City Limits: Exploring the relationship between employment and minimum wages using mobile-device location data

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Abstract

The last decade has seen noteworthy local policy decisions, especially a trend in the decentralization of wage determination. Considering that local policy changes are aimed at the local areas where boundaries are porous, there is a need for analyses that incorporate detailed and accurate geographic and time information. Using establishment locations and mobile-device location data, this study explores how the labor market responds to local minimum wage ordinances. I use a difference-in-differences approach to estimate the effect of changes in the minimum wage on the duration of visits at a location, which can be used as a proxy for employment. I find a decrease in employment by 4.5% when there is a 10% increase in the minimum wages and an increase in distance traveled from home by 1.5% when there is an increase in the minimum wage by 10%. The study further demonstrates that the local labor market, especially in the non-tradeable sector, is more responsive to changes in the local minimum wage than the state-bound minimum wage changes.(**JEL J2, J4, J6, J08, J61**)

Keywords— Minimum wage, Labor Market, Geographic Mobility, Mobile devices

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1 Introduction

In 2012, hundreds of fast-food workers walked out of their jobs in New York City demanding a higher minimum wage and started a worker's movement called "Fight for $15." More than 100 leading economists supported the movement for a gradual increase in the minimum wage to $15 at the federal level. They signed a letter in 2019 stating that the last decade has seen a wealth of rigorous academic research on the effect of minimum wages on employment, with the weight of evidence showing that previous, modest increases in the minimum wage had little or no negative effects on employment of low-wage workers[1].

However, Congress did not increase the minimum wage, citing, in part, a Congressional Budget Office forecast that an increase in the federal minimum wage would increase in the average income of low-wage workers, but also result in 1.3 million job losses. Nevertheless, since 2013, 50 cities and counties have chosen to enact their own local minimum wage ordinances with higher wages than the existing state or federal level, in some cases setting the minimum wage above $15. For instance, Hollywood, CA, increased its minimum wage to $17.64 in January 2022, which is around 140% more than the existing federal minimum wage of $7.25 and around 18% more than the existing California minimum wage of $15.

These large variations across sub-state jurisdictions have revived discussions among labor and urban economists about the potential effects of local minimum wages on economic activity. Facing no mobility cost and a large number of employers, in a competitive labor market, increasing the minimum wage leads to a (weakly) upward movement along the labor demand curve resulting in an excess supply of labor thus creating unemployment. On the other hand, the notion of monopsony power assumes the existence of a mobility cost and that individual firms, when presented with an adequate minimum wage increase, can counteract monopsonistic exploitation leading to downward movement along the labor demand curve and having no adverse consequences on employment (Azar et al., 2019; Bhaskar et al., 2002; Popp, 2021). This movement along the labor demand curve can be different for local minimum wage increases conditioned on mobility cost as compared to a state-wide or federal raise in the minimum wage. Workers may commute to/from the nearby areas for better employment opportunities and higher wages as the city boundaries are porous compared to state boundaries. Businesses

[1] https://www.epi.org/economists-in-support-of-15-by-2024/

may also choose to relocate a few miles outside the city boundaries or choose to reduce the number of employees or working hours. This may also be true for state-wide variations, but the impact might be larger for minimum wage changes that are restricted to local areas.

In this study, I use mobile device location data to explore the impact of local minimum wage variation on visits to business establishments [POIs/Places of interest]. Specifically, I ask: When a city enacts a minimum wage ordinance, are there changes in the number of visits to locations in the city? Are individuals more likely to stay longer or shorter at establishments located within cities that increase their minimum wage? Do census block groups with lower-median income or a higher number of low-education individuals respond to the increased wage differently? Further, is there a linkage between the long duration of visits and employment? Depending on the magnitude of these changes, labor market distortions created by the variations in minimum wage could be different. If geographical mobility allows people to arbitrage the gains from the variation in the minimum wage, the estimated effect using the contiguous regions as comparison groups could be upward biased if workers are traveling inward. Prior literature (Enrico, 2011; Molloy et al., 2011; Monras, 2019) in urban economics have also suggested that when agglomeration economies experience a positive economic shock or introduce minimum wage ordinances with the aim to help low-wage workers, they tend to attract more workers who migrate to take advantage of the opportunities. Dube and Lindner (2021) also note that with a possibility of spatial changes, or distortions, that "surprisingly little research has been devoted to some important aspect of [city] minimum wages." To explore short-term effects on labor markets when workers can change their commuting patterns, I use the visit duration of the mobile device for around 4.5 million establishments across the United States.

I use the number of longer duration visits, i.e. visits lasting more than 240 minutes or 120 minutes, as a measure of employee visits to analyze the effect of city-wide variation in the minimum wage. I discuss this assumption in Section 3.1.1. Prior literature (Allegretto et al., 2018; Harasztosi & Lindner, 2019; Renkin et al., 2022) suggested that employer passes the increased labor cost to the consumer. Assuming that businesses make a minimal increase the price of the product, I use short duration visits, i.e visits lasting less than 240 minutes or 120 minutes as visits by a customer to understand the price elasticity of demand.

Using the geolocation for the precise location of the establishment, and the difference-in-differences approach, this study reports that there exists a negative relationship between employee visits and local minimum wages. This negative relationship increases for the establishments which are bound by the local minimum wage. Further, I find that the distance traveled from home to an establishment increases when local minimum wages increase. I used the two-digit NAICS code to find the negative effect of minimum wages on employment in Retail & Trade industry and the Accommodation and Food industry.

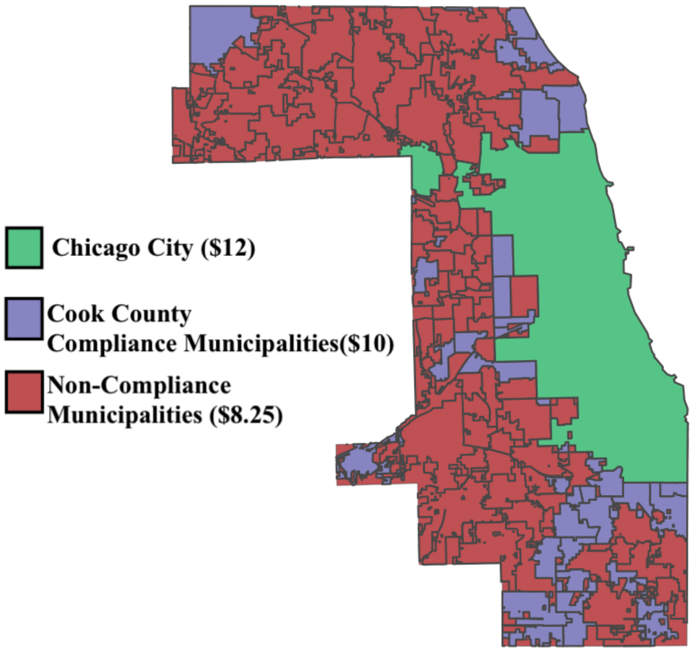
In Section 2, I provide the background on the minimum wage change, especially prior literature on city minimum wage, to understand the need of the geo-locations. I also discuss studies using cross-border comparisons as an identification strategy. Section 3 reviews the mobile location data source used to capture the commuting patterns. Section 4 further outlines the empirical strategy to explore monthly duration visits elasticity to the minimum wage at the establishment level. In Section 6, I discuss the intuition behind the results and analyses that need to be conducted to establish the relationship between minimum wages and commuting patterns. I also discuss robustness checks to understand the commuting pattern and control for labor market zones in which the establishment is located.

2 Background

The effect of the minimum wage has been extensively studied in the United States at the federal and state levels (Brown et al., 1982; Card & Krueger, 1995; Neumark, 2019; Neumark & Shirley, 2022; Neumark, Wascher, et al., 2007; Wolfson & Belman, 2019). In the last three decades, the minimum wage studies have followed two common trends. The first trends is the use of administrative data like the Quarterly Census of Employment and Wages (QCEW) by the Bureau of Labor Statistics (BLS) or American Community Survey (ACS) - the annual survey by U.S. Census Bureau. Second, the use of contiguous regions as a comparison group to estimate the causal effect of an increase in the minimum wage on change in employment.

The QCEW data is a virtual census of employment (ES-202) conducted quarterly in connection with state-level unemployment insurance systems providing rich demographic and employment details about the labor market at county, metropolitan statistical area, state, and federal levels. but the establishment is located in local areas like cities are hard to measure using this data. For instance, Cook county changed its minimum wages in 2016 but most of the municipalities opted out of the county minimum wage[2]. Moreover, Chicago City, which is the largest city in Cook County, introduced a minimum wage ordinance surpassing the County and State minimum wage, which makes it hard to capture the variation of local policy change. In Figure 1, I present minimum wage variation within Cook county. The area shaded in lavender color represent the municipalities which implemented the minimum wage ordinance passed by Cook County. The area shaded with terracotta orange represent non-compliance region within Cook county implementing the state minimum wage and the area with represented by Green is the highest minimum wage in the state and county by Chicago City. It may be difficult to explore the variations in minimum wages at small geographic areas located closely to each other using the administrative data available at county level.

Figure 1: Map of Cook County, IL with minimum wage variation in 2018



Another drawback of using administrative data is using multi-location businesses registered under one Unemployment Insurance (UI) program. QCEW uses the Multiple Worksite Report (MWR) to account for the establishments having a total of 10 or more employees combined in their secondary locations. The response rate for this report varies by state as only 31 states have MWR mandatory. States like Pennsylvania, Michigan, Illinois, and Massachusetts do not make it mandatory for multi-location establishments to report worksite at different locations

[2] Municipalities/incorporated places opted-out of Cook county Minimum wage Ordinance, 2017

within a state. Jardim et al. (2022) use the geo-location for the single UI account businesses to study Seattle's minimum wage change and find a decrease in employment compared to the synthetic controls when there is an increase in the minimum wage. In Section 3, I will discuss how mobile-device location data from SafeGraph locates the business and helps identify the visitor duration at the business.

The ACS by the U.S. Census Bureau, on the other hand, is an annual residential-based survey. It helps us understand the annual employment status and income level of households but does not provide information on employment location. It may be the case that a worker is employed in a different city but in the same county or state as his/her residence. The studies based on the ACS do not account for the workplace location, which again leads to spill-over bias.

Secondly, the use of contiguous regions as a comparison group to estimate the causal effect of an increase in the minimum wage on change in employment is very popular. Taking an analogy from Griliches (1979), if I include region-fixed effects, or equivalently look only at border regions or introduce region-by-time fixed effects, I would reduce the bias from unobservables at the regional level. However, whether the bias in the estimated employment rate is reduced using border regions depends on what generates variation between border regions relative to distant regions of the treated region or what causes the variation across time in a region. We may not be able to capture the sources of this variation when controlling for region-by-time effects.Jurisdictions that enact higher minimum wages are not exogenously determined. For instance, Albuquerque, which was a comparison group in Potter (2006), a study of the 2004 minimum wage change for Santa Fe, NM, implemented a three-year plan for the citywide wage to reach $ 7.50 by 2009. It is legitimate to be concerned about the ways to eliminate the endogeneity for better assimilation of the "Difference-in-Differences" method when discussing minimum wages.

