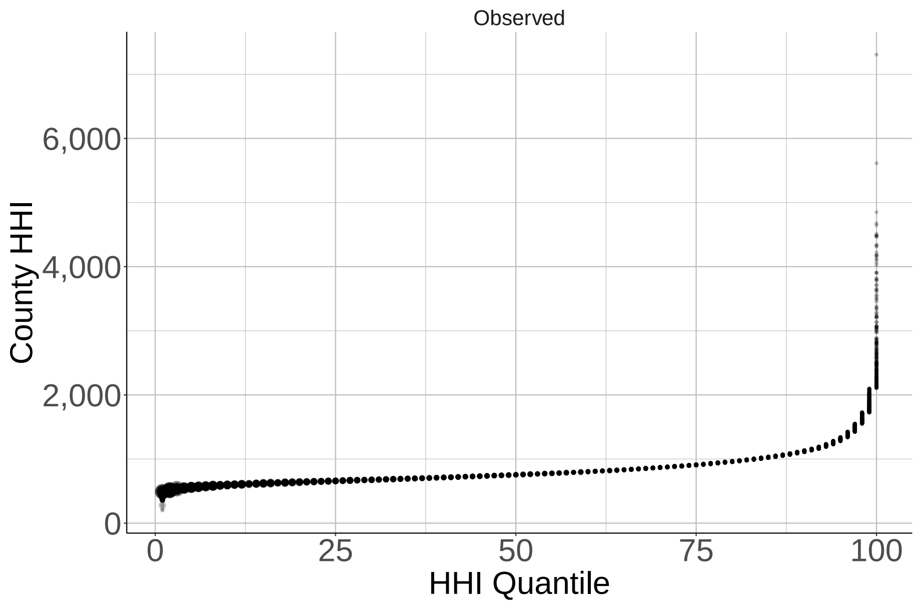
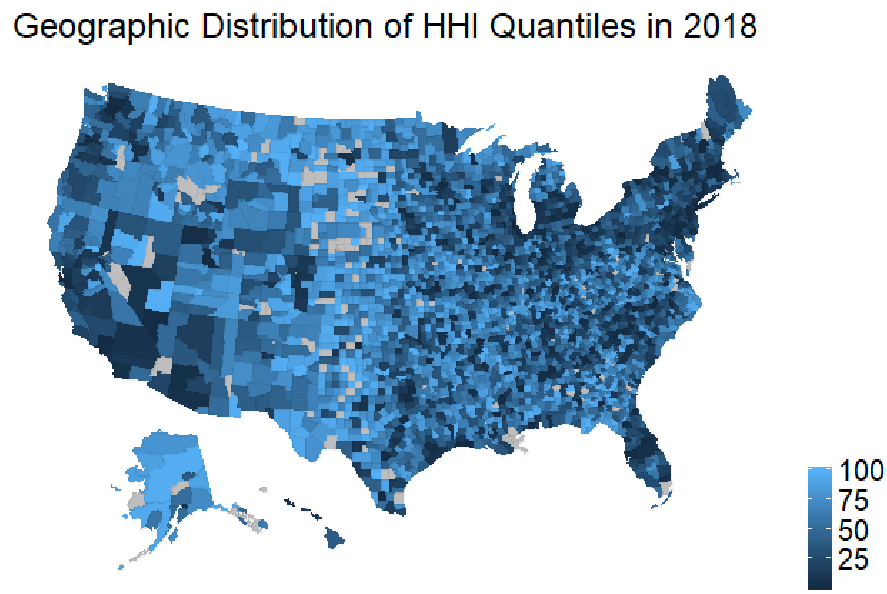


Figure A3. : This figure shows the distribution of HHI values as they are binned into 100 quantiles. The bulk of the quantile trend is linear with some extreme low HHI scores falling into the first quantile and extreme high falling into the last quantile. This highlights the advantage to using the quantile 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.



