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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. First, 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 wage 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. The prior literature shows no negative relationship between minimum wage and employment in the U.S. restaurant industry. The argument hinges on the use of the contiguous region to study the minimum wage variation by controlling for economic shock which might be correlated with the minimum wage changes. Secondly, I use mobile-device location data to study cross-area movement for local areas when local minimum wage changes. I use the spatial and temporal variation across the U.S. to assess the impact of local minimum wage changes on cross-area commuting patterns. I find that when minimum wages at home increase by 10% the visits at the destination decrease from 2% to 3% with a variation depending on the distance between the home Census Block

Group(CBG) and the destination CBG. Though the number of visitors decreases as the distance between CBGs increases, the visitor increases by 12% more at the CBG which observes an increase in minimum wages.

MOBILE-DEVICE LOCATION DATA AND LABOR MARKETS

by

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To Mahima, for your love and support.

To my father, family, and friends,

for all that you have done over the years to support me.

I would not be where I am without you.

APPROVAL PAGE

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Chapter 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 the 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 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.

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

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 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 has 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 (2021b) also note that with a possibility of spatial changes, or distortions, "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 3.1.2. Prior literature (Allegretto et al., 2018; Harasztosi & Lindner, 2019; Renkin et al., 2022) suggested that the employer passes the increased labor cost to the consumer. Assuming that businesses make a minimal increase in 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 the Retail & Trade industry and the Accommodation and Food industry. Moreover, I find that when the minimum wage at the origin increases the visits at the destination census block group decrease.

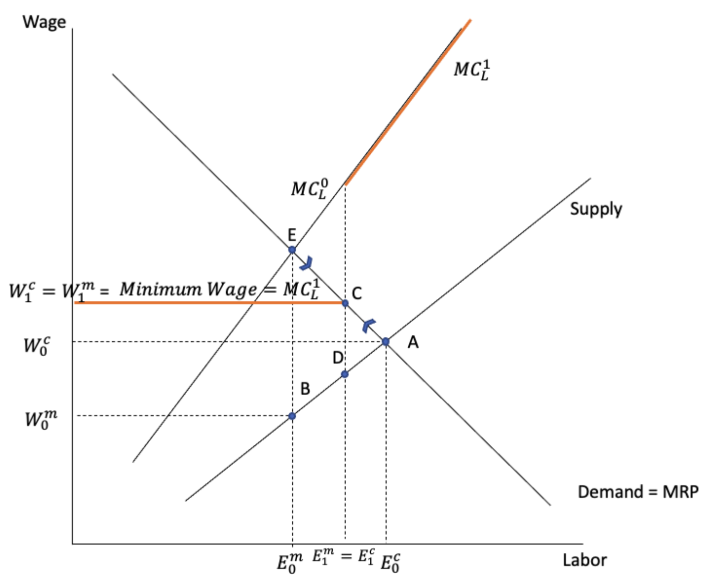
In Chapter 2, I will provide the background on the minimum wage change, especially prior literature on city minimum wage to understand the requirement of the geo-locations and discuss the studies using cross-border comparisons as an identification strategy; Chapter 3 will review the mobile location data source used to capture the commuting patterns. Chapter 4, I provide the research design and results for the effect of minimum wages on employment. In Chapter 5, I outline the empirical strategy to understand the commuting pattern from home Census Block Groups (CBGs) to the Census Block Groups of the establishment. In Chapter 6, I will discuss the intuition behind the results and policy implications that can be understood conditioned on the limitations of the data and study.

Chapter 2: Background

A simple competitive model of the labor market assumes other things equal an increase in the minimum wage, which leads to an upward movement along the labor demand curve which results in an excess supply of labor; in other words, it creates unemployment. This movement along the demand curve has been the focus of debate. In Figure 2.1, 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. Based on three assumptions, First, a large number of identical jobs offer a specific wage, Second, fully informed workers can instantly switch employers and Lastly, there exists zero mobility cost for workers a competitive labor market firm is considered a wage taker, choosing E_0^c units of labor and wage, W_0^c where marginal revenue of product is equal to the marginal cost of labor given the labor supply is perfectly elastic.

Ransom (1993) also highlighted the violation of the assumption of zero mobility cost and pointed out that the labor supply curve may not be perfectly elastic. 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 the 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. Ransom (1993) study focused on frictions in the labor market for university professors and found monopsony power of the university in the market of college professors, estimating a tenure penalty of between 5% and 15% in professors' annual earnings since the senior faculty have higher mobility costs (psychic cost) than the younger faculty members.

Figure 2.1. Monopsony and Competitive model in employment and wage space



The empirical studies of the 1970s and 1980s were based on the competitive market model and used time-series analysis to build consensus that there is an increase in labor force participation with a decrease in labor demand due to an increase in the minimum wage. This discussion of the labor market models where the employer has greater power was further led by Card and Krueger (1993) case study of New Jersey's minimum wage ordinance suggesting a monopsony market structure with no reduction in employment but, instead an increase in employment. The study renewed vigor into the research of minimum wages and led to further studies of the monopsony model of an upward-sloping labor supply schedule. Card and Krueger (1993) influence the minimum wage studies in several ways, the study amalgamated the "Difference-in-Differences" method into the minimum wage literature and use the neighboring region as the comparison group. Over the last decade, studies have used different causal estimators with various panel surveys and administrative data. I will discuss how over the last two decades Card and Krueger (2000) study influenced the literature on city-level minimum wage ordinance. Section 2.1 broadly discusses how studies with no employment effect use the contiguous areas as comparison groups to eliminate the heterogeneous bias when estimating the causal parameter. In Section 2.2, I will discuss the spillover bias introduced by the use of the nearby regions as a comparison group and explore the literature that pointed out the presence of spillover bias using different administrative data sources.

2.1 State and sub-state level studies

Neumark and Wascher (2000) used payroll data to replicate the Card and Krueger (1993) study and concluded that April 1992 increase in minimum wages in New Jersey led to a relative decline in fast-food employment in New Jersey. Card and Krueger (2000) reconciled the result from their minimum wage study based on a primary survey by using administrative data from unemployment insurance payroll data. The results were consistent with their previous study, concluding that an increase in the minimum wage has no negative effect on employment. It led minimum wage studies from the 2000s to use the Quarterly Census of Employment and Wages (QCEW) which is the virtual census of employment (ES-202) conducted quarterly in connection with the state-level unemployment insurance systems by the Bureau of Labor Statistics (BLS).

Potter (2006) used micro-data from the New Mexico state unemployment insurance system to find no effect of 2004 city-level minimum wage changes on employment for Santa Fe, NM in comparison with the nearby city of Albuquerque(60 miles from Santa Fe). Using commissioned panel survey and focusing on the restaurant industry similar to Card and Krueger (1993), Dube et al. (2007) found that an increase in the minimum wage reduces wage inequality in San Francisco, CA. They found no negative effect on employment by using nearby Alameda County as a comparison group. Schmitt and Rosnick (2011) discussed the rise in the city-minimum wage for the three cities-Washington, DC (1993), San Francisco (2004), and Santa Fe(2004). The study used QCEW data and studied minimum wages beyond the traditional sector of fast-food restaurants and food services like retail stores and other low-wage establishments of different sizes. The study of three cities used suburbs as the control group finding no systematic effect of the city-wide minimum wage increase on the employment in the affected establishments which was consistent with the previous state and sub-state level minimum wage studies using primary surveys (Card & Krueger, 1993; Dube et al., 2007).

Payroll data used by QCEW provides us with rich demographic and employment details about the labor market, but the geographic location is not based on the workplace[1]. The Unemployment Insurance (UI) payroll data assign location based on the employer's UI account. Each firm is required to have a UI account, regardless

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

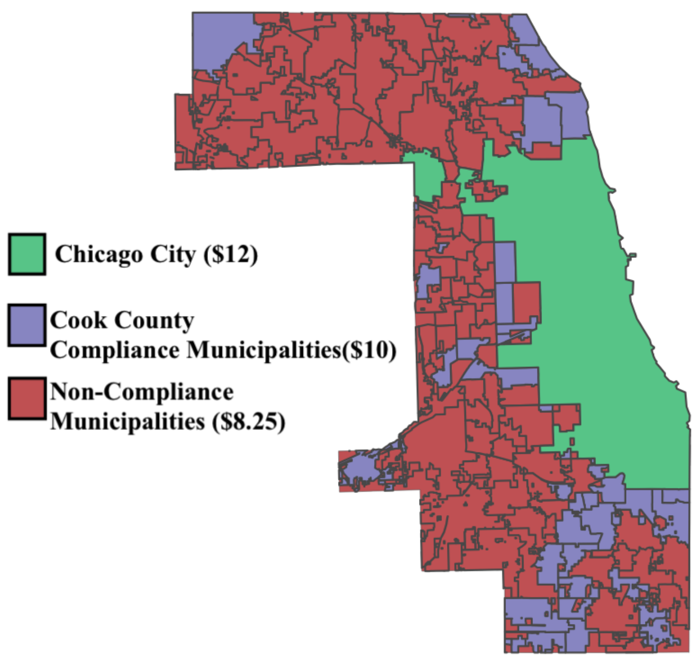
of the business location in a state. Some firms having multiple locations of business around the state might have one single UI account. QCEW uses the Multiple Worksite Report(MWR) to account for the establishment having 10 or more employees combined in their second location. The response rate for this 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 worksites at different locations 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. The payroll data provides rich demographic and employment details about the labor market at the 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, 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 2.2, I present minimum wage variation within Cook County. The area shaded in lavender color represents the municipalities that implemented the minimum wage ordinance passed by Cook County. The area shaded with terracotta orange represents a non-compliance region within Cook County implementing the state minimum wage and the area 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 in small geographic areas located close to each other using the administrative