The empirical work finding no negative result heavily relies on the neighboring jurisdictions for the control groups (Neumark & Shirley, 2021). The previous studies assume that regions located closer together have similar labor market trends, i.e. they cater to the same labor force and establishments. To eliminate the endogeneity and focus on the actual treatment effect of the policy change, studies tend to consider contiguous regions as the comparison groups. Then the causal estimates are based on the assumption of no spillover effect and no heterogeneous treatment effect. For instance, Card and Krueger (1993) compared restaurants located along the New Jersey-Pennsylvania border as they are more likely to face a similar local labor market. Using the gravity model, Kuehn (2016) analyzed five years of ACS data, finding that the minimum wage is correlated with unobserved differences among neighboring jurisdictions (counties). Contrary to the identification assumption of Dube et al. (2010), Kuehn argued that differences in minimum wages across the neighboring regions might have direct influences on employment outcomes. Similarly, Zhang (2018) discussed in a search model that lower-quality local workers tend to migrate from counties where minimum wages increase. These studies highlight that due to geographical proximity the minimum wage policy may influence the behavior of the workers. If higher minimum wages decrease the labor demand in an area, workers may commute to areas with lower minimum wages in the short run. Alternatively, if higher minimum wages increase the labor demand in an area, workers in lower minimum wage areas may commute to areas with higher minimum wages. In either case, the labor markets in both areas are interdependent when there exists a variation in the minimum wage.

To summarise, previous studies on minimum wages use contiguous regions as a control group, which helps mimic a controlled experiment and most of them find no negative effect on employment when there is a change in the minimum wage. But, if the workers commute from nearby regions for work to a higher minimum wage area, those estimates will be upward biased. This study hinges on the commuting pattern across the cities. First, I present a city-wide minimum wage analysis at the establishment level to study whether there is an upward movement along the long-duration visit curve similar to the competitive labor market model whether there is a downward movement along the long-duration visit curve as in the monopsony labor market model. I use the geo-location of the establishments to determine the city council jurisdiction that applies to each businesses. I then address whether visit duration changes at an establishment bound by city minimum wage. Second, using mobile-device location, I address whether the distance traveled from a home location to an establishment changes. These questions will provide a better understanding of the true effect of minimum wages on the local labor markets.

3 Data

This study uses mobile location data from SafeGraph. SafeGraph collects GPS information from around 45 million anonymous cellular devices and produces anonymized, aggregated extracts of mobility patterns for nearly 4.5 million establishments in the US. The establishments are identified as Places of Interest (POIs) by matching the location of the establishment, and the location of the devices using GPS pings from the consenting individuals using location-enabled mobile apps. I have restricted my data from January 1st 2018 until December 31st 2019 due to data availability and the COVID-19 pandemic. In the next sections, I discuss mobile location and local minimum wage data in detail.

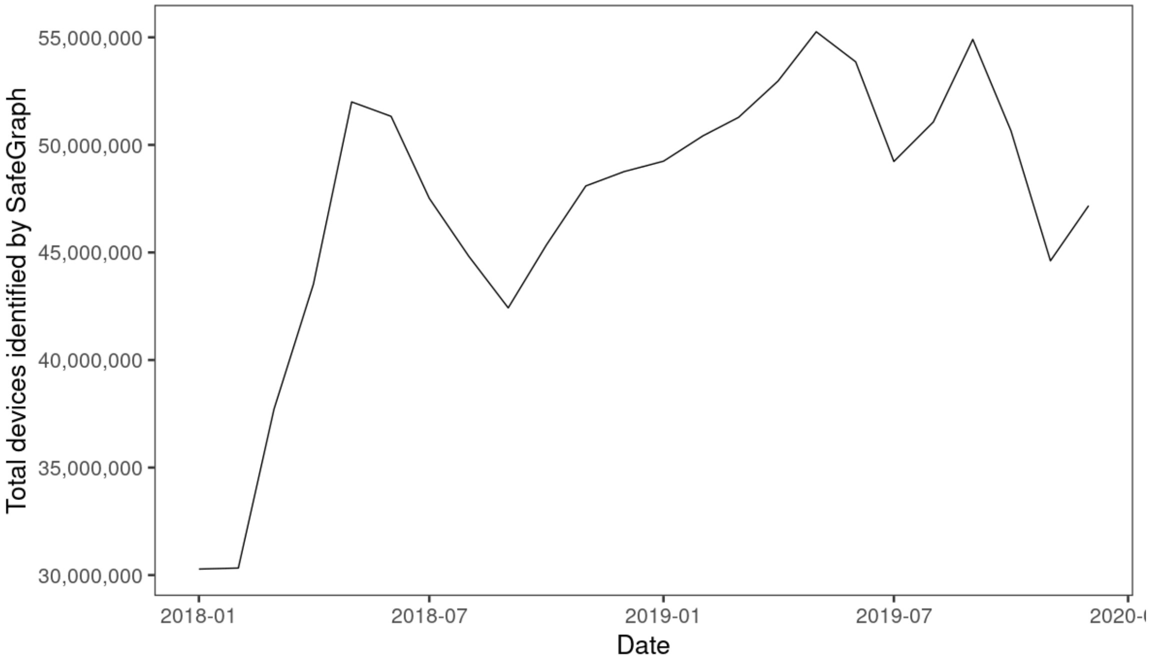
3.1 Mobile location data

The SafeGraph data provides establishment-level hourly, daily, weekly, and monthly patterns of movement for the POIs. The data reports the number of visits to the POI and the number of unique devices (visitors) that visit the POI in a given week or month. I use the number of visitors and their home census block group for each POI and the distance traveled in meters to reach the POIs to identify the CBG-level demographic characteristics. SafeGraph only reports the median value of the distance traveled if there are more than five unique visitors at a POI.

The total number of devices identified by SafeGraph across the United States has varied over the period of 2018 and 2019 as shown in the Figure 2. This may influence my analysis as the number of devices identified increases the number of visitors may also increase over the period. I normalize the monthly visits to compare my data across two years. I use the ratio of the population in the state to the total number of devices identified in the state for that month as a normalizing factor. This gives me a uniform number of devices identified across the period of two years that can be used for analysis.

SafeGraph defines a visit based on a sequence of GPS pings within a location where each ping is within six hours of the prior ping. The first and last GPS ping at a POI is used to estimate the minimum duration of the visits, or the dwell time. I use the bucketed dwell times provided by SafeGraph, which are in bins of "<5", "5-10", "11-20", "21-60", "61-120", "121-240", ">240" minutes. In order to study labor supply, I use the visits in the highest bucket until 120 minutes, in other words, if a POI has visited in bucket dwell ">240" I use that as

Figure 2: Number of devices identified by SafeGraph across the US for years 2018 and 2019



an employee visit; otherwise, I use the visits from the next bucket dwell "121-240." I assume any visits that are less than these bucketed dwell times are customer visits. In Section 3.1.1, I discuss in detail whether long-duration visits are a good proxy for the number of workers.

I use the characteristics of the POIs, like Industrial categorization, based on the North American Industry Classification System (NAICS), name of the associated brand etc. In Table 1, I compare the two-digit Industrial classification of the POIs and the number of establishments in the Census Business Pattern (CBP) based on the 2017 NAICS. CBP data identifies establishments as "A single physical location at which business is conducted or services or industrial operations are performed". Using the Employer Identification Number, it covers over 6 million single-establishments and around 1.8 million multi-establishments, but the annually collected survey only considers multi-establishments with companies employing 500 or more employees.[4]

SafeGraph data, on other hand, uses the address and the GPS ping of the device to identify the establishment as Places of Interest (POIs). It is more reflective of non-trade industries i.e the retail, fast-food, and art and entertainment industry, which are also the intensive employers of minimum wage workers in the United States (US Bureau of Labor Statistics 2019). The prior literature on minimum wage (Card & Krueger, 1993; Dube et al., 2016) has also considered

[4]https://www.census.gov/programs-surveys/cbp/technical-documentation/methodology.html,https://www.census.gov/programs-surveys/cos/about.html

Table 1: Number of establishments identified by SafeGraph data and CBPs

Industry(NAICS Code)	SafeGraph	CBPs	Ratio
Agriculture, Forestry, Fishing and Hunting(11)	1,235	23,393	0.053
Mining, Quarrying, and Oil and Gas Extraction(21)	31	25,593	0.001
Utilities(22)	7,179	19,028	0.377
Construction(23)	33,176	733,689	0.045
Manufacturing(31-33)	65,239	290,092	0.225
Wholesale Trade(42)	55,411	403,648	0.137
Retail Trade(44-45)	1,099,290	1,050,175	1.047
Transportation and Warehousing(48-49)	68,776	244,800	0.281
Information(51)	50,811	157,766	0.320
Finance and Insurance(52)	191,264	477,562	0.398
Real Estate and Rental and Leasing(53)	122,508	418,005	0.292
Professional, Scientific, and Technical Services(54)	78,219	921,521	0.084
Management of Companies and Enterprises(55)	7,933	54,726	0.144
Admin and support and waste Mng and Rmd(56)[3]	20,668	418,868	0.049
Educational Services(61)	165,678	106,939	1.538
Health Care and Social Assistance(62)	640,137	907,426	0.700
Arts, Entertainment, and Recreation(71)	274,521	147,122	1.844
Accommodation and Food Services(72)	733,245	733,134	1.003
Other Services (except Public Administration)(81)	818,001	766,761	1.052
Public Administration(92)	54,372	NA	
Total	4,487,694	7,912,405	0.563

these major industries to study the effect of minimum wages.

3.1.1 Employee Visits and State Employment

I assess the validity of long-duration visits as a proxy for employment by comparing my data to the total number of jobs at workplaces in a given census block group (CBG) from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics provided by the Bureau of Labor Studies [5]. To protect the anonymity of people, LEHD-WAC files are introduced with the "Fuzz factor" at lower geographies (Abowd et al., 2009; Manduca, 2018), such as at the CBG level. I re-weight the number of jobs (E) at the work CBG i in a state j at year t by the fraction of population in the state j to the number of jobs in the state j for a year t.

$$Normalized\ E_{ijt} = E_{jit} \times \frac{Total\ Population_{jt}}{\Sigma_i E_{jit}}$$

Similarly, I use the normalizing factor of the population in the state j to the number of

[5]https://lehd.ces.census.gov/data/

devices identified in the state j at time t for the duration of visits (V) in a CBG i at a time t.

$$Normalized\ V_{ijt} = V_{jit} \times \frac{Total\ Population_{jt}}{\Sigma_i Total\ Devices_{jit}}$$

I estimate the relationship between all visit durations in a CBG i and the number of jobs in a CBG i controlling for the CBG fixed effect μ_i and time fixed effect τ_t. I expect that as the number of employee (E_{it}) in a CBG increases, the number of visits (V_{it}) at various duration also increases.

