City Limits: The relationship between employment and minimum wage using mobile-device locations

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Abstract

The last decade has seen noteworthy local policy decisions, especially a trend in the decentralization of wage determination. Considering local policy changes are aimed at the local areas where boundaries are porous, there is a need for detailed and accurate geographic and time information. Using the establishment location and mobile-device location data by SafeGraph, this study explores how the labor market responds to local minimum wage ordinances. I use the difference-in-differences approach to estimate the effect of variation in the minimum wage on the duration of visits at a location which can be used as a proxy for employment hours. I find a decrease in employment hours when there is a proportionate increase in the local minimum wage and an increase in distance traveled from home with an increase in the minimum wage. 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, 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 demanding higher minimum wage and started a worker's movement called "Fight for $15." Over a decade, this movement expanded across the United States and led 50 cities and counties to enact their own local minimum wage ordinances with higher wages than the existing state or federal level. More than 100 leading economists including Daron Acemoglu and Nobel Laureates Angus Deaton 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 the minimum wage increase 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].

Congress failed to increase the minimum wage, Congressional Budget Office analysis forecast an increase in the average income of low-wage workers when the federal minimum wage increases, but more likely to cause 1.3 million job losses; however, many sub-state jurisdictions have taken the lead, and enacted the local minimum wage ordinances even higher than $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 the sub-state jurisdictions have revived the discussion among labor and urban economists on the potential effect of local-minimum wage on economic activities.

A local minimum wage increase may have a different impact on the local labor market than a state-wide or federal raise in the minimum wage. Businesses may choose to relocate a few miles outside the city boundaries or choose to reduce the number of employees/working hours. Workers may commute to/from the nearby areas for better employment opportunities and higher wages as the city boundaries are more cellular compared to the state. 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 [cities]. In this study, I use mobile device locations to explore the impact of city-wide minimum wage variation on visits to business establishments [POIs/Places of interest]. When a city enacts a minimum wage ordinance, are there changes in the number

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

of visits? Are individuals more likely to stay longer 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 employees? 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, it becomes important to understand the effectiveness to consider neighborhood areas as comparison groups. 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 introducing minimum wage ordinances with the aim to help low-wage workers, it tends to attract more workers who migrate to take advantage of the opportunities. Dube and Lindner (2021) also noted 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 Higher duration visits, i.e visits more than 240 minutes or 120 minutes in a day, as employee visits to analyze the effect of city-wide variation in the minimum wage. In Section 3.1.1, I discuss this assumption in detail. For shorter duration visits, i.e visits less than 240 minutes or 120 minutes in a day, assuming the employer passes the increased labor cost to the customer through a minimal increase in the price of the product as suggested by Allegretto et al. (2018) visits by a customer can be used to understand the price elasticity of demand. Using the geolocation for the precise location of the establishment, I find that there is more negative relationship between employment and local minimum wages. Also, the distance traveled increases when minimum wages increases.

In Section 2, I will provide the background on the minimum wage change especially prior literature on city minimum wage to understand the requirement of the geo-locations and discuss the studies using cross-border comparisons as an identification strategy; Section 3 will review the mobile location data source used to capture the commuting patterns. Section 4 will further outline the empirical strategy to explore monthly visits elasticity to the minimum wage at the establishment level. In Section 6, I will discuss the intuition behind the results and analyses that need to be conducted to establish the relationship between minimum wages and commuting patterns and discuss robustness checks to understand the commuting pattern and control for home Census Block Groups (CBGs) to the establishment.

2 Background

The evidence of the minimum wage effect in the United States at the federal or state level has been extensively studied and reviewed over the decades. Brown et al. (1982), Card and Krueger (1995), Neumark, Wascher, et al. (2007), Wolfson and Belman (2019), Neumark (2019), Neumark and Shirley (2022) In the last three decades, the minimum wage studies have followed two common trends, first, the use of administrative data like the Quarterly Census of Employment and Wages (QCEW) by the Bureau of Labor Statistics (BLS) or the annual American Community Survey (ACS) by the 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 the state-level unemployment insurance systems providing us with rich demographic and employment details about the labor market, but the geographic location is not based on the workplace [2]. The Unemployment Insurance (UI) payroll data assign location based on the employer's UI account. Regardless of the business location in a state, each firm is required to have a UI account. Some firms having multiple locations of business around the state might have one single UI account. Thus multi-location single UI account firms might not be reflected in the administrative data. Moreover, it is important to identify the businesses located in the city, Jardim et al., 2017 used the geo-location for the single UI account businesses to study Seattle's minimum wage change, and found 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 [establishment].