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

data available at the county level. These city-wide studies used contiguous regions as a comparison group to estimate the causal effect of an increase in the minimum wage on the change in employment. The choice of the comparison group was to address the issue of heterogeneity when using the "Difference-in-Differences" method and the UI payroll data. In the next Subsection 2.1.1, I will discuss the heterogeneity bias in more detail

Figure 2.2. Map of Cook County, IL with minimum wage variation in 2018



Note: This map of Cook County is constructed using 2019 US Census Bureau TIGER/Line Shapefiles, and minimum wage data from UC Berkeley-Labor Center. The green-shaded region is Chicago City with the highest minimum wage and the levander-shaded regions are the municipalities where Cook County minimum wage prevails; the rest of the shaded regions are municipalities that opted out of the Cook County minimum wage ordinance.

2.1.1 Heterogeneity

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.

Dube et al. (2010), discussed the spatial heterogeneity by introducing area-time trend specifications. The study presented a generalized estimate of the elasticity of employment to minimum wages for the United States using the QCEW data for the years 1990 until 2006. Using state-border contiguous county-pair, they found no adverse effect of an increase in minimum wages on employment. They presented a robustness check using interior counties to find no spillover effect and assuming that the minimum wage differences within-pair are independent of any other state employment factor. Important to note that state-border contiguous counties may have minimum wage differences independent of the other employment factors but cities close to each other with less mobility friction may not be independent of the minimum wage differences. Complementarily, Gittings and Schmutte (2016) used the Quarterly Workforce Indicators (QWI) to study industrial heterogeneity. The study demonstrated that the employment effect of the minimum wage is strongly correlated with turnover and labor market tightness i.e. the response to minimum wages is a function of the degree of competition in the market and the ability of the firm to adjust its labor input. Meer and West (2016) used Business Dynamics Statistics (BDS), QWI, and QCEW datasets to argue that the use of specifications like state-specific time trends will attenuate the minimum wage effect on the employment level rather than the employment growth. The study focused on employment growth and found a large negative relationship between state-level aggregated employment and minimum wage.

Different methods and estimators

In this subsection, I broadly discuss various techniques used in the literature to eliminate the assumption of no heterogeneous bias and use contiguous regions. Jardim et al. (2018) studied the change in the minimum wage of Seattle, which has a higher average income compared to other cities in Washington. The study used UI data similar to QCEW data but with the geo-code mailing addresses to identify the establishment under the city council jurisdictions and found a negative elasticity to wage for workers below 25$ but a positive employment effect for restaurants using the synthetic control method. This study highlighted that the identification of establishments in the city is very important when using administrative data based on state or federal payroll identification numbers. The study excluded the multi-establishments as they could not identify the location of the businesses.

By using Pesaran (2006) estimator, Totty (2017) addressed the unobserved heterogeneity. The estimator does not estimate common factor or common factor loading similar to interactive fixed effects estimators but uses cross-sectional averages of the dependent and independent variables as a proxy for factors. The study presented insignificant and null employment effects of minimum wages. Meanwhile, in order to address unobserved heterogeneity, Allegretto and Reich (2018) used the QCEW data for synthetic control analysis to discuss thirteen minimum wage changes across six big cities - Chicago, the District of Columbia, Oakland, San Francisco, San Jose, and Seattle of which three belongs to the state of California. The study estimated positive individual and average effects on the cities with the implementation of new wage policies. They found no negative employment elasticity in the food-service industry for the six cities and a statistically insignificant dis-employment effect for Seattle comparing it with the synthetic controls which are consistent with the Jardim et al. (2017).

A recent study by Cengiz et al. (2019) estimated the employment changes around the minimum wages. They created bins for wage percentile to study the excess jobs that are created slightly at and above the minimum wages. In order to focus on this minimum wage bite, they use the NBER individual-merged outgoing rotation group of the current population survey. They bunched the minimum wage changes from 1976 to 2016 as annual events to find that the missing jobs below the minimum wage match the number of excess jobs just above the minimum wage, concluding that increases in the minimum wage do not have a negative effect on employment. Dube and Lindner (2021a) using the American Community Survey(ACS) data controlled for the local pre-treatment covariates like the cost of living, employment to population ratio, average wages, and share of employment below wage cutoffs. The study used the same "bins" approach to conclude that the modest rise in the minimum wage does not change the employment probabilities for the cities in the United States.

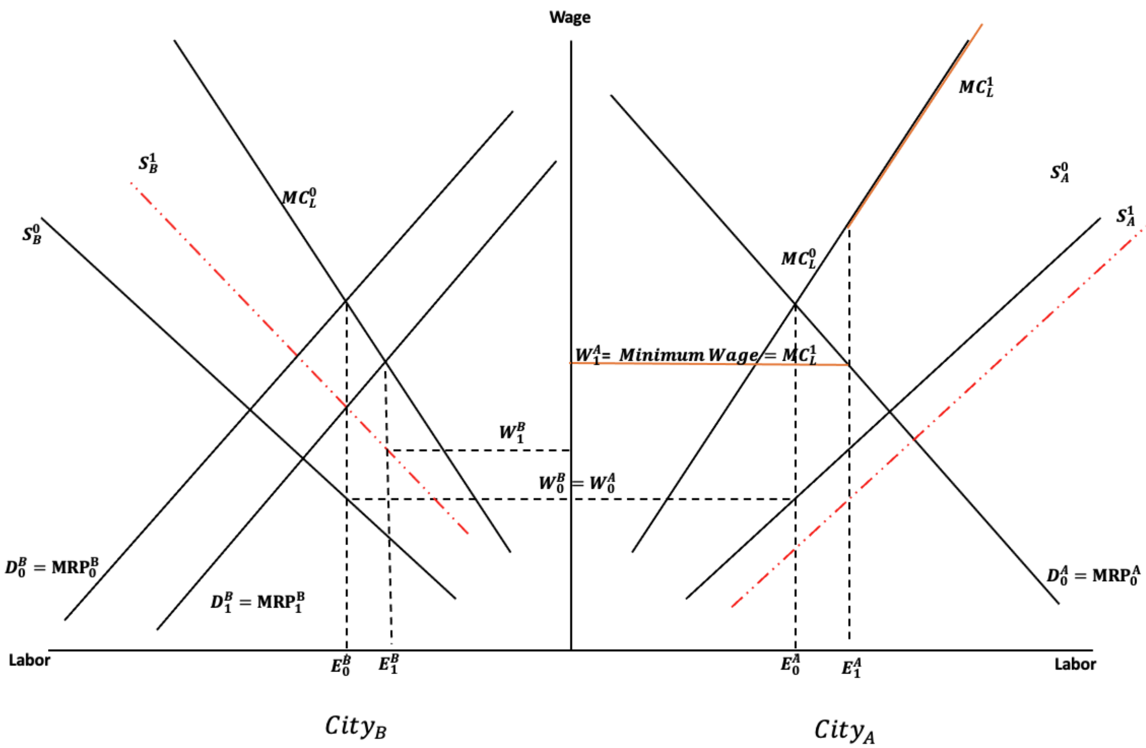
In this section, prior literature using different methods like synthetic control methods finds a negative effect of an increase in minimum wages on employment. In the next section 2.2, I will discuss the spillover effect that may be created in either labor market model and the empirical studies on how contiguous control groups can lead to biased estimates by introducing spillover bias and why important is the residential and workplace locations.

2.2 Cross-Border

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. This condition helps authors mimic controlled experiments.

Baum-Snow et al. (2020) noted that urban highway construction has increased residential and job decentralization. It also makes us think if there is a change in the mobility costs how does it respond to the frictions in the labor market in the short-run? The studies using a residential-based survey could underestimate the unemployment effect dues to this spillover bias i.e. individuals may choose to commute across the borders. In Figure 2.3, I present a simple two-economy (Cities) for a monopsony

Figure 2.3. Monopsony model for wages and labor markets for two economies (Cities).