$$log(V_{it}) = \beta_1 log(E_{it}) + \mu_i + \tau_t + \epsilon_{it} \tag{1}$$

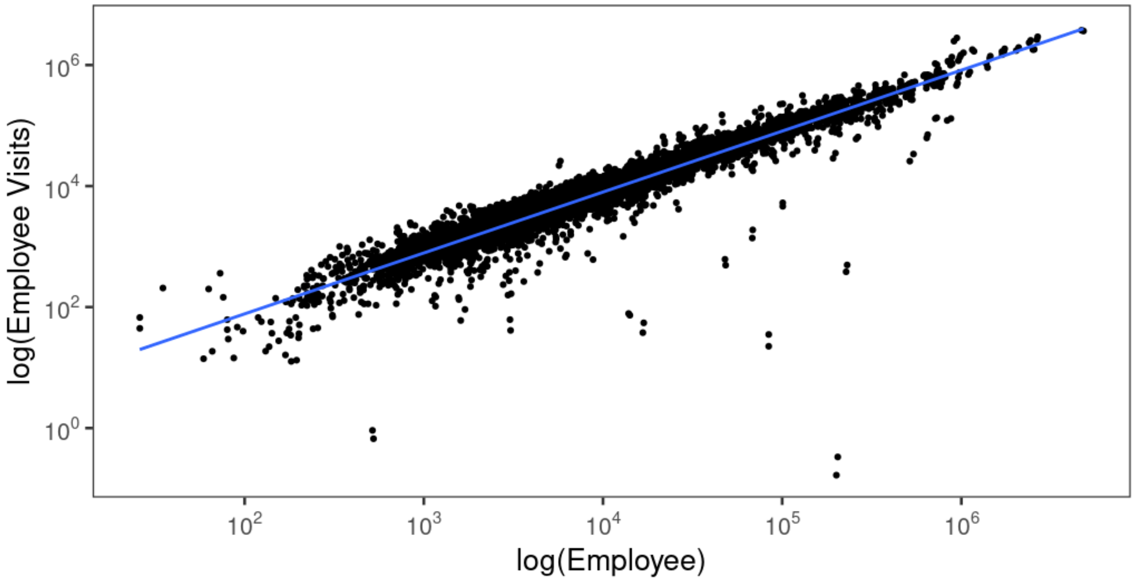
The estimates in Table 2 reveal a positive relationship that is significant at the 1%. In column (1), I present estimates from a panel of non-normalized data from the LEHD with CBG and year fixed effects. I also present the normalized employee visits and the number of employee from LEHD in column (2). The visits with a duration of more than 240 minutes have a higher correlation with the number of jobs in a CBG, I find similar correlation from the constructed variable combined by visits with a duration of more than 240 minutes and visits up until 120 minutes if no visit in 240 minutes i.e. if a POI in a CBG i did not have any visits for more than 240 minutes, I consider visits for more than 120 minutes. I use a similar method to define variables with the highest bucket up until 60 minutes visit. To understand the fitness for each variable among the CBG panel units, I use the $Within\ R^2$ as a measure of selection. I find that visits with the highest duration bucket up until 120 minutes a better fit for employee visits with the highest $Within\ R^2$ of 0.00018 along with higher correlation. In Figure 3, I present a county-level relation with the log number of employee visits [Visit in highest duration bucket up until 120 minutes] and the number of jobs from the LEHD-WAC data. I also present a positive correlation between the number of jobs and the number of employee visits at the state level in Appendix Figure 8. These high correlations with the number of jobs at CBG, county, and state-level provide evidence that supports using the number of visits in the highest duration bucket up until 120 minutes as employee visits. I consider the rest of the visits as consumer visits at a POI.

Table 2: Number of jobs and duration visits at Census Block Group level

Independent Variable:	Number of total employes in the LEHD	
Model:	(1)	(2)
Dependent Variables(in log):		
Visits greater than 240 mins	0.0139***	0.0140***
	(0.0033)	(0.0032)
Fit statistics		
R^2	0.98657	0.98657
Within R^2	0.00016	0.00016
Visits greater than 120 mins	0.0133***	0.0134***
	(0.0029)	(0.0029)
Fit statistics		
R^2	0.98871	0.98871
Within R^2	0.00017	0.00018
Visits in highest duration bucket	0.0139***	0.0140***
until 120 minutes	(0.0030)	(0.0030)
Fit statistics		
R^2	0.98725	0.98725
Within R^2	0.00017	0.00018
Visits greater than 60 mins	0.0117***	0.0117***
	(0.0027)	(0.0027)
Fit statistics		
R^2	0.99028	0.99028
Within R^2	0.00015	0.00015
Visits in highest duration bucket	0.0129***	0.0129***
until 60 minutes	(0.0029)	(0.0028)
Fit statistics		
R^2	0.98754	0.98754
Within R^2	0.00016	0.00016
Fixed-effects		
Census Block Group	Yes	Yes
Year	Yes	Yes
Observations	386,120	386,120

Clustered (Census Block Group) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 3: Log the number of jobs and log number of employee visits at County-level



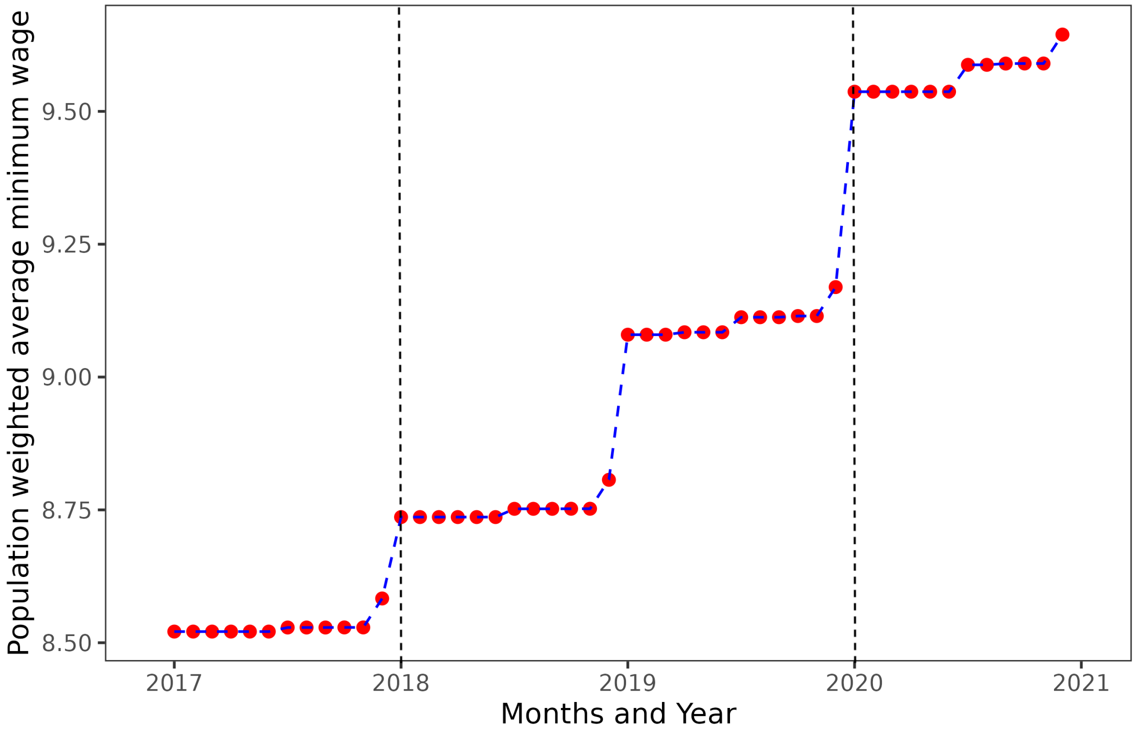
3.2 Minimum wage

I construct a monthly city-wide minimum wage panel by using the sub-state level minimum wage data from the UC Berkeley, Labor Center (August-2021)[6] and the state-level monthly data by Vaghul and Zipperer (2021)[7] to study the time variation in minimum wages across jurisdictions. Figure 4 presents a population-weighted average minimum wage for the period of 2017 until 2021. Beginning of every year, January records a higher magnitude of minimum wage ordinance roll-out, the majority of which are state-level minimum wage ordinances. In Table 8, I list the sub-state and state minimum wage ordinances that are enacted within my study period of January 2018 on-wards until December 2019.

It is important to notice that many city councils have implemented policy changes in the middle of the year, for example, the City council of Berkeley, CA, and Santa Fe, NM, revised minimum wages on October 1st and April 1st respectively. Similarly, 19 sub-state councils implement minimum wage revisions around July every year across 7 states. In Section 4, I discuss in detail how the estimate may differ if we have multiple treatments over multiple time periods. In order to consider this mid-year minimum wage change, I used the SafeGraph monthly pattern file to capture the effect of the policy change and adjust the comparison and the treatment groups.

[6] https://laborcenter.berkeley.edu/inventory-of-us-city-and-county-minimum-wage-ordinances/
[7] https://github.com/benzipperer/historicalminwage

Figure 4: Population-weighted average minimum wage change



Based on the longitude and latitude of the POIs and the geospatial file of city boundaries defined by the US Census Bureau (presented in tigris r-package), SafeGraph identifies the city for each POI. I match the cities in the minimum wage data with the SafeGraph data for each POI. I balance the panel for the visits by assigning zero to the visits at POIs for the dates where the data for visits is missing. To estimate the changes in median distance traveled by the visitor, I only consider POIs that have data for all the months to balance the panel. Accordingly, I eliminate the POIs with missing values since replacing zeros for distance travel would mean assuming no distance traveled to the POI . I also present results for the balanced panel for visit duration using POI, which was tracked for all 24 months.

4 Methodology

Businesses may change the working hours for an employee or change the number of employees at an establishment located in the jurisdiction where the minimum wage ordinance is enacted. Employees may choose to work (full-time or part-time) at different locations to arbitrage the variation in the minimum wage and change their commuting patterns in the short term. Customers may also alter commuting patterns according to their price elasticity of demand. To capture the spatial and temporal variation across the minimum wage ordinances and how this variation affects visits (employee visits, customer visits, and total visits) at a POI, I estimate the visits elasticity with respect to minimum wages from 2018 until 2019 mentioned in Table 8 on a balanced panel of monthly visits at a POI. I use a two-way fixed effect model conditioned on the place of interest (POI) fixed effect and date fixed effect to estimate the minimum wage elasticity on duration visits (employee, customer, and total visits).

$$log(V_{it}) = \beta_2 log(MW_{it}) + \mu_i + \rho_t + u_{it} \tag{2}$$

I use the Equation 2 to estimate the causal effect β_2. In equation 2, MW_{it} is the effective minimum wage (local, state, or federal) faced by a POI i in the month t, and μ_i and ρ_t are the POI and date (month-year) fixed effects respectively. My outcome of interest $log(V_{it})$ is the log visits (employee visits, customer visits, visits greater than 240 minutes, visits greater than 240 minutes, visits less than 5 minutes, total visits and distance traveled) at a POI. there exists a nontrivial number of true zero in the data so I have used inverse-hyperbolic sine transformation for the dependent variables. I cluster the standard errors at the city level and also present the estimates clustered at the state level. I use the normalized visits to estimate all my results. The POIs which are engaged in short-term lodging identified by NAICS code 7211 may show more long-duration visits which might be more reflective of the customer visits than the employee visits, to avoid contamination of the estimates I eliminate these POIs.