The ACS by the U.S. Census Bureau on the other hand is an annual residential-based survey.

[2] https://lehd.ces.census.gov/doc/QWI_101.pdf

It helps us understand the annual employment status and income level of households but does not provide information based on the employment destination. It may be the case were a worker was employed in a different city but in the same county or state. The studies based on the ACS do not consider the workplace location which again leads us to the 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 the region fixed effect, or equivalently look only at border regions, I reduce the bias from the unobservable 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 vs distant regions of the treated region. The jurisdiction which enacts a higher minimum wage is not chosen exogenously. 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 aimed to reach $ 7.50 by 2009. It becomes legitimate to be concerned about the ways to eliminate the heterogeneity for better assimilation of the "Difference-in-Differences" method when discussing minimum wages.

The empirical work presenting no negative result heavily relies on the neighboring jurisdictions for the control groups, Neumark and Shirley (2021). The previous studies assume that the regions located closer have similar labor trends i.e they cater to the same labor force and establishments. To eliminate the heterogeneous effect and focus on the actual treatment effect of the policy change, studies tend to consider the contiguous regions as the comparison groups. Then the causal estimates are based on the assumption of no spillover effect and no heterogeneous treatment. For instance, Card and Krueger (1993) used the restaurants located along the New Jersey-Pennsylvania border as they are more likely to face a similar local labor market to help authors mimic controlled experiments. Using the gravity model, Kuehn (2016) analyzed ACS data for five years to indicate that minimum wage is correlated with unobserved differences among the neighboring jurisdiction (counties). Contrary to the identification assumption of Dube et al. (2010), the author 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 workers tend to migrate from counties where minimum wages increase. The study used the QCEW and ACS (2005-2015) data set to conclude that the disemployment effect of using neighboring counties as control areas can be due to labor mobility. 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 with lower minimum wages area 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.

I present a city-wide minimum wage analysis at the establishment level to study if there is an upward movement along the long-duration visit curve similar to the competitive labor market model or if there is a downward movement along the long-duration visit curve as in the monopsony labor market model. I use the exact longitude and latitude coordinates of the establishment, to locate within city council jurisdiction businesses. This will help in a better understanding of the true effect of minimum wages on labor demand.