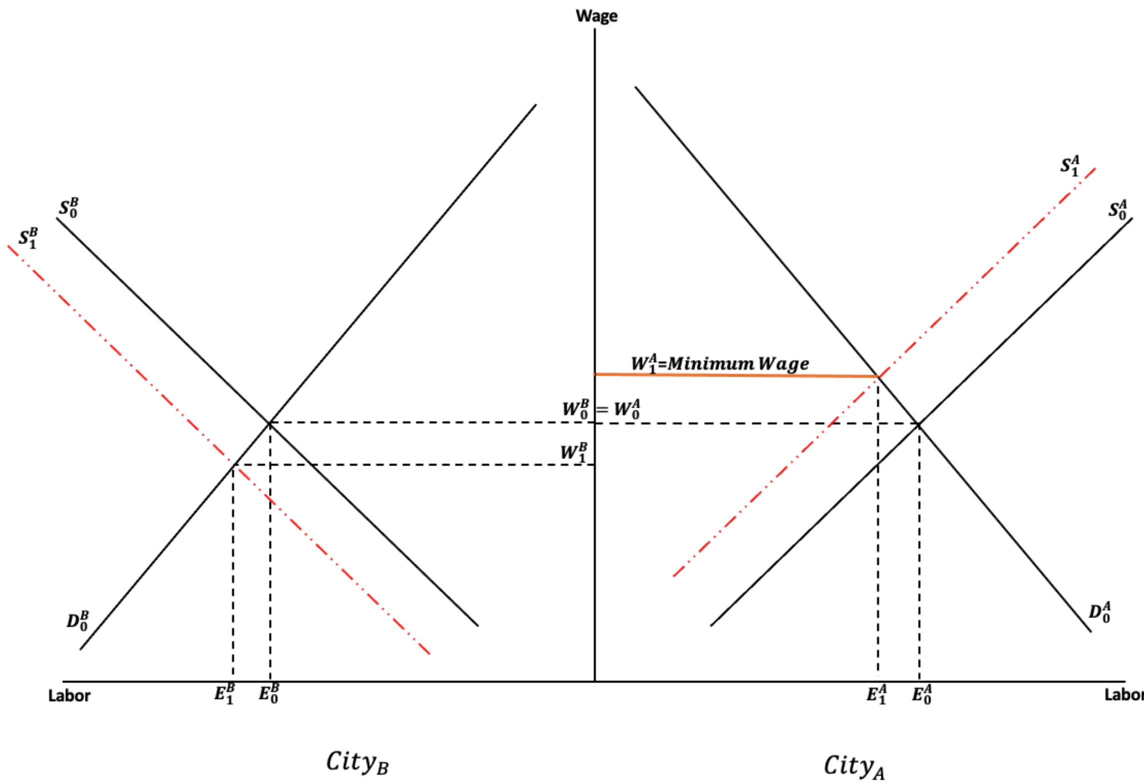


Note: This is a two-city Monopsony labor market model with a constant labor force, City A implements a minimum wage ordinance which increases W_0^A to W_1^A resulting in the shift of the labor supply curve from S_A^0 to S_A^1. Moreover, the labor supply curve for City B also shifts from S_B^0 to S_B^1 as more workers from City B are attracted to higher wages in City A.

labor market model. Assuming the combined labor force remains constant, when minimum wage increases in $City_A$, there is an increase in labor demand E_0^A to E_1^A. In the short-run, it also attracts workers from the neighboring $City_B$ to commute and work. As a result, there is a shift in the labor supply curve in $City_B$ to S_B^1. Higher mobility cost could decrease the marginal productivity to MRP_1^B for workers who stayed in $City_B$ at an increased wage of W_1^B, which will then results in a decrease in the unit of labor employed from E_0^B to E_1^B in $City_B$. In these cases, the true effects of an increase in the minimum wage when considering contiguous regions as a control group are underestimated.

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). He used different buffer zones (25, 50, 75, and 100 miles) around the state border to identify the county pairs and estimated commuter flow from the origin county to the destination county. Contrary to the identification assumption of Dube et al. (2010), he found that differences in minimum wages across the neighboring regions might have direct influences on employment outcomes. McKinnish (2017) concluded in her study that low-wage workers are more likely to commute out of state when the minimum wage in their residential state increases, using public use microdata areas (PUMAs) she found similar but insignificant results. Using the Longitudinal employer-Household dynamics program's local origin and destination employment statistics (LODES) from the unemployment insurance claim data, Pérez (2022) explained the negative association between the minimum wage and commuting in cities adjacent to the state borders. Similar to McKinnish (2017) he suggested an outward flow from higher minimum wage areas to low minimum wage areas when looking at the state-border counties. In Figure 2.4, I construct a competitive labor market model, with the combined labor force being constant and zero mobility cost. An increase in minimum wages would decrease the units of labor demanded and shift the labor supply curve to the right in $City_A$. Assuming zero mobility cost, this may increase the labor supply to the left in $City_B$. An increase in labor supply would lead to a decrease in minimum wages to W_1^B and an increase in the unit of labor demanded to E_1^B from E_0^B. This interdependence may overestimate the results of minimum wages on employment. 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 from using neighboring counties as control areas can be due to labor mobility, rather than the spatial heterogeneity that Dube et al. (2010) emphasizes.

Figure 2.4. Competitive model for wages and labor markets for two economies (Cities).



Note: This is a two-city Competitive labor market model with a constant labor force, City A implements a minimum wage ordinance that increases W_0^A to W_1^A resulting in the shift of the labor supply curve from S_A^0 to S_A^1. Moreover, the labor supply curve for City B also shifts from S_B^0 to S_B^1 as more workers from City A are now seeking employment in City B.

The studies emphasizing the spillover bias focus on migration and commuting across the regions with minimum wage variations. The studies highlighted 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.

2.3 Contribution

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 or 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 business. I then address whether visit duration changes at an establishment bound by city minimum wage. In Chapter 5, I discuss the variation in the commute when the city experiences a higher minimum wage to help in a better understanding of the true effect of minimum wages on labor demand.

Chapter 3: Data

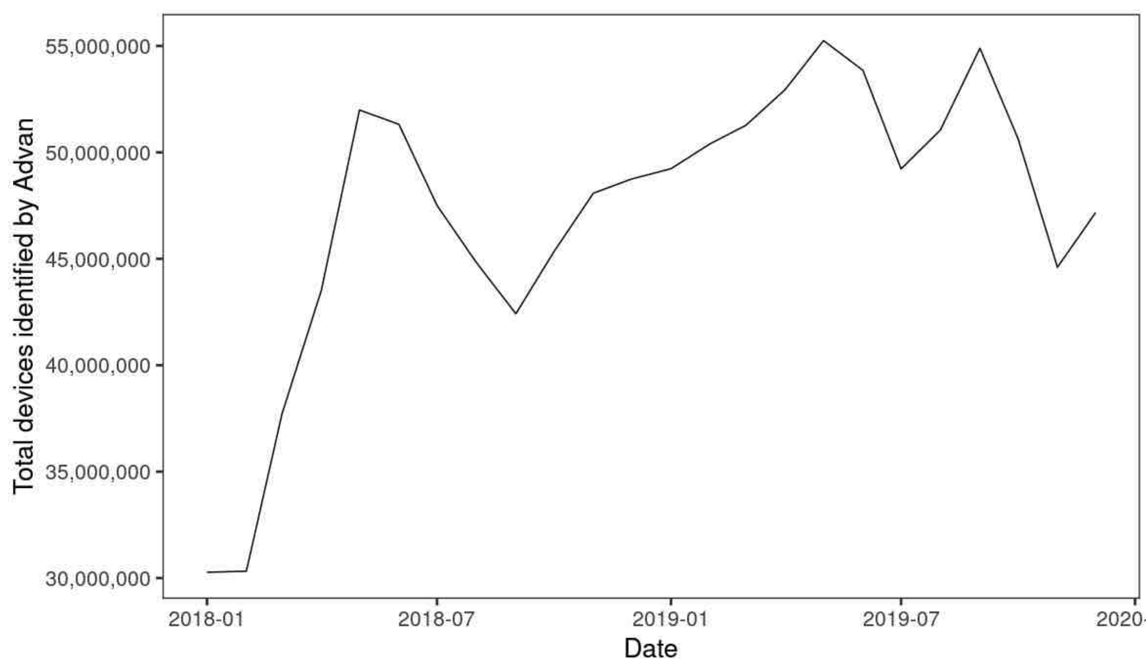
This study uses mobile location data from Advan. Advan collects GPS information from around 45 million anonymous cellular devices and produces anonymized, aggregated extracts of mobility patterns for nearly 4.5 million establishments in the US. The establishments are identified as Places of Interest (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 Mobility-Pattern Data

The Advan 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. Advan 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 Advan across the United States has varied over the period of 2018 and 2019 as shown in Figure 3.1. 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 gives me a uniform number of devices identified across the period of two years that can be used for analysis. Advan defines a visit based on a sequence of GPS pings within a location

Figure 3.1. Number of devices identified by Advan across the US for years 2018 and 2019



Note: This figure shows the number of unique devices observed across the U.S. in the Advan data. After the normalization, I am left with horizontal lines of population estimates for years 2018 and 2019 as the number of aggregated unique visitors at the POI is equal to the number of unique devices identified across the United States by Advan data.