It is natural to question the estimates since the time of the treatment varies across the US and minimum wage ordinances are implemented programmatically over the years which means multiple treatments with annual or sometimes with a short window. Recent literature, (Callaway & Sant'Anna, 2021; De Chaisemartin & D'Haultfoeuille, 2022; Goodman-Bacon, 2021; Sun & Abraham, 2021) also pointed out that TWEF model similar to equation 2 with binary treatment could be difficult to interpret when the units are treated multiple times and different units are treated in different time periods. Callaway et al. (2021) raised similar concerns for continuous treatment estimates.

To estimate this heterogeneous time treatment across two years (2018-2019) across differently treated POIs, I use an event study design to estimate the continuous average treatment effect.

$$log(V_{it}) = \Sigma_{\tau \neq -3}^{24} \alpha_\tau \Delta log(MW_{i,t-\tau}) + \mu_i + \rho_t + u_{it} \quad (3)$$

I constructed a data set with a continuous treatment variable of 24-month lead-lag calculating the monthly change in the minimum wages with $\tau = 0$ as the base period when the minimum wages starts. To eliminate the multicollinearity problem between the event-time, I drop $\tau = -3$, assuming establishments may start adjusting to the changes for the quarter a few months ahead but post the previous quarter. The event study provides a visual test to the pre-treatment parallel trends assumption but more importantly, POI-level data for visits helps me understand the non-parametric dynamics, like visits and duration of visits. For instance, a change in visit could be a reduction in hours worked by an employee for temporary time period, or there could be a replacement of lower-skill worker to a high-skill worker or horizontal replacement like change in employment to another POI or industry. This event study design using Δ, which is the monthly difference operator for $log(MW)$, helps by eliminating the untreated potential outcome by making a cross-dose comparison.

The identification strategy for the Equation 3 is to exploit variation among POI i across the time t with different minimum wages using continuous treatment. I construct a model where V_{it}, the outcome of interest with inverse-hyperbolic sine transformation for the duration of visitors at location i for a month t. I use the Δ in the monthly difference operator for the continuous treatment $log(MW_{i,t-\tau})$ to estimate the variable of interest α_τ. By adding μ_i, I control for the individual establishments affected by changes not related to minimum wage ordinances; also I used ρ_t to control for differences across time periods. My identification assumption is $E(u_{it}|logMW_{i,t-\tau}) = 0$. In other words, the monthly minimum wage differences are uncorrelated with differences in residual employee (or customer) visits at a POI. I report 12-lead and lag to avoid reporting periods outside my window of two years. Similar to equation 2 specification I cluster my standard errors around city level. My estimates could be biased if the time-varying difference in the visits is not captured by controlling for the POI and time-fixed effect.

Table 3: Duration visits at a POI and Minimum wages

Model	Full Sample (1)	Sample without short-term Lodging (2)	Retail & Trade Industry (3)	Acc. & Food Industry (4)
Dependent Variables(log)				
Employee Visit	-0.4623***	-0.4651***	-0.4222***	-0.5594***
	(0.0751)	(0.0750)	(0.0689)	(0.1047)
Descriptive statistics				
Mean	198.3497	189.011	151.9585	179.7724
Standard Deviation	2234.4	2234.143	602.2081	1193.097
Customer Visit	-0.5387***	-0.5431***	-0.6204***	-0.7640***
	(0.0895)	(0.0799)	(0.1074)	(0.1261)
Descriptive statistics				
Mean	1224.509	1215.5	1482.751	1657.064
Standard Deviation	7658.424	7620.679	3801.534	3290.2
Visit > 240 mins	-0.4784***	-0.4808***	-0.4412***	-0.5904***
	(0.0761)	(0.0935)	(0.0694)	(0.1062)
Descriptive statistics				
Mean	197.1404	187.7887	150.9564	178.6717
Standard Deviation	2234.49	2234.228	602.426	1193.232
Visit < 5 mins	-0.7297***	-0.7320***	-1.022***	-1.066***
	(0.0945)	(0.0935)	(0.1387)	(0.1980)
Descriptive statistics				
Mean	32.8617	32.7264	50.6921	50.8337
Standard Deviation	182.6269	181.5455	113.7372	110.6568
Total visits	-0.5448***	-0.5494***	-0.6082***	-0.7503***
	(0.0875)	(0.0876)	(0.1025)	(0.1230)
Descriptive statistics				
Mean	1422.858	1404.511	1634.71	1836.836
Standard Deviation	9414.043	9375.445	4165.4	4073.397
Fixed-effects				
POI	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Observations	107,704,656	106,378,560	26,382,960	16,271,784

Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

5 Results

5.1 Main Results

Table 3 presents my main results using equation (2). Column (1) presents results using all POIs in my data while column (2), which is my preferred model, omits POIs in the short-term lodging industry since customers typically stay for long periods of time conflating the customer and employee counts. Columns (3) and (4) present results for POIs in the retail and trade and accommodation and food service industries respectively. For the most part, columns (1) and (2) are similar, with a 10% increase in the minimum wage decreasing employee visits by approximately 4.6%. Customer visits also decrease, with an elasticity of 0.54. Total visits also decreases as the minimum wage increases, with a total visits elasticity of 0.55.

The retail and trade industry in column (3) provides similar overall results with a negative customer visits elasticity of 0.62. The customer visits elasticity for the accommodation and food industry in column (4) is larger in magnitude compared to the sample in column (2). Customer visits to accommodation and food industry establishments may be more elastic if the minimum wage affects their costs more and they pass those costs through to the end consumer. This could be the result of the transfer of input cost by businesses to the customer, in other words, the estimates for the customer visits are also an approximation of the price elasticity to customer duration visits. Importantly, when the minimum wage increases there is a large decline in short-term visits (less than 5 minutes) which could represent a decline in pick-up and delivery services where GPS is switched on once at a POI, or it could be a decline in "check-ins" once per day which is default setting by a lot of apps using location from the devices. I present the estimates from the unbalanced panel of POI and the balanced panel with only POIs that have no missing values for 24 months in Appendix Table 9. The estimates are slightly higher in magnitude but stay negative.

When the number of visitors changes, the median distance traveled from home to the POI can also change. In Table 4, I present the estimates from the balanced panel of POI median distance traveled, as I cannot insert a zero for the missing value of distance traveled to balance the panel. instead, I used POIs which were tracked for all 24 months. I find that a 10% increase in minimum wages increases the monthly median distance traveled by the visitor increases by around 1.6%. It is important to note that the mobile-device location data provides the monthly median distance traveled. POIs which has customers coming from longer distances may not influence the distribution of the distance traveled but the number of visits may influence the estimates by pulling the median value upward if there are more short-duration visitor coming from long distances. I try to estimate the minimum wage elasticity on the median distance traveled conditional on the duration of the visits, there is a slight variation but it stays statistically significant close to 0.15. I present estimates for the retail and food industry in the Appendix Table 10. Conditioned on the total visits, the distance traveled to the POIs in both the Retail & Trade industry and the Accommodation & Food industry is more elastic than the total sample. When controlled for state trend the estimated effect of an increase in median distance traveled is also more than the total sample. These estimates may be the results of either customer traveling longer distances due to increases in cost or employees traveling longer for work, I cannot distinguish between distance travel by an individual visitor from this variable.

Table 4: Distance traveled from home and Minimum wages

Model:	(1)	(2)	(3)	(4)	(5)
Variables in log					
Minimum Wage	0.1558***	0.1526***	0.1488***	0.1604***	0.1467***
	(0.0553)	(0.0549)	(0.0543)	(0.0556)	(0.0536)
Visits < 5 mins		-0.0035***			
		(0.0003)			
Employee Visits			-0.0135***		
			(0.0004)		
Customer Visits				0.0081***	
				(0.0025)	
Total Visits					-0.0159***
					(0.0025)
Fixed-effects					
POI	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	45,908,976	45,908,976	45,908,976	45,908,976	45,908,976
R^2	0.77494	0.77496	0.77512	0.77495	0.77498
Within R^2	6.75×10^{-5}	0.00015	0.00088	0.00011	0.00025

Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In Figure 5, I present the event study with 12 months before and after the treatment month using estimated results from Equation 3. I observe a decrease in employee visits, customer visits, and visits more than 240 minutes, and less than 5 minutes which validates the results in Table 3 from Equation 2. I also present an event study for median distance traveled on the balanced panel which also shows an increase in distance traveled when minimum wage increases. I perform sensitivity tests for event study pre-trends in Section 5.3.

5.2 Local bonded minimum wage

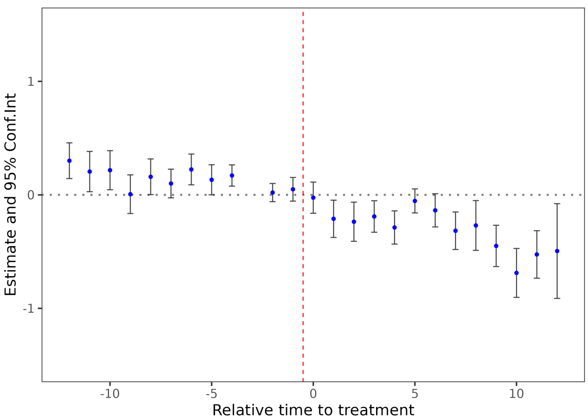
Given, the porous local boundaries, POIs bound by local minimum wage ordinances can respond differently than the state bound ordinances. Businesses [POIs] have the option to move out a few miles of the city. On the other hand, employees have the option to commute to the nearby city for higher wages, which might not be the case when there is a variation in wages across the state. To capture the elasticity of duration visits and distance traveled, when the POI is binding to the local-level ordinance rather than the state ordinance, I additionally control for time-invariant "City binding" dummy, which is equal to one if the POI had to increase the minimum wage to abide by the city/county ordinance. The indicator stays zero if the POI was bound by a higher state minimum wage. Table 5 uncovers statistically significant estimates, if the local-level minimum wage is binding the POI the wage elasticity for employee visits is around -0.7 more than the POI bound by the state-level minimum wage and the wage elasticity for customer visits is around -0.98 more than the POIs bound by the state minimum wage ordinances. This negative elasticity compared to the state minimum wage change is also reflected in the distance traveled by the visitor when there is an increase in the local minimum wage is more elastic than the increase in state increase in minimum wage. I also represented industry-specific estimates in the Appendix which also present higher magnitude and negative elasticity when compared to state ordinances.