3 Data

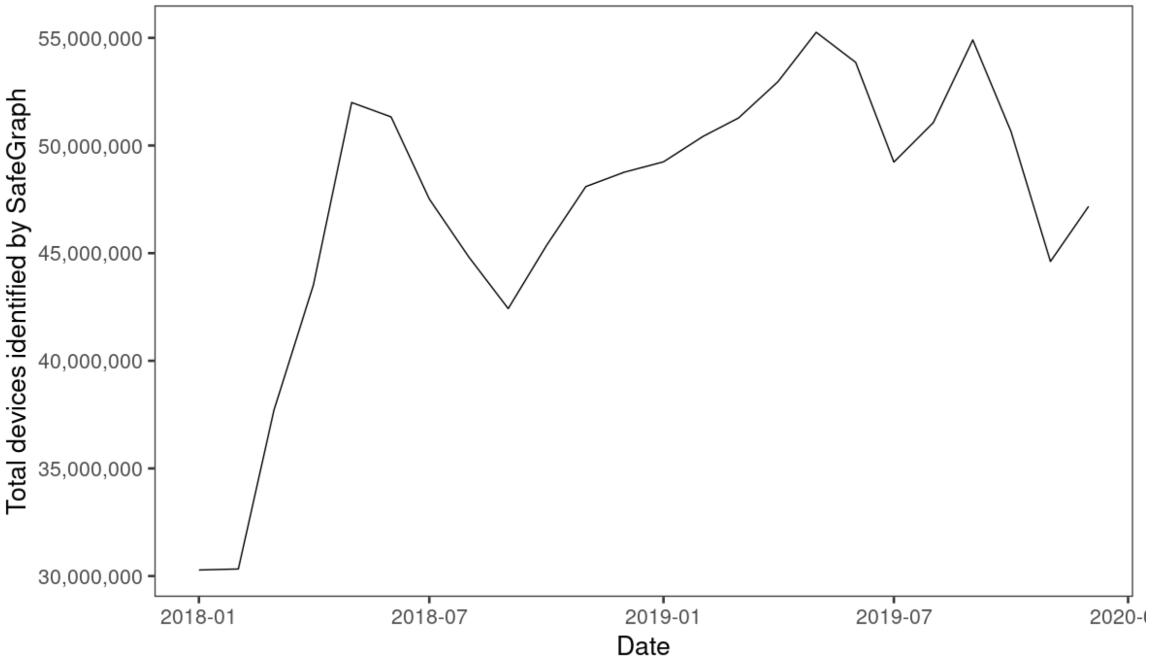
This study uses mobile location data from SafeGraph. The data uses GPS information from anonymous cellular devices and produces anonymized, aggregated extracts of mobility patterns to 4.5 million establishments in the US. The establishments are identified as Places of Interest (POIs) by matching the 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 1st January 2018 until 31st December 2019 due to 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 nearly 4.5 million POIs. The data reports the number of visits to the POI as visits and the number of the unique device identified at a POI as visitors. I use the number of visitors and their home census block group for each POIs, 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 the SafeGraph across the United States has varied over the period of 2018 and 2019 as shown in the Figure 1. 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 will help me get a uniform number of devices identified across the period of two years which can be used for analysis.

Figure 1: Number of devices identified by SafeGraph across the US for years 2018 and 2019



SafeGraph uses the first and last GPS ping at a POI to identify the minimum duration of the visit or the dwell time. I use the bucketed dwell times i.e the bins for the duration of visits by minutes, these bins are "<5", "5-10", "11-20", "21-60", "61-120", "121-240",">240." 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 an employee visit else I use the visits from the next bucket dwell "121-240." I assume any visits are less than these bucketed dwell times as customer visits. In Section 3.1.1 I discuss in detail whether long-duration visits are a good proxy for workers.

I use the POIs characteristics of the POIs like Industrial categorization based on the North American Industry Classification System (NAICS), name of the brand associate, 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 estab-

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

lishments 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 these major industries to study the effect of minimum wages.

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

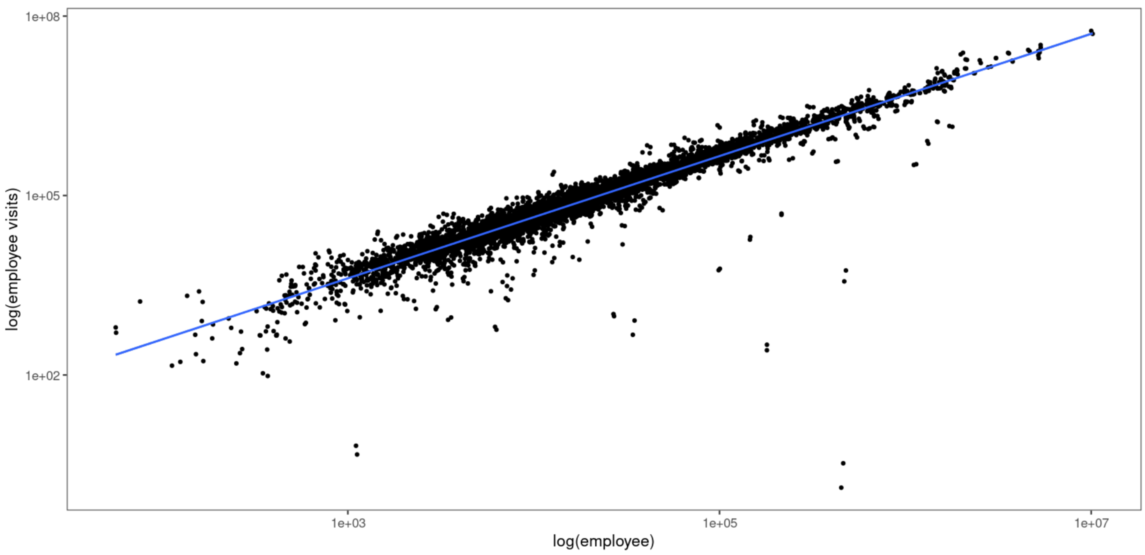
3.1.1 Employee Visits and State Employment