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 Advan, 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 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 3.1.2, I discuss in detail whether long-duration visits are a good proxy for the number of workers.

Table 3.1. Number of establishments identified by Advan data and CBPs

Industry(NAICS Code)	Advan	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)[1]	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

I use the characteristics of the POIs, like Industrial categorization, based on the North American Industry Classification System (NAICS), the name of the associated brand, etc. In Table 3.1, I compare the two-digit Industrial classification of the POIs and the number of establishments in the County Business Pattern (CBP) based on the 2017 NAICS. Census Business Patterns(CBPs) data identifies the establishments

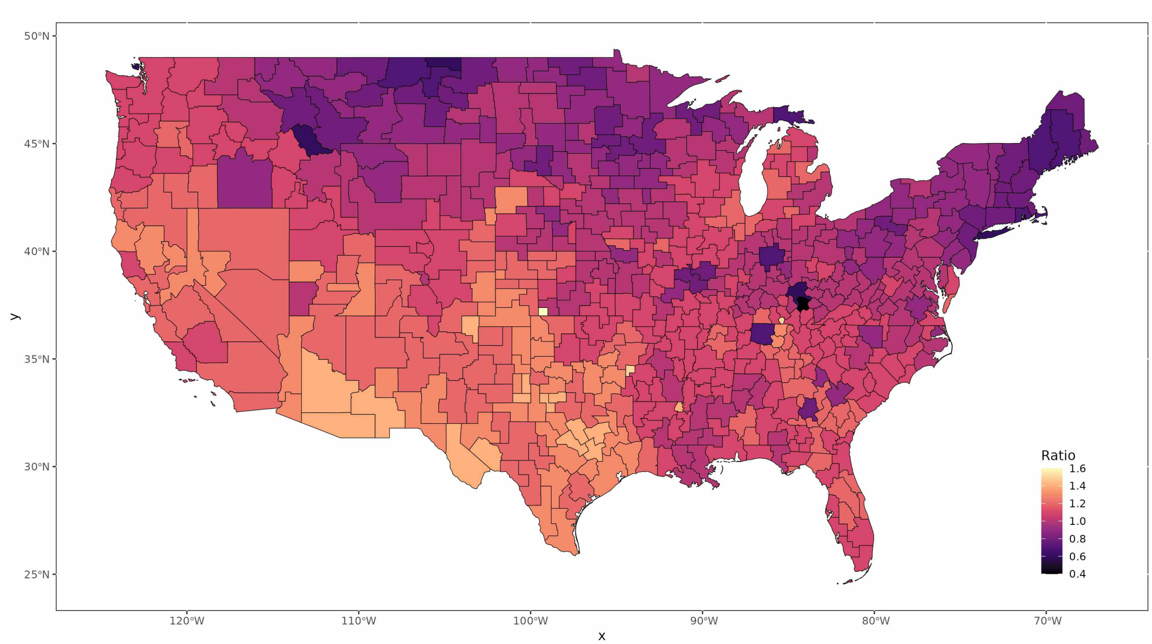
Table 3.2. Number of establishments identified by Advan data and QCEW in 2018-2019

Industry(NAICS Code)	Advan	QCEW	Ratio
Agriculture, Forestry, Fishing and Hunting(11)	1,235	106,489	0.012
Mining, Quarrying, and Oil and Gas Extraction(21)	31	32,551	0.009
Utilities(22)	7,179	18,666	0.384
Construction(23)	33,176	820,457	0.040
Manufacturing(31-33)	65,239	355,170	0.184
Wholesale Trade(42)	55,411	615,249	0.090
Retail Trade(44-45)	1,099,290	1,053,223	1.044
Transportation and Warehousing(48-49)	68,776	258,060	0.267
Information(51)	50,811	178,937	0.284
Finance and Insurance(52)	191,264	494,946	0.386
Real Estate and Rental and Leasing(53)	122,508	409,196	0.300
Professional, Scientific, and Technical Services(54)	78,219	1,246,696	0.063
Management of Companies and Enterprises(55)	7,933	68,304	0.116
Admin and support and waste Mng and Rmd(56)[2]	20,668	559,713	0.037
Educational Services(61)	165,678	125,107	1.324
Health Care and Social Assistance(62)	640,137	1,610,970	0.400
Arts, Entertainment, and Recreation(71)	274,521	151,375	1.814
Accommodation and Food Services(72)	733,245	719,789	1.020
Other Services (except Public Administration)(81)	818,001	858,474	0.953
Public Administration(92)	54,372	NA	NA
Total	4,487,694	9,718,467	0.462

based on the Employer Identification Number as “A single physical location at which business is conducted or services or industrial operations are performed”. The data covers over 6 million single-establishments and around 1.8 million multi-establishments.

The CBP has less dependency on the multi-establishments. It is based on collected[3] The Reports of Organisation, an annually collected survey that only considers multi-establishments with companies employing 500 or more employees[4].

Figure 3.2. Ratio of Accommodation and Food Industry (NAICS Code:72) for Advan and QCEW across the US for years 2018 and 2019.

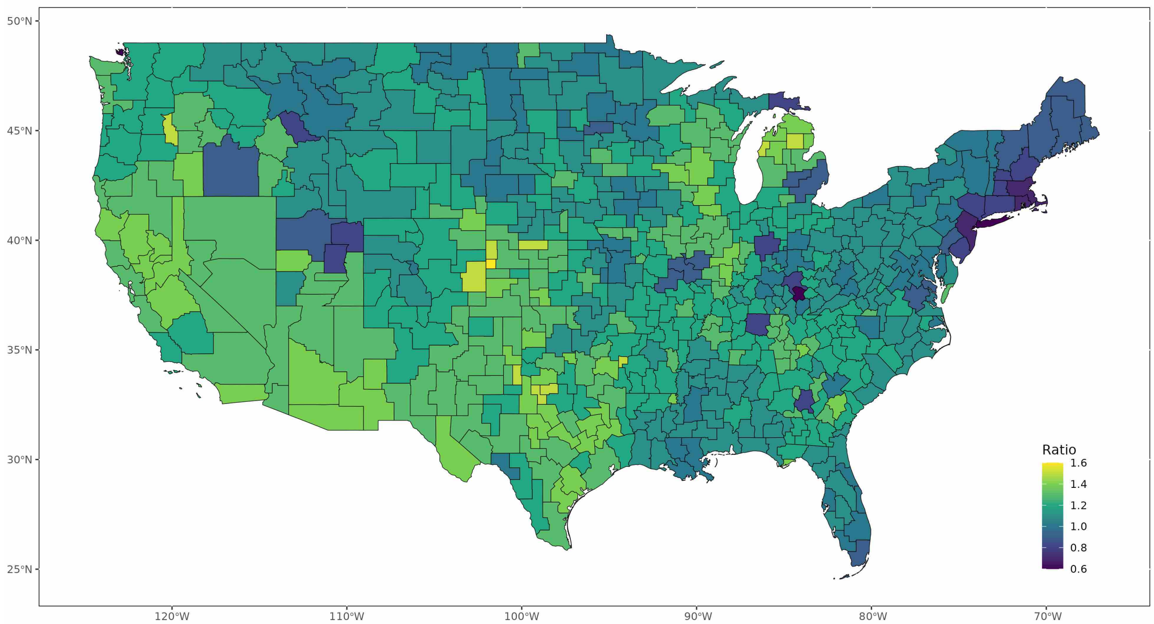


Note: This map shows the ratio of the number of establishments identified by the Advan data to the number of establishments identified by the QCEW data under Accommodation and Food Industry(NAICS Code:72) for the year 2018 and 2019. This map shows us that the ratio is equal or close to one for most parts of the United States except for places where broadband service might not be good.

Advan data, on the other hand, use 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. In Table 3.2, I compare the industrial coverage

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

Figure 3.3. Ratio of Retail Industry (NAICS Code:44-45) for Advan and QCEW across the US for years 2018 and 2019.