5.3 Sensitivity check

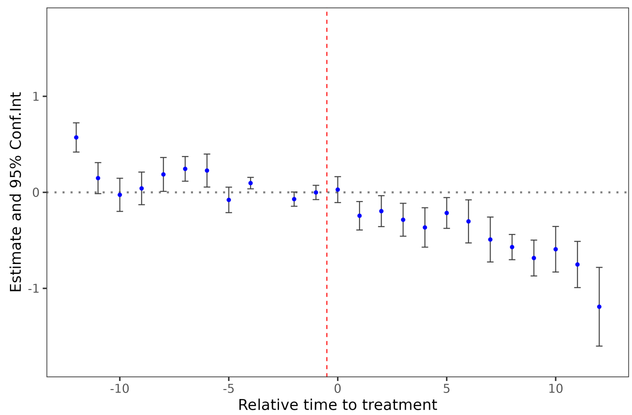
In this section, I discuss the estimates with labor market zone identified at the county level and geographical area trend control using the sample from column (2) in Table 3. In Table 6, column (2) presents estimates controlling for state trends which will also take off the trends for state-level minimum wage changes along with other state-level policy changes. The employee

Figure 5: Effect of Minimum Wages on duration visits and distance traveled over time

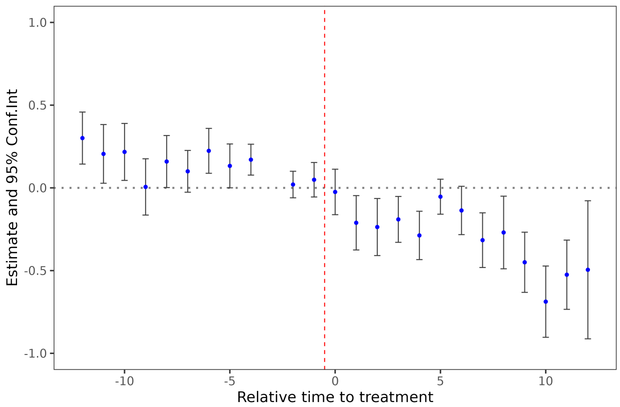
(a) Employee Visits



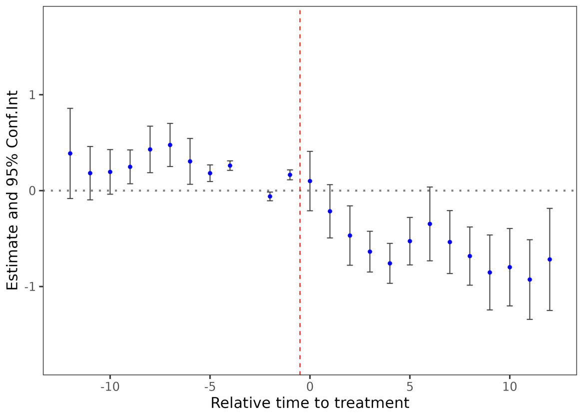
(b) Customer Visits



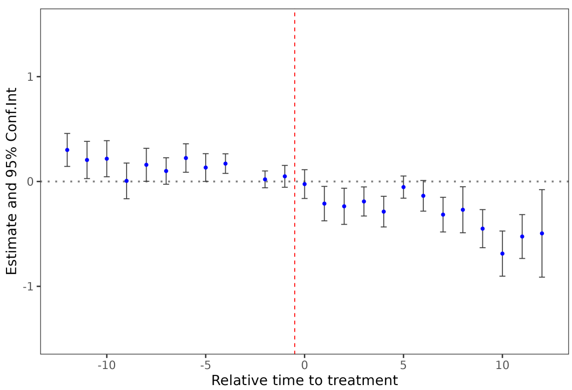
(c) Duration of Visit more than 240 min



(d) Duration of Visit less than 5 minutes



(e) Total visitor



(f) Distance traveled

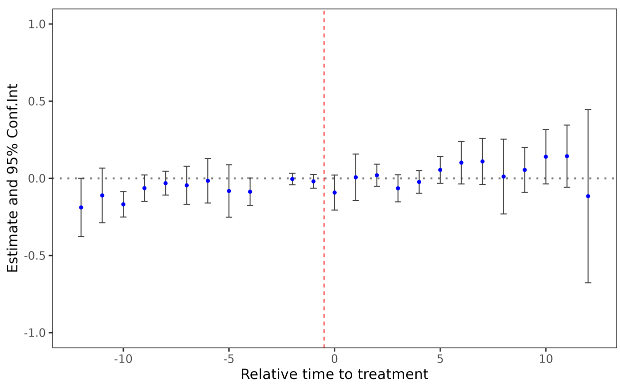


Table 5: Local binding minimum wage ordinance and duration visits

Dependent : Variables Model:	Employee Visits (1)	Customer Visits (2)	Total Visits (3)	Distance Traveled (4)
Variables				
log(MW)	-0.2232***	-0.2168***	-0.2301***	0.0033
	(0.0533)	(0.0474)	(0.0494)	(0.0251)
log(MW) × City Binding	-0.7214***	-0.9735***	-0.9525***	0.4510***
	(0.1193)	(0.1330)	(0.1262)	(0.1010)
Fixed-effects				
placekey	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	106,378,560	106,378,560	106,378,560	45,908,976
R^2	0.76917	0.87035	0.85489	0.77498
Within R^2	0.00014	0.00030	0.00027	0.00023

Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

visits from column (2) validate our estimate of city bound minimum wage changes in Table 5. Considering, Census divisions like Pacific, New England, and Middle Atlantic have more areas implementing local minimum wage ordinances to control for potential selection bias in column (3) I control for the census division trend.

In Appendix Table 11 and Table 12, I show the estimates for the retail & trade industry and the accommodation and food industry respectively. I also control for the census region trend to show negative elasticity of employment when the minimum wage increases. Visitors may choose to commute across labor market areas, based on Fowler and Jensen (2020) delineation of labor market zones following the U.S. Department of Agriculture, Economics research service methodology.[8] I spatially merged the POIs into the labor market zones. In column (5), I control for the labor market zones which also present statistically significant negative elasticity of visits. I present estimates with labor market zone trends control in column (5) and state trend in column (2) of Table 7, compared to column (1) both are statistically significant and more elastic to the change in minimum wages.

The results in Table 6 and Table 7 validates that there is an increase in movement across

[8] USDA ERS-2010, County-level commuting zones and labor market areas

Table 6: Minimum wages and duration visits with time-varying economic conditions fixed effect

Model:	(1)	(2)	(3)	(4)	(5)
Variables in log					
Employee visits	-0.4651***	-0.8119***	-0.3002***	-0.3339***	-0.4453***
	(0.0750)	(0.0992)	(0.0885)	(0.0886)	(0.1005)
Customer Visits	-0.5431***	-0.8383***	-0.3546***	-0.4207***	-0.3779***
	(0.0895)	(0.1283)	(0.0953)	(0.0929)	(0.1030)
Visits $<$ 5 mins	-0.7320***	-0.7795***	-0.3348***	-0.4149***	-0.3099***
	(0.0935)	(0.1957)	(0.1069)	(0.0968)	(0.0882)
Total Visits	-0.5494***	-0.8622***	-0.3531***	-0.4143***	-0.4045***
	(0.0876)	(0.1224)	(0.0958)	(0.0939)	(0.1045)
Fixed-effects					
POI	Yes	Yes	Yes	Yes	Yes
Date	Yes				
State× Date		Yes			
Census Division× Date			Yes		
Census Region× Date				Yes	
LMz × Date					Yes
Observations	106,378,560	106,378,560	106,378,560	106,378,560	106,270,392

LMz is labor market zones based on the USDA ERS-2010 labor-shed delineation
Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Distance traveled and Minimum wages with time-varying economic conditions fixed effect

Model:	(1)	(2)	(3)	(4)	(5)
Variable in log					
Minimum Wage	0.1558***	0.3634***	0.0812	0.0825	0.3149***
	(0.0553)	(0.0883)	(0.0545)	(0.0545)	(0.0880)
Fixed-effects					
POI	Yes	Yes	Yes	Yes	Yes
Date	Yes				
State × Date		Yes			
Census Division × Date			Yes		
Census Region × Date				Yes	
LMz × Date					Yes
Fit statistics					
Observations	45,908,976	45,908,976	45,908,976	45,908,976	45,860,472

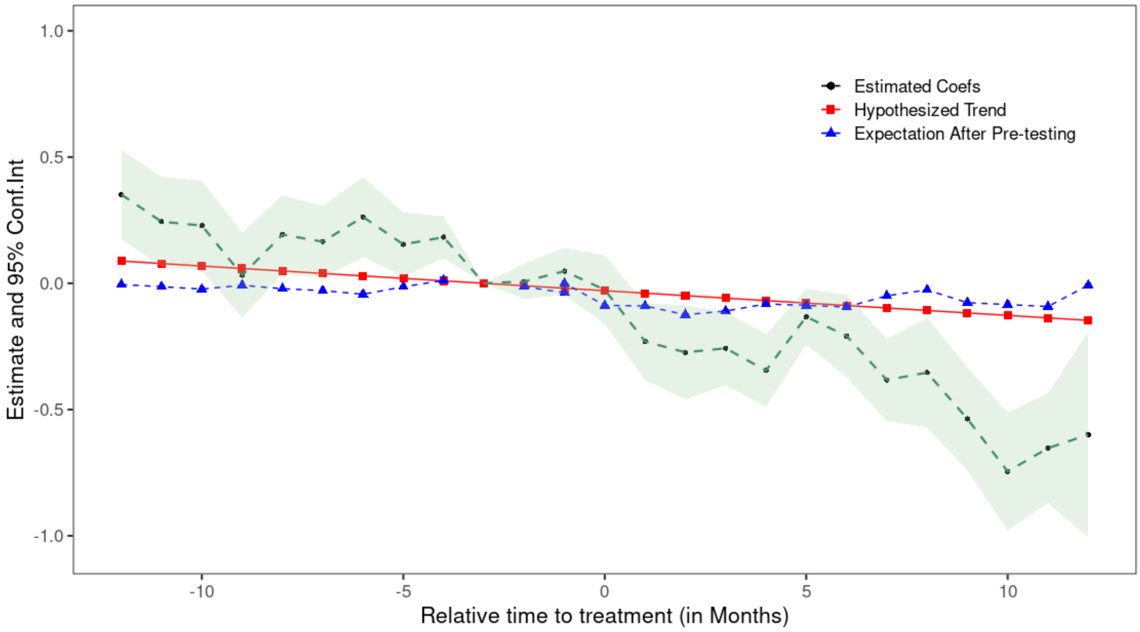
LMz is labor market zones based on the USDA ERS-2010 labor-shed delineation
Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

the labor market zones and a decline in employment when minimum wages change. As expected, When we control for the census division trend or census region trend the estimates are insignificant as the long-distance travel may not be affected by a change in the minimum wage. Overall, the estimated response to the variation in local minimum wages when controlled for various geographic trends is more negatively elastic.

5.4 Pre-trend testing

The estimates around 4 months, 6 months, and 12 months before the treatment are statistically significant, as presented in Appendix Table 13. Since the policy change is announced months prior to the implementation, also some policies are programmatic in nature. It gives the firm the to adjust prices or employment and prepare for the treatment. Given the low power of the event study against the relevant violations of the parallel trends, I use 80 percent power to construct hypothesized nonlinear trends for the post-treatment estimates for Employee visits using the pre-treatment suggested by Roth (2022) Figure 6. I also construct a similar hypothesis for using pre-existing trends for Customer visits, Total visits, and Distance traveled in Figure 9. I observe that the estimates from the dynamic DiD model present a more negative relationship than the expected estimates after pre-testing.

Figure 6: Pre-trend and Effect of Minimum Wages on Employee visits



6 Discussion and Conclusion

This study contributes to the debate on the relationship between employment and minimum wages, by arguing that when the workers can commute to nearby areas to arbitrage the variation in minimum wages using contiguous regions as a control group might create an upward bias estimates especially for small geographic areas. In this study, I use the visit duration at business establishments [POIs] as a proxy for employment to show that local labor markets with porous boundaries are competitive in nature. Throughout this study, I use the geo-location of the POI to identify the jurisdiction of the minimum wage ordinance to assign the minimum wage for the local area.