I use the total number of jobs at workplace census block group (CBG) from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics provided by the Bureau of Labor Studies [5] for the years 2018 and 2019 to find the best fit proxy for the employee. I normalize the number of jobs at the work CBG i in a state j by the fraction of population in the state j to the number of jobs in the state j for a year t. Similarly, I use the normalizing factor of the population in the state j to the number of devices identified in the state j at time t for the duration of visits in a CBG i at a time t. Using equation 1, I estimate the relationship between all the duration visits in a CBG i and the number of jobs in a CBG i by control for the CBG fixed effect μ_i and time fixed effect τ_t .

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

The estimates in Table 2 present a positive relationship at 0.01 level of significance. The visits duration for more than 240 minutes has a higher correlation with the number of jobs in a CBG but I considered the highest duration buckets as the employee visits which is formed by considering visits from 120 minutes bin if a POI in a CBG i did not have any visits for more than 240 minutes.

Figure 2: Log the number of jobs and log number of employee visits at County-level



I use a similar method to form variables with the highest bucket until 10 minutes visit but

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

Table 2: Number of jobs and duration visits at census block group level

Independent Variable:	Number of total employee in LEHD	
Model:	(1)	(2)
Dependent Variables:		
asinh(Visits greater than 240 mins)	0.0140***	0.0158***
	(0.0033)	(0.0034)
Fit statistics		
R^2	0.98622	0.98477
Within R^2	0.00016	0.00018
asinh(Visits greater than 120 mins)	0.0134***	0.0144***
	(0.0029)	(0.0030)
Fit statistics		
R^2	0.98841	0.98784
Within R^2	0.00017	0.00019
asinh(Visits in highest duration bucket until 120 minutes)	0.0140***	0.0157***
	(0.0030)	(0.0032)
Fit statistics		
R^2	0.98692	0.98546
Within R^2	0.00018	0.00020
asinh(Visits greater than 60 mins)	0.0113***	0.0131***
	(0.0027)	(0.0030)
Fit statistics		
R^2	0.99005	0.98987
Within R^2	0.00014	0.00016
asinh(Visits greater than 20 mins)	0.0106***	0.0108***
	(0.0025)	(0.0025)
Fit statistics		
R^2	0.99178	0.99177
Within R^2	0.00015	0.00015
asinh(Visits in highest duration bucket until 10 minutes)	0.0124***	0.0141***
	(0.0027)	(0.0029)
Fit statistics		
R^2	0.98601	0.98761
Within R^2	0.00016	0.00018
Fixed-effects		
Census Block Group	Yes	Yes
Year	Yes	No
Observations	386,555	386,555

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

the variable with the highest duration visits until 120 presents a higher correlation with the number of jobs and a better fit with the highest $Within\ R^2$ of 0.00018. In Figure 2, I present a county-level relation with the log number of employee visits [Visit in highest duration bucket 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 5. These high correlations with the number of jobs at CBG, County, and State-level provide enough confidence to use the number of visits in the highest duration bucket until 120 minutes as Employee visits. I consider the rest of the visits as consumer visits at a POI.

3.2 Minimum wage

I constructed 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 use study the time variation in minimum wages across jurisdictions. Figure 3 presents a population-weighted average minimum wage for the period of 2017 until 2021. Beginning of every year i.e January records a higher magnitude of minimum wage ordinance roll-out, the majority of which are state-level minimum wage ordinances. In Table 3, I list the sub-state and state minimum wage ordinances that is 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 1st October and 1st April respectively. Similarly, 19 sub-state councils implement minimum wage revisions around July every year across 7 states. In Section 4, I will 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.