Note: This map shows the ratio of the number of establishments identified by the Advan data to the number of establishments identified by the QCEW data under Retail Industry(NAICS Code:44-45) for the year 2018 and 2019. This map shows us that the ratio is equal or close to one for most parts of the United States except for places where broadband service might not be good.

among the 2-digit NAICS codes from the QCEW data for 2018 and 2019. Similar to the CBPs coverage non-tradeable Industries are more represented. In Figure 3.2 and 3.3, I present the ratio of the Accommodation and Food Industry to the number of establishments identified in the QCEW data and the ratio of the Retail Trade Industry to the number of establishments identified in the QCEW data respectively at the ERS labor market zones level across the U.S. for the year 2018 and 2019. Both the Figures 3.2 and 3.3 present a similar picture that was discussed in the national-wide Industry level coverage in Table 3.2. Except for the labor market zone in Maine or some areas in Midwest, the ratio is either around 1 or above. This provides enough confidence that the visits captured especially in two industries will provide a better analysis of the labor market across the United States. In the next Section, I discuss the duration of visits.

3.1.1 Duration Visits

Advan uses the first and last GPS ping at a POI to identify the minimum duration of the visit or the dwell time. The data provides us with bucketed dwell times i.e. the bins for the duration of visits by minutes. We have seven duration bins "<5", "5-10", "11-20", "21-60", "61-120", "121-240", and ">240".

3.1.2 Employee Visits and State Employment

I assess the validity of long-duration visits as a proxy for employment by comparing Advan 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 devices identified in the state j at time t for the duration of visits (V) in a CBG i at a time t.

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

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

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 employees (E_{it}) in a CBG increases, the number of visits (V_{it}) at various duration also increases.

$$log(V_{it}) = \beta_1 log(E_{it}) + \mu_i + \tau_t + \epsilon_{it} \tag{3.1}$$

The estimates in Table 3.3 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 employees 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 a similar correlation from the constructed variable combined with 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 to 120 minutes are a better fit for employee visits with the highest $Within\ R^2$ of 0.00018 along with a higher correlation. In Figure 3.4, 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.

Table 3.3. Number of jobs and duration visits at Census Block Group level

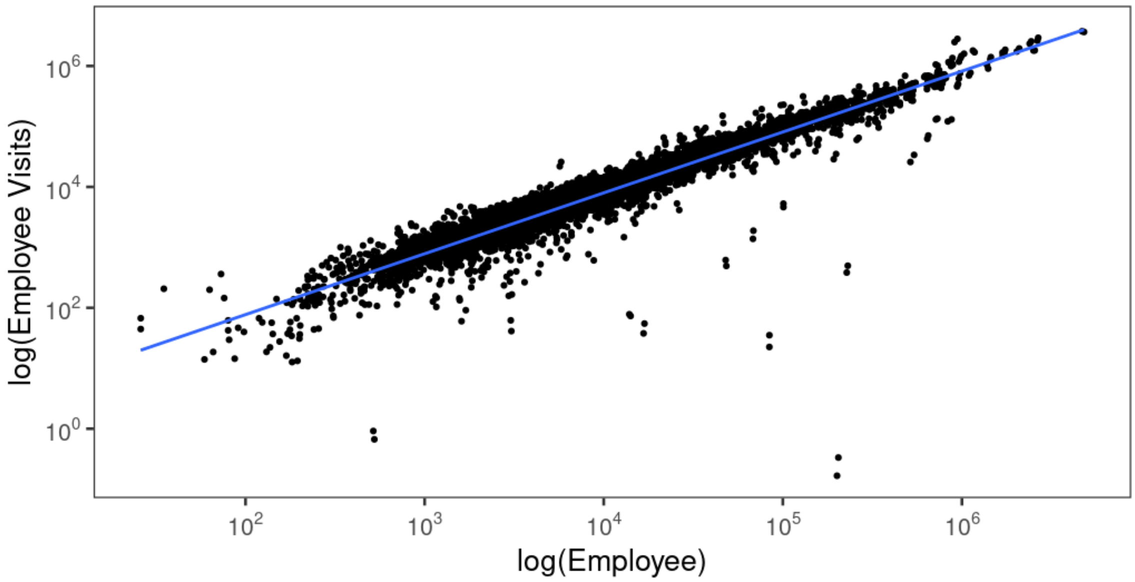
Independent Variable:	Number of total employees in the LEHD	
Model:	Non-Normalised (1)	Normalised (2)
Dependent Variables(in log):		
Visits greater than 240 mins	0.0139***	0.0140***
	(0.0033)	(0.0032)
Fit statistics		
R^2	0.98657	0.98657
Within R^2	0.00016	0.00016
Visits greater than 120 mins	0.0133***	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 until 120 minutes	0.0139***	0.0140***
	(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 until 60 minutes	0.0129***	0.0129***
	(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*

These high correlations with the number of jobs at CBG, county, and state levels 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.

I find a more robust relationship with my assumption of employer visits by using the correlation between the per capita employee from the QCEW and per capita long-duration visits. First, I use the LEHDs-LODES data to find the correlation among all the long-duration visits. I use the 45° and the line of best fit to identify the cut-off for the employee visitors. I find that the assumption of using the highest duration bucket up to 120 minutes is the best choice for the number of employees at the county level. Finally, I use the QCEW per capita employee counts for each month for 2018 and 2019 for the Accommodation and Food Industry along with the Retail Trade Industry. In Figure 3.6 and 3.7, I observe that the closer the line of best fit to the red 45° line the better match proxy it is for the number of employees.

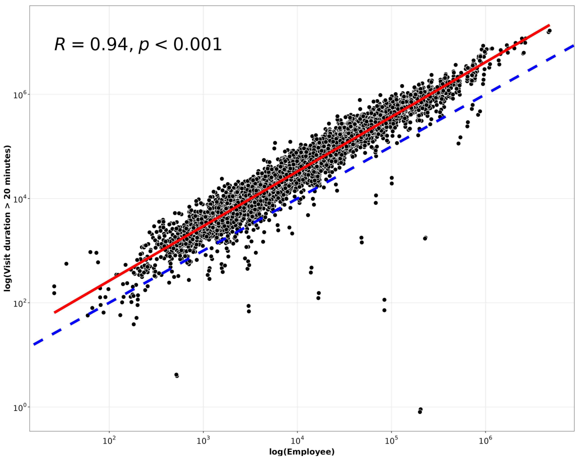
Figure 3.4. Log number of jobs and log number of employee visits at County-level



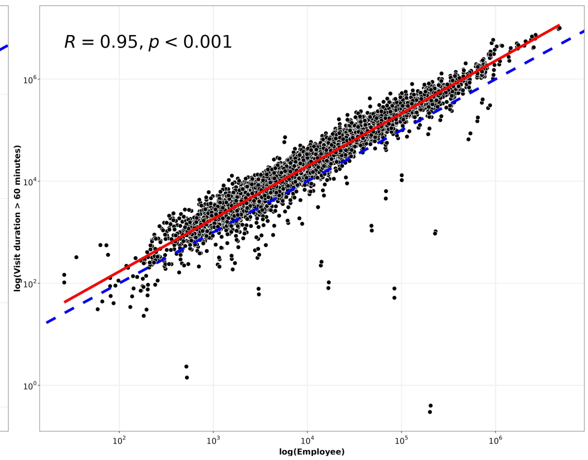
Note: I use the number of visitors in the duration bucket more than 240 minutes if none than visitors more than 120 minutes to define the employee visits from the Advan data. For the number of employees, I use the LEHD-WAC data at the county level for the years 2018 and 2019.