First, I show that there is a negative relationship between employee visits and minimum wages. I find that as minimum wages increase by 10%, employee visits decrease by 4.6%. Further, I find that employee visits in the Accommodation and Food Industry are more negatively elastic than in the Retail and Trade Industry. Moreover, I find that establishments that are bound by local minimum wage comparatively observe a 7% decline in employee visits when minimum wages increase by 10%. Second, I find that there is an increase in the median distance traveled by the visitor to a POI with an increase in minimum wage. This indicates that worker face comparatively less the mobility cost as assumed in the monopsony labor market model and provides evidence that the labor market at the local level faces an elastic labor supply curve and behaves more competitively than at the state level. Third, as prior literature (Allegretto et al., 2018; Harasztosi & Lindner, 2019; Renkin et al., 2022) suggested businesses tend to transfer increased operational costs to the customer, to shed light on the good market, I also estimate negative elasticity between customer visits and minimum wage and find that the visits of less than 5 minutes decrease when there is an increase in the minimum wage. This may reflect the high price elasticity of demand in case of the delivery picks up/online orders. In my future results I will explore this further.

A limitation to this study is that I do not observe individual-device level data, which makes it difficult to ascertain whether there is a decrease in duration of lower-wage workers or workers with lower skills at thier jobs. My future research looks to address the minimum wage "bite", by identifying commuting patterns. The duration of the visits is based on the GPS-pings of unique devices. In practice, an individual may carry two or more devices at the same time which then may increase the magnitude of the estimates. Despite these limitations, the study makes a significant contribution to the discussion of the minimum wage by looking at the commuting pattern at the establishment level when local councils decide to increase the minimum wage.

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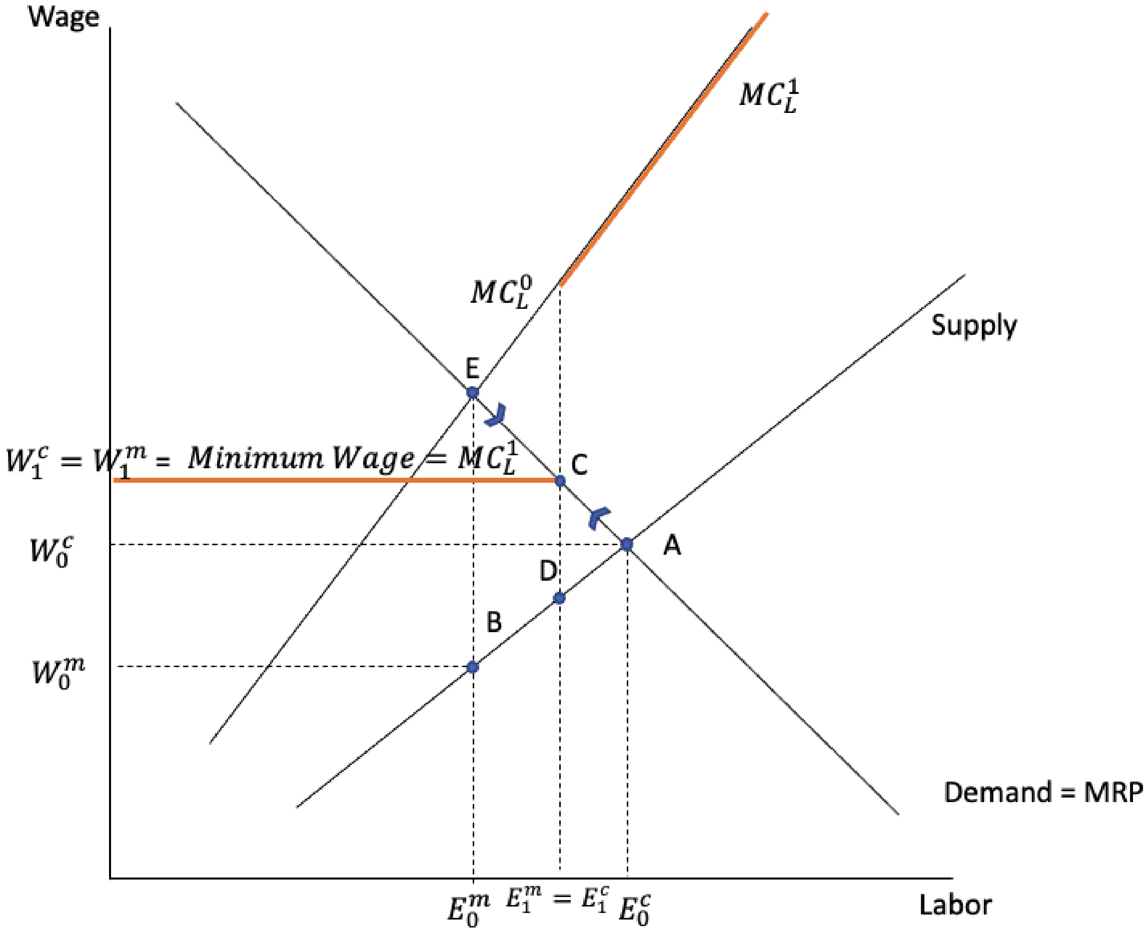
7 Appendix

Figure 7: Perfect competition and Monopsony Labor market

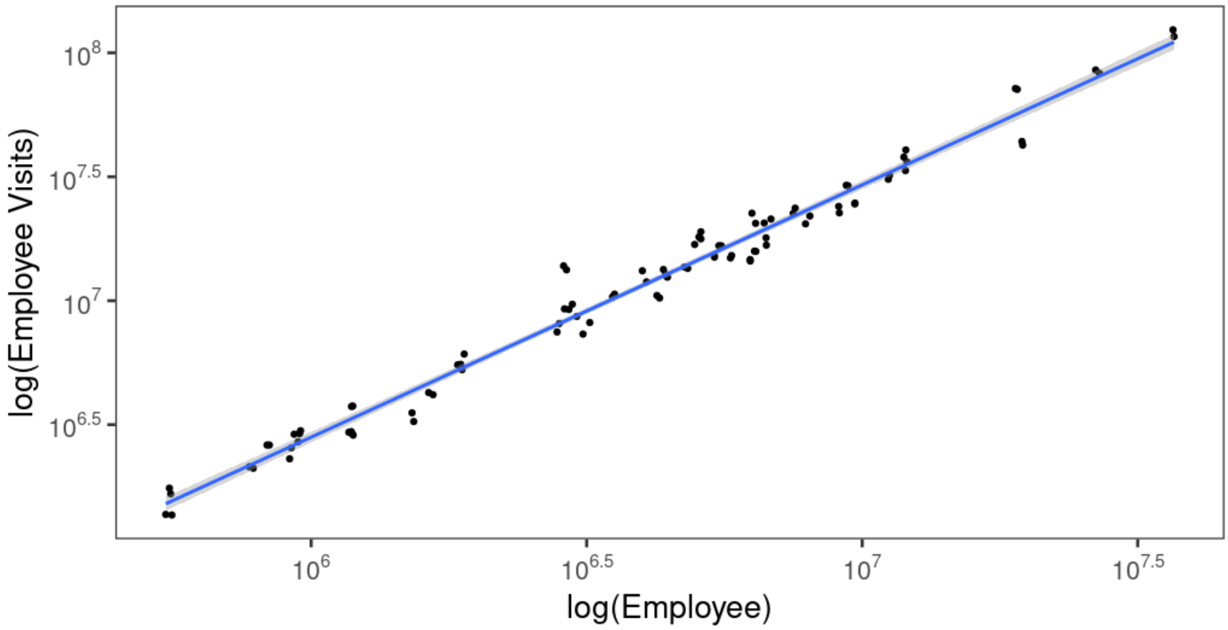


Using the textbook labor market model, In figure 7, at a point, A in the labor market model, E_0^c units of labor are willing to work at a wage W_0^c offered in a competitive labor market. When minimum wage W_1^c is introduced, the units of labor demanded by the firm decrease to E_1^c and there is a movement along the labor demand curve from point A to C. In a monpsony labor market model, a firm can maximize its profit by employing E_0^m units of labor where the marginal cost of labor is equal to the marginal revenue of product at a wage of W_0^m on the labor supply curve. When the minimum wage is introduced at W_1^m above the equilibrium point A, for each unit of labor employed firm has to offer a minimum wage of W_1^m, and thus marginal cost curve is equal to the marginal revenue of the product curve at E_1^m units of labor. At this point, the units of labor employed increased from E_0^m to E_1^m but still less than the initial competitive labor market equilibrium level E_0^c.

7.1 State-level LODES data

In Subsection 3.1.1, I presented the estimates for the number of employees at the census block group and the number of higher bucket visits duration. In Figure 8, I present the state-level relationship between a number of employees in annual LODES data and the number of employee visits.

Figure 8: Log number of jobs and log number of employee visits at State-level



7.2 Minimum Wage Changes

I used the January 2018 minimum wages as given and study the changes in minimum wage after first month of 2018 until December 2019. In Table 8, there are different cities treated at different time of the year.

7.3 Balanced and Unbalanced Panel

I have used zero to replace the missing values for the POIs visits in my main results. In Table 9, I present an unbalanced panel with missing values and a balanced panel by considering POI

Table 8: Sub-state and State minimum wage Ordinances from January 2018 until December 2019

Year & Month	**Ordinance Jurisdiction**		**State**
	Sub-State	State	
2018			
March	Santa Fe City		NM
July	Montgomery County	State-wide change	MD
	Portland City	State-wide change	OR
	Cities:- Alameda, Belmont, Emeryville, Los Angeles, Malibu, Milpitas, Pasadena, San Francisco, San Leandro, Santa Monica		CA
	Cook County & Chicago City		IL
	Portland City		ME
	Minneapolis		MN
October	Berkeley		CA
2019			
January		State-wide change	OH,SD, FL,MO, ME,CO, DE
	Bernalillo County & Cities:- Albuquerque, Las Cruces		NM
	Cities :- Seattle, SeaTac, Tacoma	State-wide change	WA
	New York City & Nassau, Westchester, and Suffolk Counties	State-wide change	NY
	Cities:- Cupertino, Belmont, Daly, El Cerrito, Los Altos, Palo Alto, Redwood, Richmond, Milpitas, Mountain View, San Jose, San Mateo, Santa Clara, Sunnyvale, Oakland	State-wide change	CA
	Flagstaff		AZ
March	Santa Fe City		NM
April		State-wide change	MI
July		State-wide change	MD,OR, NJ
	Portland City		OR
	Montgomery County		MD
	Cities:- Alameda, Berkeley, Emeryville, Fremont, Los Angeles, Malibu, Pasadena, San Francisco, San Leandro, Santa Monica		CA
	Cook County & Chicago City		IL
	Portland City		ME
	Minneapolis		MN
October		State-wide change	CT,DE

which was tracked for all 24 months. Model (1) presents results from an unbalanced panel for the full sample, Model (2) presents the estimates for the Retail & Trade industry, and Model (3) estimates for the Accommodation & Food industry. Similarly, Model (4) presents a full balanced panel with the POIs tracked for all 24 months, and Model (5) and Model (6) present a balance for the Retail & Trade and Accommodation & Food industry respectively when the POIs tracked for all 24 months. All estimates are clustered at the city level.

Table 9: Minimum wages and duration visits for unbalanced panel and balanced panel with 24 months tracking.