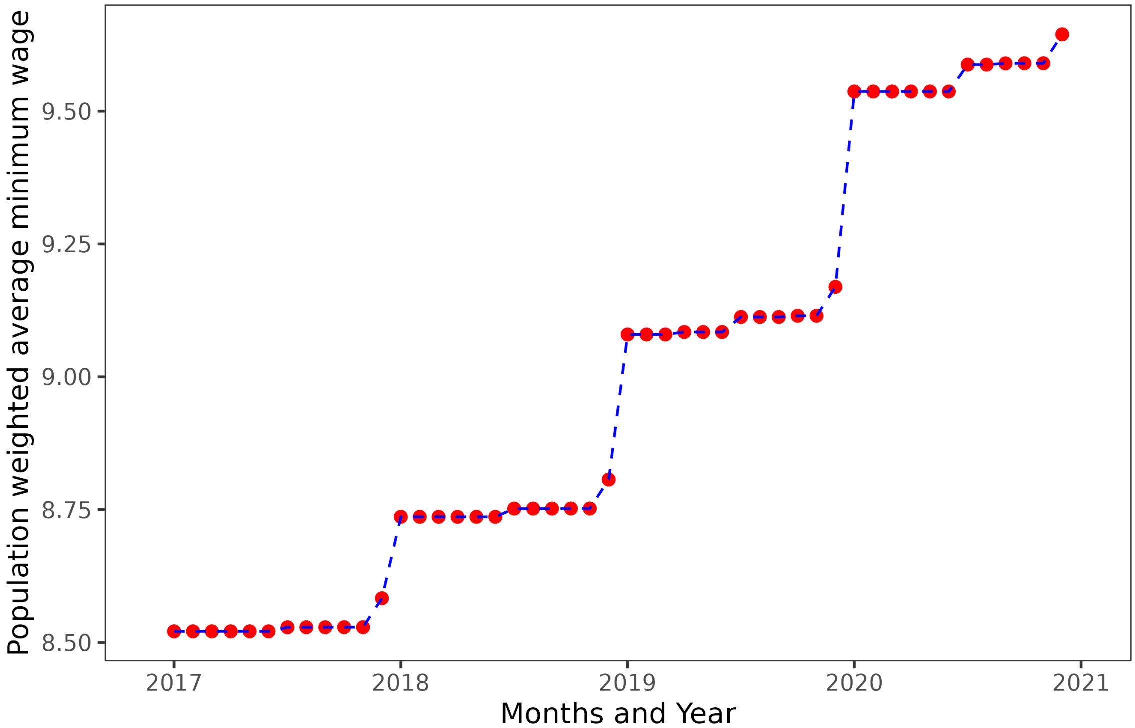
Based on the longitude and latitude of the POIs and the geospatial file of city boundaries defined by the US Census Bureau (presented in tigris r-package), SafeGraph identifies the city

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

Table 3: 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

Figure 3: Population-weighted average minimum wage change



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 having data for all the dates to balance the panel and eliminate the POIs with missing values.

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 by changing their commuting patterns in the short term. Customers may also alter commuting patterns based on the 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 3 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 for MW_{it} which is the effective minimum wage (local, state, or federal) faced by a POI i in the month t, where μ_i and ρ_t are the POI and date (month-year) fixed effect respectively. My outcome of interest V_{it} is the 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 pragmatically over the years which means multiple treatments with annual or sometimes with a shorted window. Recent literature like Sun and Abraham (2021), Callaway and Sant'Anna (2021), Goodman-Bacon (2021), De Chaisemartin and D'Haultfoeuille (2022) etc. 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. providing a possible solution, to estimate the difference across unit experiencing different dose of treatment.

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

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

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 multicolinearity problem between the event-time, I drop $\tau = -3$. This method of event study provides a visual test to the pre-treatment parallel trends assumption, more importantly with POI-level data for visits it helps me understand the non-parametric dynamics like visits and duration of visits, for instance, a change in visit could be 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 i.e employment to other POI or industry. This event study design using Δ which is the monthly difference operator for $log(MW)$, helps in eliminating the untreated potential outcome by making a cross-dose comparison.