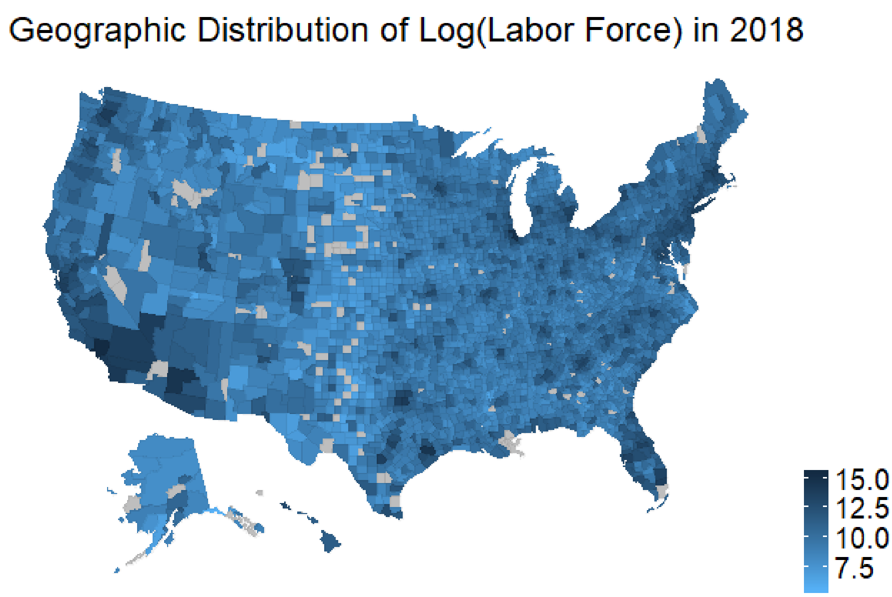


Figure A4. : The figures above depict the geographic distribution of HHI quantiles and the log of the county labor force in 2018. Counties which are not included in the sample are shown in grey.

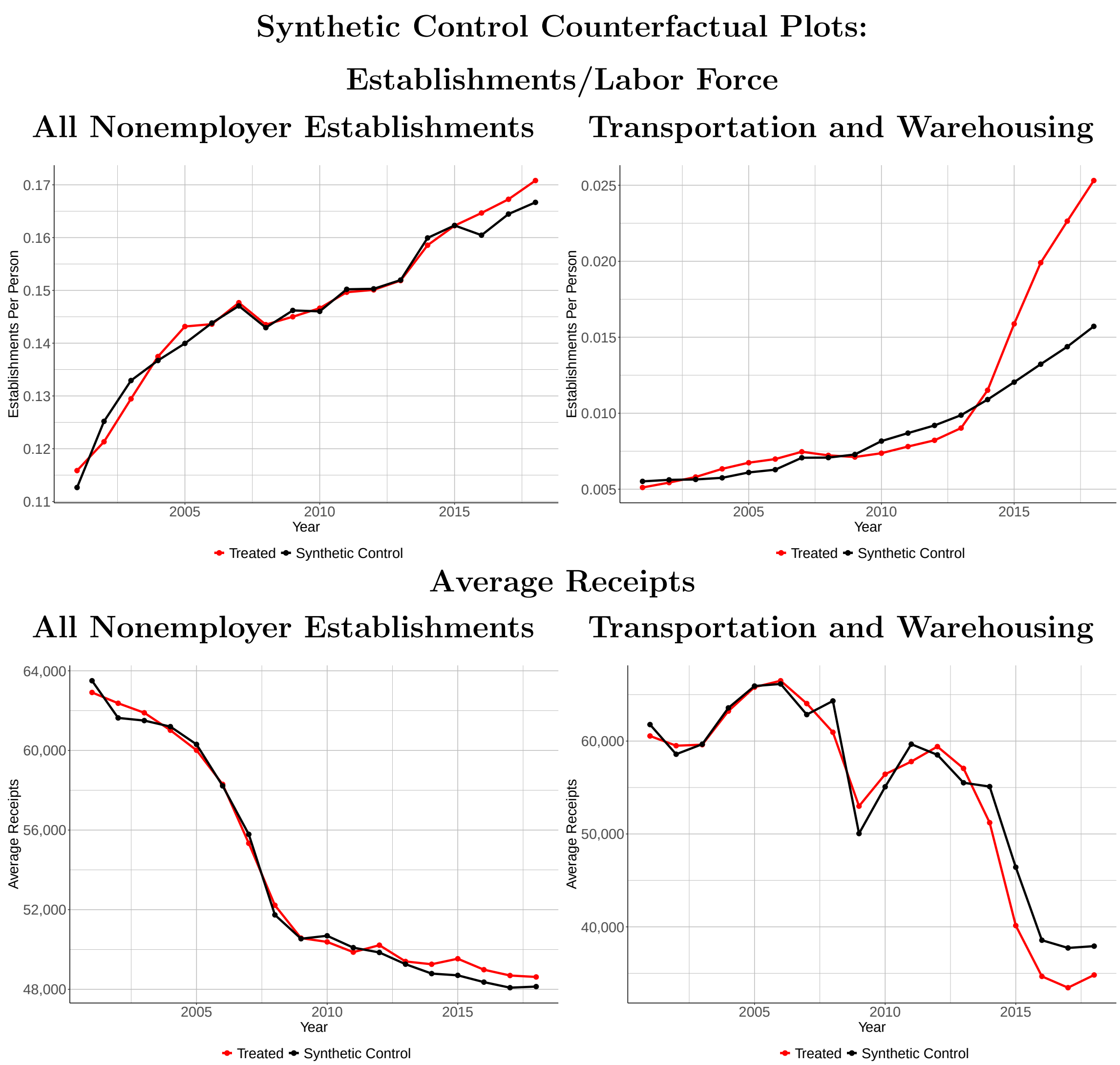


Figure A5. : These figures illustrate the treated and counterfactual group trends in e_{cit} and r_{cit} for both transportation and warehousing services and all nonemployer establishments.