	Unbalanced Panel			**Balanced Panel**		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Employee Visit	-0.4702***	-0.4385***	-0.5229***	-0.5104***	-0.4735***	-0.5580***
	(0.0727)	(0.0689)	(0.0939)	(0.0763)	(0.0740)	(0.0924)
Customer Visit	-0.5295***	-0.6529***	-0.7472***	-0.5548***	-0.6490***	-0.7422***
	(0.0868)	(0.1062)	(0.1205)	(0.0879)	(0.1044)	(0.1187)
Visits > 240 mins	-0.4921***	-0.4590***	-0.5576***	-0.5467***	-0.4999***	-0.5983***
	(0.0749)	(0.0700)	(0.0956)	(0.0794)	(0.0761)	(0.0940)
Visits < 5 mins	-0.7876***	-1.086***	-1.080***	-0.8486***	-1.113***	-1.102***
	(0.1034)	(0.1452)	(0.2018)	(0.1134)	(0.1489)	(0.1148)
Total visits	-0.5294***	-0.6399***	-0.7361***	-0.5615***	-0.4735***	-0.7499***
	(0.0811)	(0.0994)	(0.1149)	(0.0843)	(0.0816)	(0.0924)
Fixed-effects						
POI	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	96,234,811	24,970,615	17,063,877	57,961,055	11,309,784	27,515,328

Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

7.4 Median Distance Traveled

In Subsection 7, I presented the distance traveled for the full sample. In Figure 10, I show the results for the Accommodation & Food industry with a two-digit NAICS code of 72 and the Retail & Trade industry with two-digit NAICS code of 44-45.

7.5 Industrial heterogeneity

Table 10: Median Distance traveled and minimum wage for retail & trade and accommodation & food industry

Industry by 2-digit NAICS code	Acc. & Food (72)		Retail & Trade (44-45)	
Model:	(1)	(2)	(3)	(4)
Variables in log				
Minimum Wage	0.1884**	0.4328***	0.1596**	0.3555***
	(0.0731)	(0.1095)	(0.0627)	(0.0891)
Total visits	0.0120**	0.0062	0.0077**	0.0043
	(0.0059)	(0.0055)	(0.0031)	(0.0029)
Fixed-effects				
POI	Yes	Yes	Yes	Yes
Date	Yes		Yes	
State × Date		Yes		Yes
Fit statistics				
Observations	9,685,944	9,685,944	14,370,936	14,370,936
R^2	0.84163	0.84391	0.83146	0.83287
Within R^2	0.00022	0.00018	0.00013	9.24×10^{-5}

Clustered (city-region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Minimum wages and duration visits in the Retail & Trade Industry with geographic trends

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Employee Visits	-0.4245***	-0.7578***	-0.2583***	-0.2898***	-0.3859***
	(0.0688)	(0.1018)	(0.0860)	(0.0851)	(0.0958)
Customer Visits	-0.6212***	-0.9383***	-0.3723***	-0.4525***	-0.4179***
	(0.1074)	(0.1571)	(0.1150)	(0.1111)	(0.1137)
Fixed-effects					
POI	Yes	Yes	Yes	Yes	Yes
Date	Yes				
State × Date		Yes			
Census Division ×Date			Yes		
Census Region × Date				Yes	
LMz×Date					Yes
Fit statistics					
Observations	26,358,072	26,358,072	26,358,072	26,358,072	26,358,072

Clustered (City) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Minimum wages and duration visits in the Accommodation & Food Industry with geographic economics shocks fixed effect

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Employee Visits	-0.5612***	-0.9650***	-0.3387***	-0.3862***	-0.5753***
	(0.1044)	(0.0837)	(0.1233)	(0.1229)	(0.1101)
Customer Visits	-0.7657***	-1.050***	-0.4325***	-0.5276***	-0.5644***
	(0.1260)	(0.1765)	(0.1352)	(0.1301)	(0.1166)
Fixed-effects					
POI	Yes	Yes	Yes	Yes	Yes
Date	Yes				
State × Date		Yes			
Census Division ×Date			Yes		
Census Region × Date				Yes	
LMz×Date					Yes
Fit statistics					
Observations	16,249,272	16,249,272	16,249,272	16,249,272	16,249,272

Clustered (City) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: 24-months leads and lag relative to the time of treatment estimates for duration visits

Dependent Variables:	Visits greater than 120 min	Employee Visits	Customer Visits	Visits greater than 240 min	Visits less than 5 min
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
MW_{21}	-1.730***	-1.284***	-0.7222***	-2.172***	-2.366***
	(0.1410)	(0.1444)	(0.1323)	(0.1544)	(0.1434)
MW_{20}	0.5630**	0.7359***	2.926***	0.8607***	1.518***
	(0.2213)	(0.2178)	(0.1798)	(0.2295)	(0.1836)
MW_{19}	-4.147***	-3.437***	-1.400***	-3.580***	-1.545***
	(0.1143)	(0.1151)	(0.1376)	(0.1225)	(0.1581)
MW_{18}	-5.003***	-4.395***	-2.402***	-6.386***	-2.557***
	(0.1572)	(0.1564)	(0.1451)	(0.1593)	(0.1774)
MW_{17}	-1.442***	-1.354***	-1.554***	-1.293***	-1.423***
	(0.2907)	(0.2897)	(0.2632)	(0.2810)	(0.2333)
MW_{16}	-1.456***	-1.468***	-0.9943***	-1.450***	-0.9679***
	(0.3231)	(0.3257)	(0.2585)	(0.3250)	(0.2558)
MW_{15}	-0.7677***	-0.6427***	-1.225***	-0.4897***	-0.9969***
	(0.1078)	(0.1002)	(0.1929)	(0.0859)	(0.2017)
MW_{14}	-0.6437***	-0.5134***	-1.114***	-0.4085***	-0.9066***
	(0.1549)	(0.1419)	(0.2251)	(0.1368)	(0.2343)
MW_{13}	-1.083***	-0.9915***	-1.400***	-0.9134***	-1.279***
	(0.1834)	(0.1879)	(0.2121)	(0.1785)	(0.2362)
MW_{12}	-0.5993***	-0.4950**	-1.191***	-0.4338**	-0.7173***
	(0.2079)	(0.2129)	(0.2091)	(0.1980)	(0.2715)
MW_{11}	-0.6527***	-0.5249***	-0.7512***	-0.4616***	-0.9273***
	(0.1107)	(0.1067)	(0.1228)	(0.1054)	(0.2119)
MW_{10}	-0.7451***	-0.6877***	-0.5924***	-0.6648***	-0.7984***

	(0.1190)	(0.1099)	(0.1210)	(0.1121)	(0.2058)
MW_9	-0.5367***	-0.4497***	-0.6839***	-0.3853***	-0.8531***
	(0.1043)	(0.0928)	(0.0952)	(0.0960)	(0.1994)
MW_8	-0.3536***	-0.2696**	-0.5699***	-0.2282*	-0.6826***
	(0.1103)	(0.1119)	(0.0671)	(0.1230)	(0.1549)
MW_7	-0.3828***	-0.3160***	-0.4911***	-0.2980***	-0.5363***
	(0.0828)	(0.0843)	(0.1193)	(0.0957)	(0.1675)
MW_6	-0.2085**	-0.1365*	-0.3023***	-0.0901	-0.3472*
	(0.0830)	(0.0745)	(0.1144)	(0.0751)	(0.1962)
MW_5	-0.1328**	-0.0534	-0.2147***	-0.0319	-0.5271***
	(0.0559)	(0.0539)	(0.0818)	(0.0607)	(0.1263)
MW_4	-0.3455***	-0.2874***	-0.3655***	-0.2923***	-0.7584***
	(0.0728)	(0.0746)	(0.1047)	(0.0844)	(0.1063)
MW_3	-0.2572***	-0.1904***	-0.2854***	-0.1623**	-0.6363***
	(0.0744)	(0.0707)	(0.0874)	(0.0781)	(0.1084)
MW_2	-0.2734***	-0.2367***	-0.1956**	-0.2246**	-0.4684***
	(0.0949)	(0.0880)	(0.0821)	(0.1022)	(0.1580)
MW_1	-0.2300***	-0.2110**	-0.2438***	-0.2057**	-0.2155
	(0.0776)	(0.0838)	(0.0756)	(0.0963)	(0.1417)
MW_0	-0.0259	-0.0246	0.0285	0.0098	0.0996
	(0.0693)	(0.0701)	(0.0689)	(0.0767)	(0.1580)
MW_{-1}	0.0481	0.0491	-0.0012	0.0952	0.1646***
	(0.0473)	(0.0532)	(0.0379)	(0.0595)	(0.0264)
MW_{-2}	0.0073	0.0202	-0.0707*	0.0336	-0.0605***
	(0.0358)	(0.0409)	(0.0379)	(0.0482)	(0.0231)
MW_{-4}	0.1826***	0.1705***	0.0964***	0.1671***	0.2608***
	(0.0425)	(0.0476)	(0.0304)	(0.0478)	(0.0253)
MW_{-5}	0.1540**	0.1330**	-0.0786	0.1755**	0.1816***
	(0.0646)	(0.0676)	(0.0676)	(0.0713)	(0.0442)
MW_{-6}	0.2628***	0.2239***	0.2270***	0.2970***	0.3048**
	(0.0806)	(0.0692)	(0.0876)	(0.0853)	(0.1219)
MW_{-7}	0.1649**	0.1000	0.2445***	0.1548**	0.4759***
	(0.0719)	(0.0644)	(0.0656)	(0.0770)	(0.1147)
MW_{-8}	0.1929**	0.1592**	0.1867**	0.2579***	0.4295***
	(0.0793)	(0.0803)	(0.0900)	(0.0967)	(0.1237)
MW_{-9}	0.0322	0.0058	0.0413	0.0687	0.2480***
	(0.0859)	(0.0868)	(0.0866)	(0.1055)	(0.0901)
MW_{-10}	0.2286**	0.2174**	-0.0258	0.3223***	0.1951
	(0.0904)	(0.0878)	(0.0880)	(0.0976)	(0.1187)
MW_{-11}	0.2440***	0.2053**	0.1481*	0.2936***	0.1820
	(0.0907)	(0.0905)	(0.0824)	(0.1011)	(0.1419)
MW_{-12}	0.3516***	0.3010***	0.5719***	0.3779***	0.3877
	(0.0905)	(0.0803)	(0.0777)	(0.0864)	(0.2399)
MW_{-13}	0.3299**	0.3324***	0.6695***	0.3987***	0.2384
	(0.1539)	(0.1286)	(0.1176)	(0.1302)	(0.4122)
MW_{-14}	0.2307	0.2543**	0.4451***	0.3358***	0.1626
	(0.1467)	(0.1268)	(0.1300)	(0.1188)	(0.3794)
MW_{-15}	0.3311**	0.3697***	0.4695***	0.3840***	0.0153
	(0.1418)	(0.1386)	(0.1457)	(0.1281)	(0.3406)
MW_{-16}	0.3716***	0.4028***	0.0539	0.4836***	-0.3980
	(0.1311)	(0.1209)	(0.1081)	(0.1355)	(0.2878)
MW_{-17}	0.1640	0.1316	0.0898	0.2738*	-0.5108*
	(0.1296)	(0.1104)	(0.1454)	(0.1416)	(0.2639)
MW_{-18}	0.1641	0.1148	0.3581**	0.2236	-0.2102
	(0.1543)	(0.1233)	(0.1687)	(0.1391)	(0.2854)
MW_{-19}	0.1310	0.1896*	0.4777***	0.3773***	-0.5659***
	(0.1182)	(0.1103)	(0.1411)	(0.1048)	(0.2174)
MW_{-20}	-0.1961**	-0.1768**	0.4555***	-0.0293	-0.6947***
	(0.0831)	(0.0795)	(0.1683)	(0.0990)	(0.1486)
MW_{-21}	-0.0891	-0.0256	0.2621	0.1067	-0.4626**
	(0.1003)	(0.0903)	(0.1908)	(0.1012)	(0.2005)
MW_{-22}	-0.6846***	-0.5663***	-0.7947***	-0.4724**	
	(0.0868)	(0.0842)	(0.0964)	(0.1916)	*Collinear*
MW_{-23}	-0.5353***	-0.4130***	-0.5942***	-0.4343	