The identification strategy for the Equation 3 is to exploit variation between 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 visitors at location i for a month t. I used 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 exogenous time variance. My identification assumption would be $E(u_{it}|logMW_{i,t-\tau}) = 0$ i.e 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 period 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.

5 Results

5.1 Main Results

In Table 4, I present results with the full sample and the sample without POIs involved in short-term lodging in column (1) and column (2) respectively estimated using equation 2. I will refer to the results in column (2) as estimates for the effect of minimum wage on the labor market because the full sample could show up more number of longer duration visits as employee visits which are actually customer visits. Though I do not observe much difference

Table 4: 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*

in magnitude, I will interpret that a 10% increase in minimum wage decreases employee visits by 4.6%. The customer visits estimate is also statistically significant and in similar lines with the negative elasticity of 0.54 to the minimum wage which also accounts for the majority of the total visits at a POI. The retail and trade industry [NAICS code - 44-45] in column (3) holds similar results overall with a negative effect on customer visits of -0.62. The customer visits for the accommodation and food industry [NAICS code - 72] in column (4) are larger in magnitude as compared to the sample in column (2) which could be the result of the transfer of input cost by businesses to the customer, in other words, the estimates for the customer visits is also an approximation of the price elasticity to customer duration visits. Importantly, when minimum wage increases there is a large decline in the short-term visits for less than 5 minutes which could be the representative of the decline in the pick-up and delivery services where the GPS is switched on once at a POI or it could be a decline in "check-in" 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 which has 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 5, I present the estimates from the balanced panel of POIs 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 customers 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 5: 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

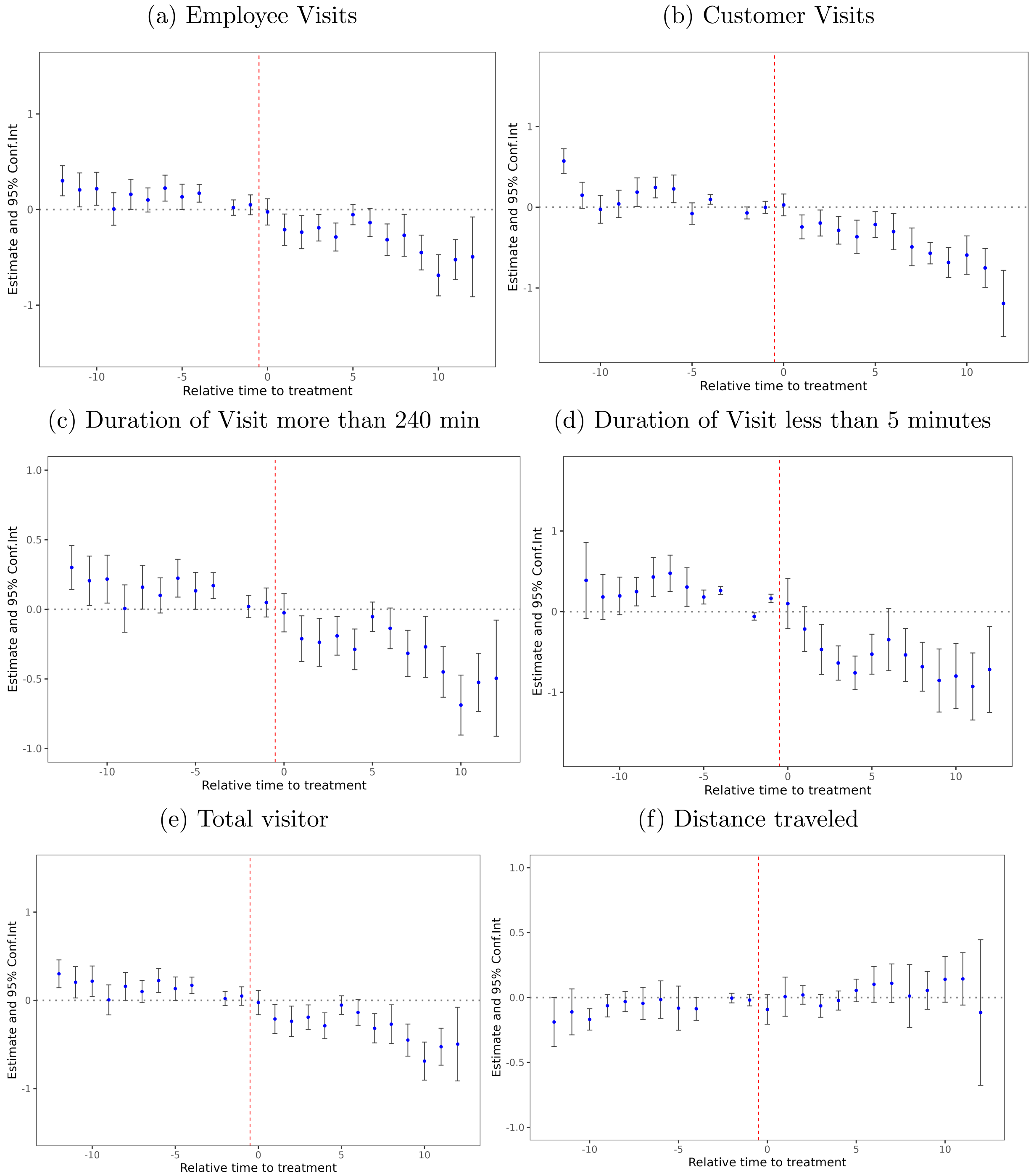
Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In Figure 4, 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 4 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 binded by local minimum wage ordinances can respond differently than the state binded ordinances. Businesses [POIs] have the option to move out a