Figure 3.5. Log number of jobs and log number of employee visits at County-level

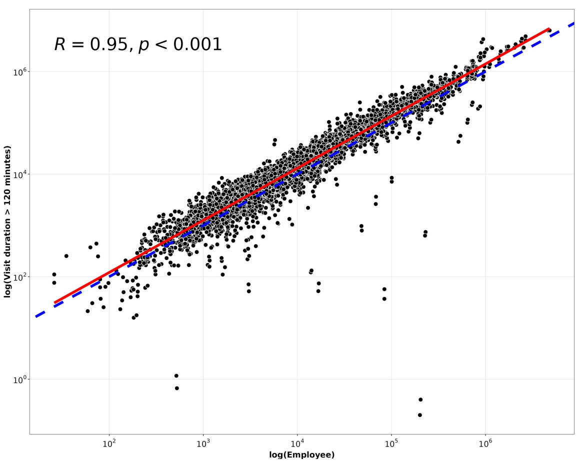
(a) Visits greater than 20 minutes



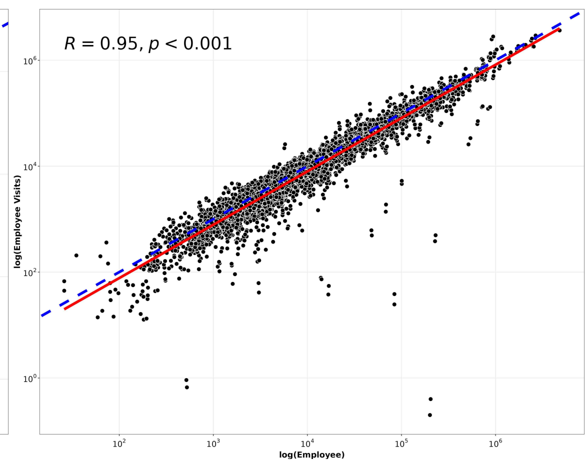
(b) Visits greater than 60 minutes



(c) Visits greater than 120 minutes



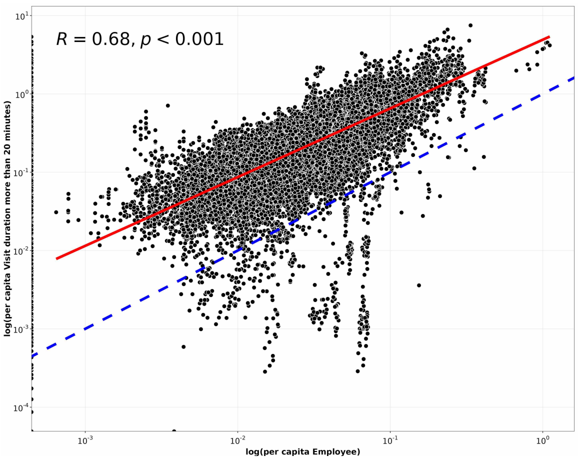
(d) Visits greater than 240 minutes or 120 minutes



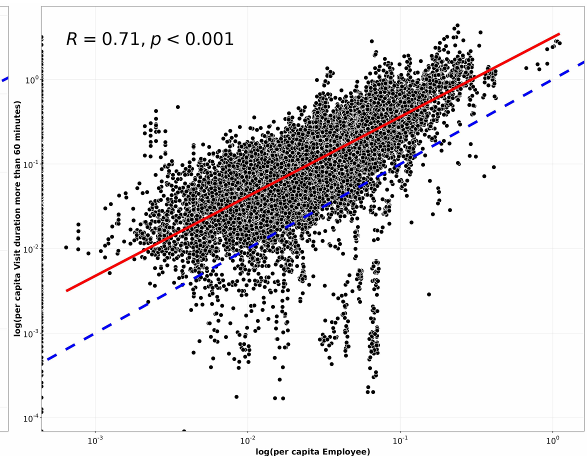
Note: I use the number of visitors in the duration bucket more than 240 minutes if none than visitors more than 120 minutes to define the employee visits from the Advan data. For the number of employees, I use the QCEW data at the county level for the years 2018 and 2019.

Figure 3.6. Log number of jobs and log number of employee visits for the Accommodation and Food Industry at County-level from QCEW Data

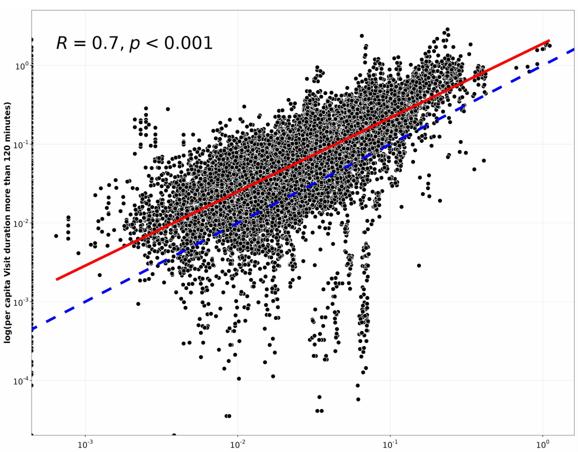
(a) Visits greater than 20 minutes



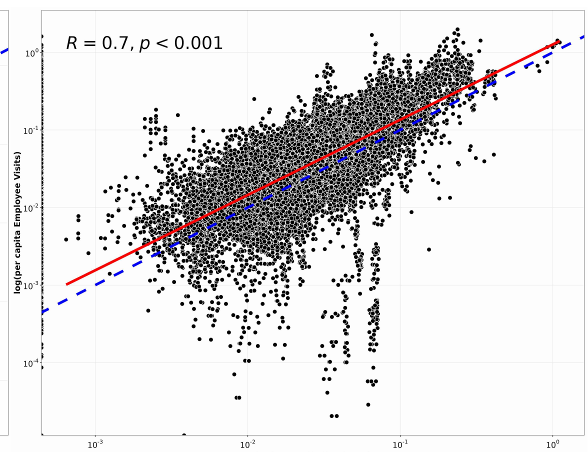
(b) Visits greater than 60 minutes



(c) Visits greater than 120 minutes

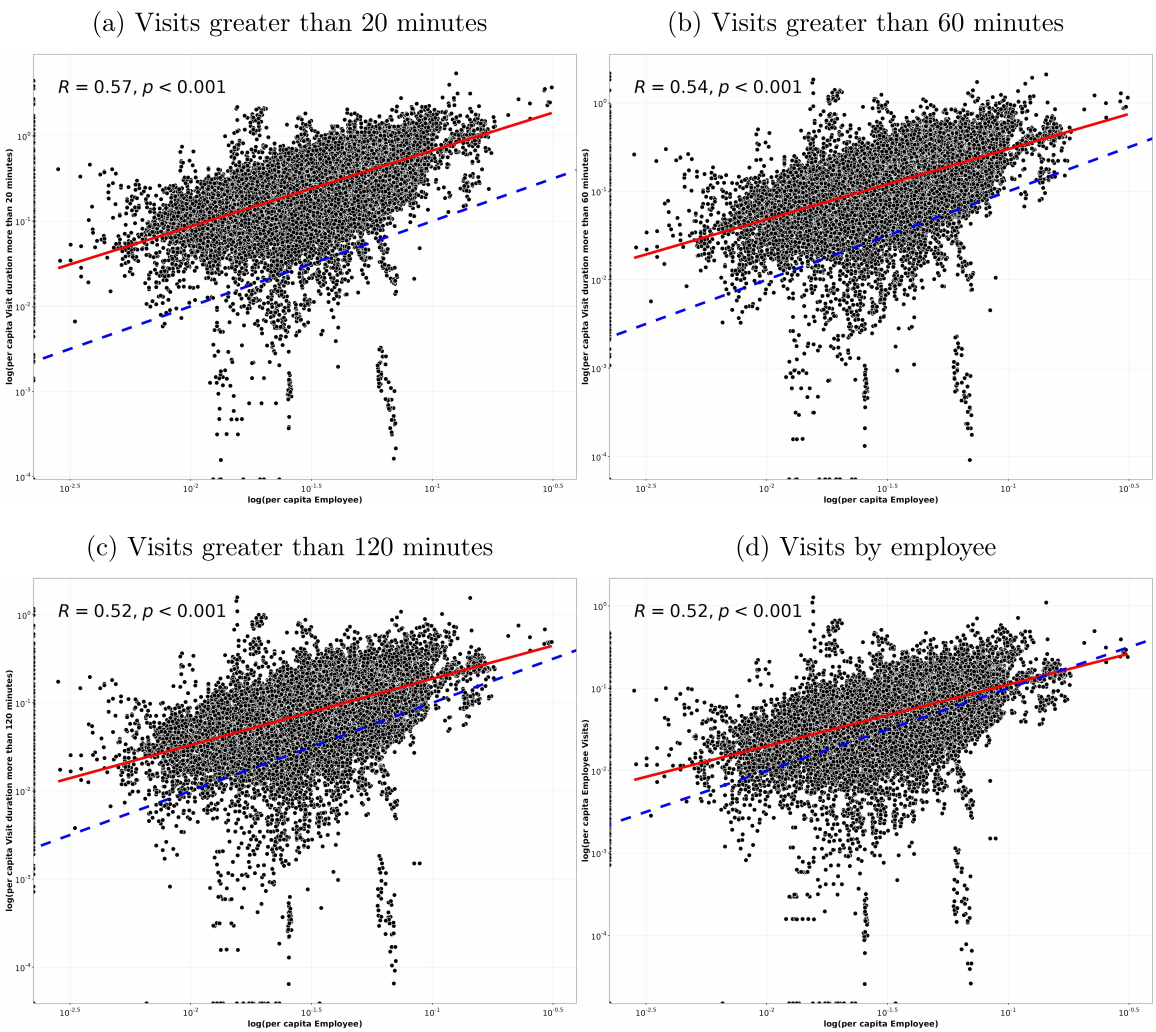


(d) Visits greater than 240 minutes or 120 minutes



Note: I use the number of visitors in the duration bucket from the Advan data. For the per capita employees, I use the QCEW data and the US Census Bureau for the number of employees in the Private Accommodation and Food Industry and population respectively at the county level for the years 2018 and 2019.