	(0.0986)	(0.0796)	(0.0801)	(0.2861)	*Collinear*
Fixed-effects					
placekey	Yes	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	106,378,560	106,378,560	106,378,560	106,378,560	106,378,560
R^2	0.78908	0.76918	0.87035	0.75194	0.74239
Within R^2	0.00021	0.00019	0.00032	0.00018	0.00048

Clustered (city-region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 14: 24-months leads and lags relative to the time of treatment estimates for total visits and distance traveled

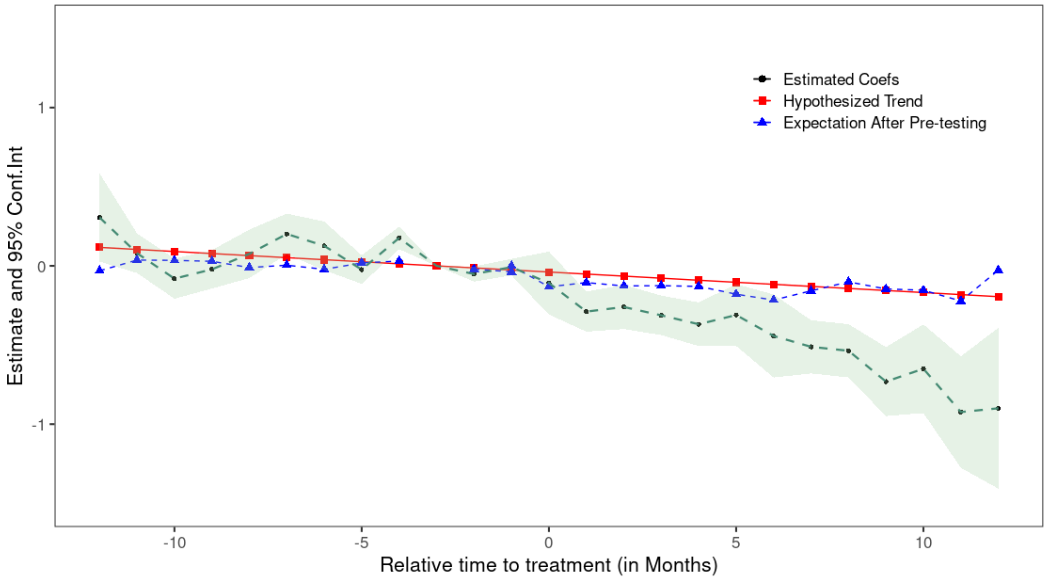
Dependent Variables:	Total Visitors	Total Visits	Distance traveled
Model:	(1)	(2)	(3)
MW_{21}	-0.8039***	-0.7140***	6.509***
	(0.1557)	(0.1362)	(0.1035)
MW_{20}	2.802***	1.862***	0.9467***
	(0.2045)	(0.1952)	(0.1346)
MW_{19}	-1.932***	-1.425***	7.834***
	(0.1330)	(0.1279)	(0.0797)
MW_{18}	-2.856***	-2.249***	4.103***
	(0.1704)	(0.1638)	(0.1338)
MW_{17}	-1.708***	-1.537***	0.3033
	(0.3068)	(0.2814)	(0.2193)
MW_{16}	-1.265***	-1.257***	0.3190**
	(0.2996)	(0.2895)	(0.1563)
MW_{15}	-1.257***	-1.124***	0.0635
	(0.2037)	(0.1905)	(0.1030)
MW_{14}	-1.119***	-0.9954***	0.2108
	(0.2332)	(0.2122)	(0.1474)
MW_{13}	-1.449***	-1.228***	0.4205***
	(0.2399)	(0.2376)	(0.1586)
MW_{12}	-0.9017***	-0.8645***	-0.1748
	(0.2480)	(0.2299)	(0.2937)
MW_{11}	-0.9355***	-0.8192***	0.1103
	(0.1572)	(0.1447)	(0.0996)
MW_{10}	-0.7379***	-0.7107***	0.1162
	(0.1340)	(0.1301)	(0.0881)
MW_9	-0.7450***	-0.6512***	0.0275
	(0.1117)	(0.1088)	(0.0742)
MW_8	-0.5251***	-0.4410***	-0.0365
	(0.0922)	(0.0887)	(0.1383)
MW_7	-0.5161***	-0.4066***	0.0851
	(0.0828)	(0.0773)	(0.0854)
MW_6	-0.4279***	-0.3446***	0.0934
	(0.1219)	(0.1163)	(0.0786)
MW_5	-0.3031***	-0.2442***	0.0360
	(0.0874)	(0.0835)	(0.0459)
MW_4	-0.3876***	-0.3369***	-0.0436
	(0.0623)	(0.0555)	(0.0418)
MW_3	-0.3045***	-0.2331***	-0.1114**
	(0.0646)	(0.0537)	(0.0502)
MW_2	-0.2669***	-0.1782***	-0.0132
	(0.0725)	(0.0645)	(0.0412)
MW_1	-0.3096***	-0.2006***	-0.0283
	(0.0571)	(0.0588)	(0.0898)
MW	-0.1357	-0.0869	-0.1286*
	(0.0895)	(0.0801)	(0.0673)

MW_{-1}	-0.0479*	-0.0200	-0.0472*
	(0.0272)	(0.0250)	(0.0253)
MW_{-2}	-0.0722***	-0.0420**	-0.0271
	(0.0219)	(0.0207)	(0.0218)
MW_{-4}	0.1796***	0.1663***	-0.0993**
	(0.0422)	(0.0413)	(0.0484)
MW_{-5}	-0.0190	-0.0136	-0.0980
	(0.0490)	(0.0452)	(0.0981)
MW_{-6}	0.1166	0.0895	-0.0550
	(0.0719)	(0.0672)	(0.0881)
MW_{-7}	0.1605***	0.1320**	-0.0545
	(0.0617)	(0.0586)	(0.0749)
MW_{-8}	0.0641	0.0322	-0.0595
	(0.0725)	(0.0655)	(0.0503)
MW_{-9}	-0.0177	-0.0439	-0.0878
	(0.0659)	(0.0559)	(0.0546)
MW_{-10}	-0.0519	-0.0822	-0.2015***
	(0.0715)	(0.0612)	(0.0482)
MW_{-11}	0.0403	-0.0054	-0.1452
	(0.0672)	(0.0613)	(0.1029)
MW_{-12}	0.2588**	0.1767	-0.2279**
	(0.1221)	(0.1132)	(0.1106)
MW_{-13}	0.1756	0.1466	-0.2775***
	(0.2424)	(0.2303)	(0.0556)
MW_{-14}	0.0054	0.0078	-0.0308
	(0.2322)	(0.2262)	(0.0752)
MW_{-15}	0.1560	0.1186	-0.1820*
	(0.1875)	(0.1833)	(0.1075)
MW_{-16}	-0.0908	-0.1620	-0.4218***
	(0.1178)	(0.1095)	(0.1558)
MW_{-17}	-0.1549	-0.2190*	-0.0741
	(0.1399)	(0.1315)	(0.0932)
MW_{-18}	-0.0658	-0.1322	-0.0906
	(0.2047)	(0.1922)	(0.0638)
MW_{-19}	-0.4332***	-0.5087***	0.0473
	(0.1664)	(0.1465)	(0.1071)
MW_{-20}	-0.5550***	-0.6257***	0.1118**
	(0.1275)	(0.1171)	(0.0438)
MW_{-21}	-0.4379***	-0.4768***	0.1984***
	(0.1294)	(0.1184)	(0.0430)
MW_{-22}	-0.3880***	-0.3538***	0.6011***
	(0.0843)	(0.0885)	(0.1035)
MW_{-23}	-0.2595	-0.2644*	0.1138**
	(0.1717)	(0.1585)	(0.0567)
Fixed-effects			
placekey	Yes	Yes	Yes
date	Yes	Yes	Yes
Fit statistics			
Observations	106,378,560	106,378,560	82,578,403
R^2	0.85489	0.86279	0.72814
Within R^2	0.00030	0.00030	0.00023

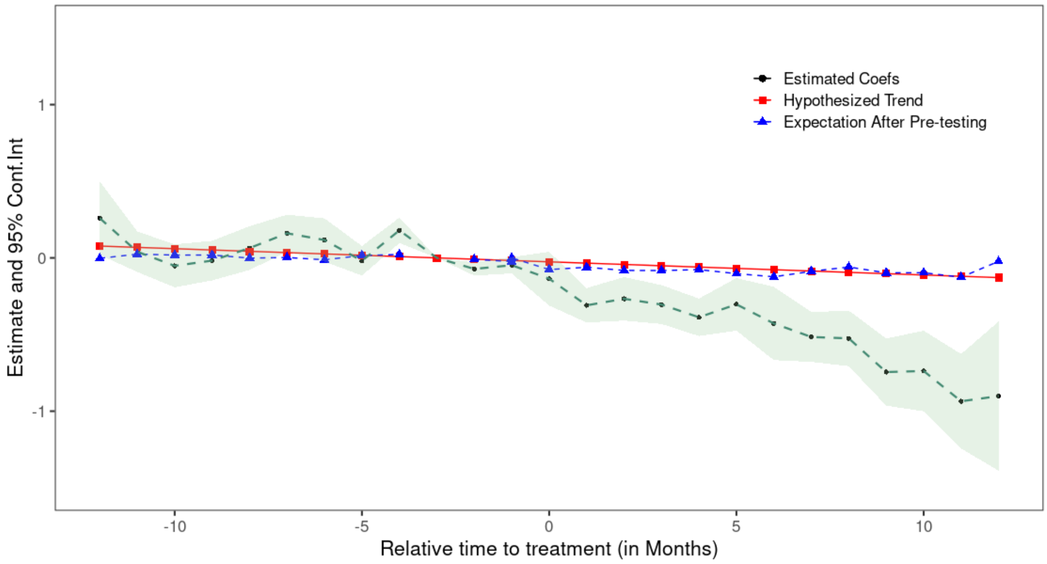
Clustered (city-region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 9: Pre-trend and Effect of Minimum Wages on duration visits and distance traveled over time

(a) Customer Visits



(b) Total visitor



(c) Distance traveled