Figure 4: 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

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 6 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 binded by the state-level minimum wage and the wage elasticity for customer visits is around -0.98 more than the POIs binded 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 the minimum wage. I also represented industry-specific estimates in the Appendix which also present higher magnitude and negative elasticity when compared to state ordinances.

Table 6: Local binded 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 Binded	-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*

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 4. In Table 7, 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 visits from column (2) validate our estimate of city binded minimum wage changes in Table 6. 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.

Table 7: Minimum wages and duration visits with Trend controls

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*

In Appendix Table 11 and Table **??**, 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 8, compared to column (1) both are statistically significant and more elastic to the change in minimum wages.

Table 8: Distance traveled and Minimum wages with trend controls

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
R^2	0.77494	0.77609	0.77532	0.77519	0.77808
Within R^2	6.75×10^{-5}	7.16×10^{-5}	1.22×10^{-5}	1.37×10^{-5}	6.56×10^{-5}

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 results in Table 7 and Table 8 validates that there is an increase in movement across 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.

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

6 Discussion and Conclusion

This study uses the visit duration at business establishments [POIs] as a proxy for employment to find the relationship between employment and minimum wages. Throughout this paper, I used the geo-location of the POI to identify the jurisdiction of the minimum wage ordinance to assign the minimum wage for the local area. Prior, literature has used the contiguous region as a control to estimate no or positive effect on employment using administrative data but the place of worker might be different from the place of residence or place of business may be different from the place of state-level UI registered account. When the workers can commute to nearby areas to arbitrage the variation in minimum wages. The labor supply curve tends to be more elastic, similarly, labor demand may be more elastic when businesses can relocate outside the local jurisdiction. I show that there is a negative elastic relationship between employee visits and minimum wages. Moreover, the employee visits are more negatively elastic to the local minimum wage change. Next, I show that there is an increase in the median distance traveled by the visitor to a POI. These results help explain that the labor market at the local level behaves more competitively than at the state level. The estimates of the customer visits shed light on the goods market, as the businesses tend to transfer increased operational costs to the customer, the demand is more elastic to the prices in the local market. I do not observe individual-device level data which makes it difficult to infer the decrease in duration of lower-wage workers or workers with lower skills. In future study, I will try to identify the census block group of the lower worker and estimate the direction of the commute. It is important to note that, the minimum wage is a lower bound to wage determination, many big private employers are choosing to implement higher wages which may have spillover effects in the local market and other employers may also choose to implement higher wages which is not reflected in this study but part of my future work.