Figure 3.7. Log the number of jobs and log the number of employee visits for the Retail Industry at the County-level from QCEW Data



(a) Visits greater than 20 minutes

(b) Visits greater than 60 minutes

(c) Visits greater than 120 minutes

(d) Visits by employee

Note: I use the number of visitors in the duration bucket from the Advan data. For the per capita employees, I use the QCEW data and the US Census Bureau for the number of employees in the Private Retail Industry and population respectively at the county level for the years 2018 and 2019.

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 3.8 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 Figure 3.9, I present 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 Chapter 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 Advan 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), Advan identifies the city for each POI. I match the cities in the minimum wage data with the Advan data for each POI. I balance the panel for the visits by assigning zero

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

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.

Figure 3.8. Population-weighted average minimum wage change

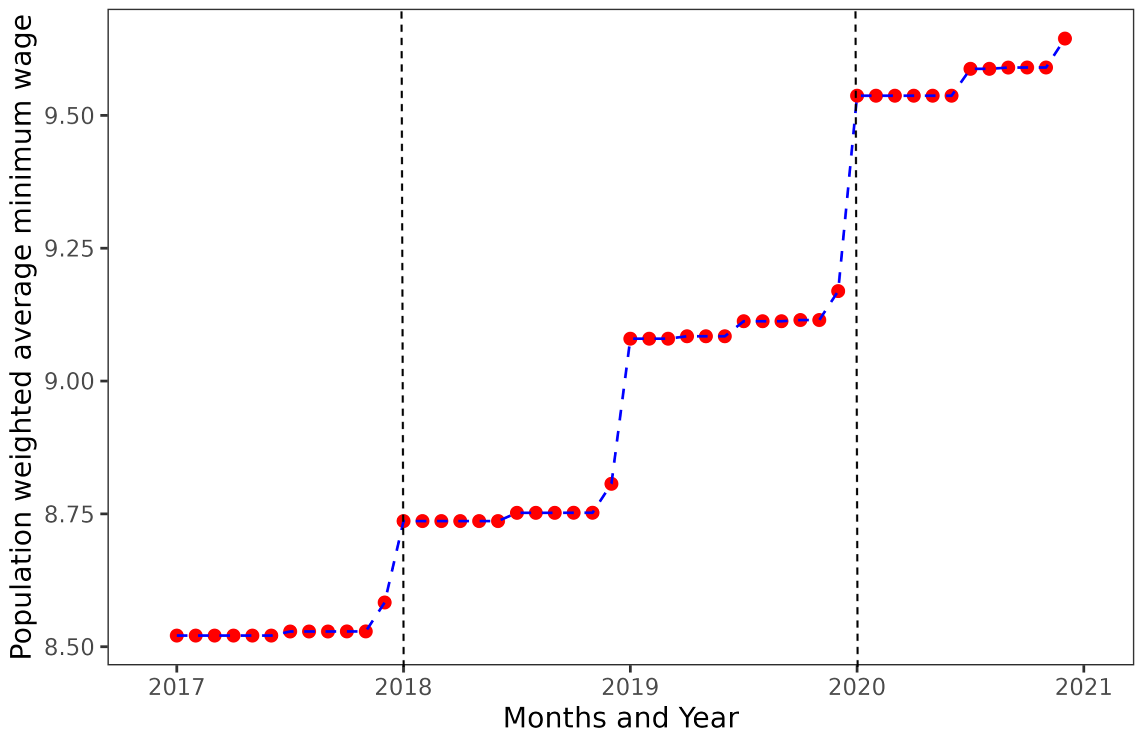
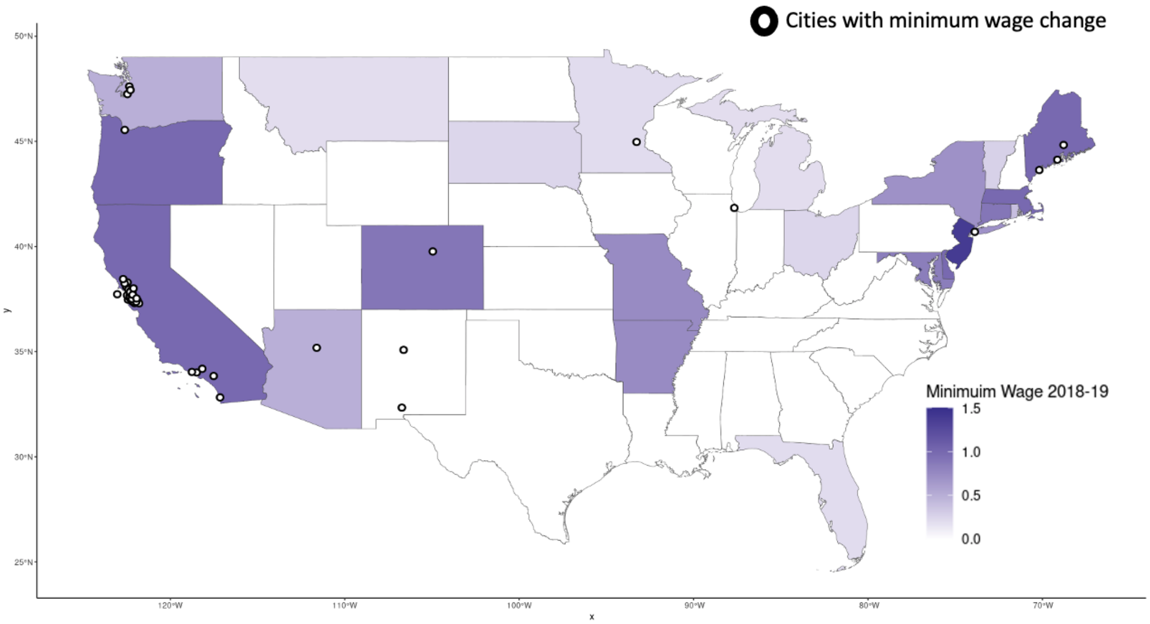


Figure 3.9. Minimum wage change across the United States and Cities which increased its Minimum Wages in 2018-2019



Note: The shaded regions in the map are the states which implemented State Minimum Wage Ordinances in the year 2018 and 2019, and the white-shaded regions are the states which have a federal minimum wage of $7.25. The dots represent the sub-state regions that have minimum wages higher than the state level.

Chapter 4: Minimum Wages and Employment

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 Place of Interest(POI), I estimate the visits elasticity with respect to minimum wages from 2018 until 2019 presented in Table 4.1 using Equation 4.1 on a balanced panel of monthly visits at a POI.

4.1 Research Design

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.

$$log(V_{it}) = \beta_2 log(MW_{it}) + \mu_i + \rho_t + u_{it} \tag{4.1}$$

In equation 4.1, MW_{it} is the effective minimum wage (local, state, or federal) faced by a POI "i" in the month "t". Thus, the parameter of interest, β_2 presents the percentage change in the visits when there is a percentage increase in the minimum wages conditioned on unit i.e. POI (μ_i), and time i.e. month (ρ_t) fixed effects, assuming $E(u_{it}|logMW_{it}) = 0$. The outcome of interest, $log(V_{it})$ is the visits (employee visits, customer visits, visits greater than 240 minutes, visits less than 5 minutes, total visits) at a POI. There exists a nontrivial number of true zeros in the data that represent no visits for the duration bucket at the POI in a given month. Thus, I have used inverse-hyperbolic sine transformation for the dependent variables instead of the log. Since the treatment happens at the city and state levels, I choose to cluster the standard errors at the city level. I use the normalization factor discussed in Chapter 3 for the duration-visits to calculate the dependent variable i.e. normalized visit. There could be POIs that are engaged in short-term lodging identified by NAICS Code-7211 that may present long-duration visits as employee visits which are indeed customer visits, to avoid contamination of estimates I eliminate these POIs. Moreover, there could also be POIs that are not business units but public spaces like parks I also eliminate all these units to present the results in column (2) of Table 4.1.

It is natural to question the estimates since the time of the treatment varies across the US. Moreover, the minimum wage ordinances are implemented programmatically over the years which means multiple treatments affect the same units on an annual or sometimes with a shorter window in a year. For instance, cities in California experience an increase in wages in the month of January when a new state minimum wage is implemented but many cities in the state increase the city minimum wage in the middle of the year. For this reason, I use continuous treatment instead of the binary treatment of 0 or 1. Recent literature(Callaway & Sant'Anna, 2021; De Chaisemartin & D'Haultfoeuille, 2022; Goodman-Bacon, 2021; Sun & Abraham, 2021) pointed out that the TWEF model is similar to equation 4.1 with binary treatment could be challenging to interpret when the units are treated in different time periods. Similar concerns are raised by Callaway et al. (2021) for continuous treatment estimates. Staggered treatment in this case is both horizontal and vertical in nature in other words, there is a difference in the timing of the treatment and multiple units are treated multiple times which makes it more complex and may not be understood by using binary treatment of 0 and 1.