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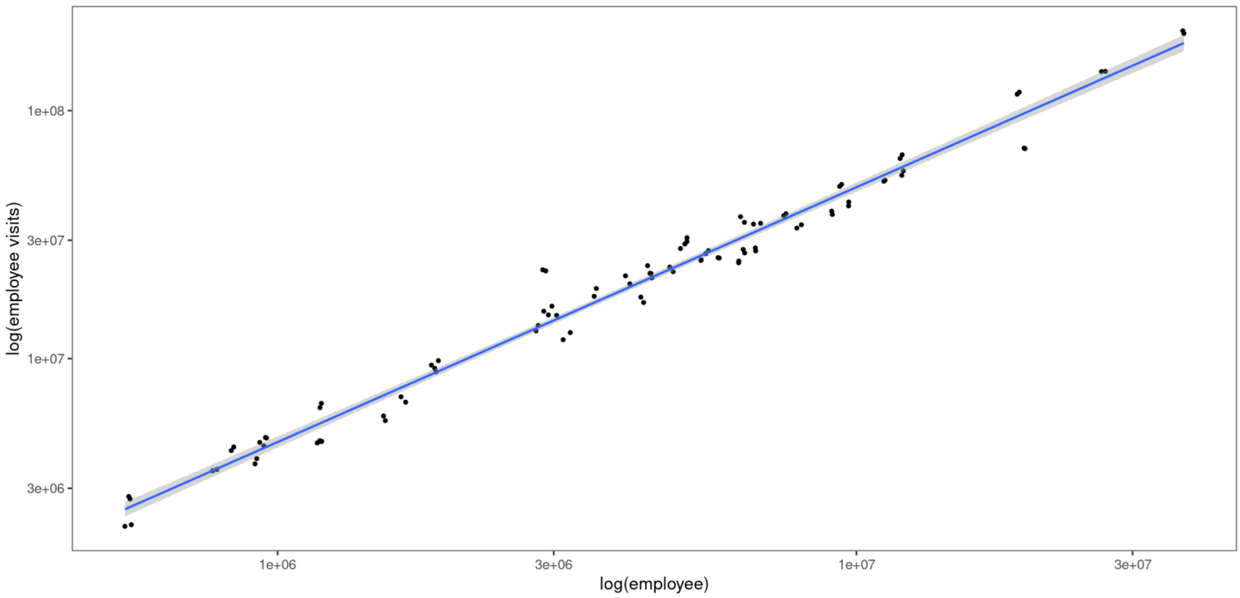
7 Appendix

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 5, I present the state-level relationship between a number of employees in annual LODES data and the number of employee visits.

Figure 5: Log number of jobs and log number of employee visits at State-level



7.2 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 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*

7.3 Median Distance Traveled

In Subsection 8, 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.

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*

7.4 Industrial heterogeneity

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

Table 12: 24-months leads and lag relative to the time of treatment estimates for duration visits

Dependent Variables: Model:	Visits greater than 120 min (1)	Employee Visits (2)	Customer Visits (3)	Visits greater than 240 min (4)	Visits less than 5 min (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 13: 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*

Dependent Variables in asinh:	Visit greater than 5 mins	Visit greater than 10 mins	Visit greater than 20 mins	Visit greater than 60 mins	Visit greater than 120 mins	Visit greater than 240 mins	Visits in highest bucket for 10 mins
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Normalised Variables							
Total workers	0.0099***	0.0101***	0.0106***	0.0113***	0.0134***	0.0140***	0.0124***
	(0.0022)	(0.0024)	(0.0025)	(0.0027)	(0.0029)	(0.0033)	(0.0027)
Fixed-effects							
poi_cbg	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	386,555	386,555	386,555	386,555	386,555	386,555	386,555
R^2	0.99335	0.99236	0.99178	0.99005	0.98841	0.98622	0.98761
Within R^2	0.00016	0.00014	0.00015	0.00014	0.00017	0.00016	0.00016

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