To estimate this heterogeneous time treatment across two years (2018-2019) across differently treated POIs, I use an event bunching design similar to Cengiz et al. (2019) in order to estimate the continuous average treatment effect.

$$log(V_{it}) = \Sigma_{\tau \neq -3}^{24} \alpha_\tau \Delta log(MW_{i,t-\tau}) + \mu_i + \rho_t + u_{it} \tag{4.2}$$

I constructed a data set with a continuous treatment variable of 24-month lead-lag. These are different from a TWFE-$log(MW)$ or binary treatment event-study model, Cengiz et al. (2019) argue that the major difference in the event-study design and models like in equation 4.2 is the comparisons with distant observations outside of the event window. Also, in equation 4.2, the treatment value goes from zero to $\Delta log(MW_{i,t-\tau})$ at event date $\tau = 0$ instead of switching to 1. This helps in understanding the effect of the difference in the minimum wage from the existing wage. Establishments may start adjusting to the minimum wages from the beginning of the quarter or a few months ahead of the minimum wage changes which may create a problem of multicollinearity to control for this problem I use the reference period as $\tau = -3$. This event bunching model 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 the temporary time period, or there could be a replacement of a lower-skill worker to a high-skill worker or a horizontal replacement like a change in employment to another POI or industry. This event bunching design using $\Delta log(MW_{i,t-\tau})$, 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 4.2 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 4.1 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 4.1. Duration visits at a POI and Minimum wages

Model	Full Sample (1)	Sample w/o 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*

4.2 Main Results

Table 4.1 presents my main results using equation 4.1. 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 decrease 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 Table

Table 4.2. 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*

4.8. 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 4.2, 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.

Table 4.3. 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*

I present estimates for the retail and food industry in Table 4.3. 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.

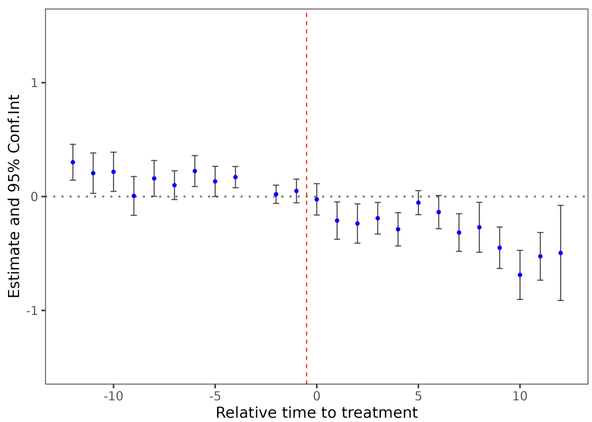
In Figure 4.1, I present the event study with 12 months before and after the treatment month using estimated results from Equation 4.2. I observe a decrease in employee visits, customer visits, and visits more than 240 minutes, and less than 5 minutes which validates the results in Table 4.1 from Equation 4.1. 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 4.2.2.

4.2.1 Local bonded minimum wage

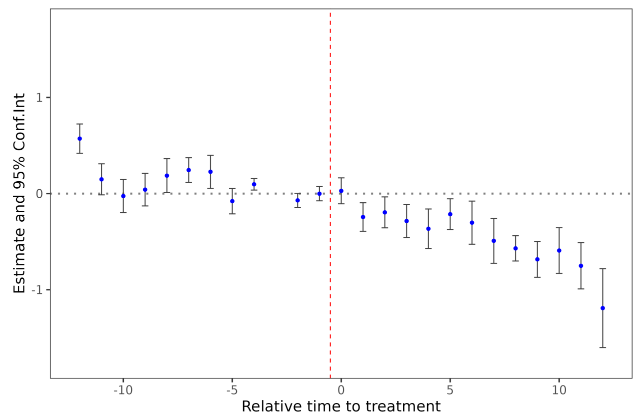
Given, the porous local boundaries, POIs bound by local minimum wage ordinances can respond differently than the state-bound ordinances. Businesses [POIs] have the option to move out a few miles of the city. On the other hand, employees have the option to commute to the nearby city for higher wages, 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 a 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 4.4 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

Figure 4.1. Effect of Minimum Wages on duration visits and distance traveled over time

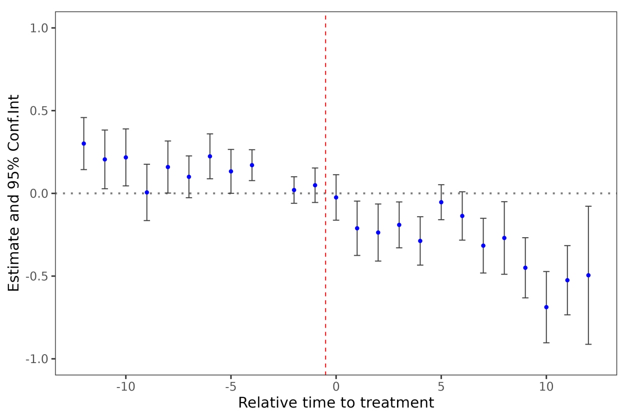
(a) Employee Visits



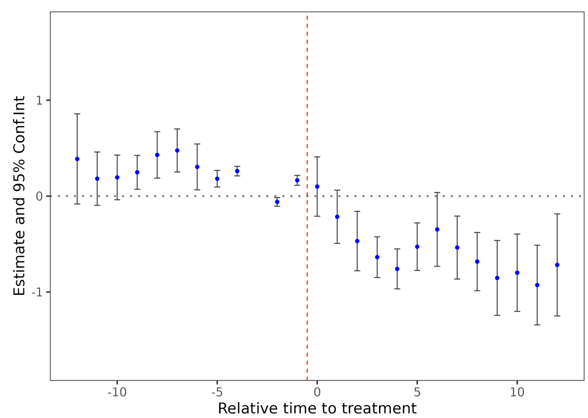
(b) Customer Visits



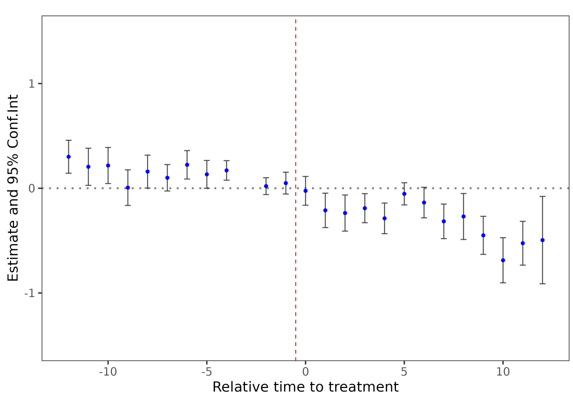
(c) Duration of Visit more than 240 min



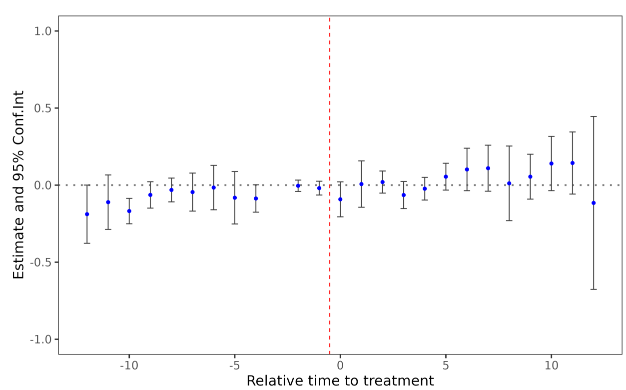
(d) Duration of Visit less than 5 minutes



(e) Total visitor



(f) Distance traveled



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 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 4.4. 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*

4.2.2 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 4.1. In Table 4.5, 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-bound minimum wage changes in Table 4.4. 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 4.5. 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$\times$ Date		Yes			
CD$\times$ Date			Yes		
CR$\times$ Date				Yes	
LMZ $\times$ Date					Yes
Observations	106,378,560	106,378,560	106,378,560	106,378,560	106,270,392

Note: *CD and CR are the Census Division and Census Region where the POI is located. LMZ is labor market zone 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 Section 4.2.2, Table 4.7, I show the estimates for the retail & trade industry and the accommodation and food industries 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.[1] 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 4.6, compared to column (1) both are statistically significant and more elastic to the change in minimum wages.

Table 4.6. 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			
CD × Date			Yes		
CR × Date				Yes	
LMz × Date					Yes
Fit statistics					
Observations	45,908,976	45,908,976	45,908,976	45,908,976	45,860,472

Note: *CD and CR are the Census Division and Census Region where the POI is located. LMZ is labor market zone based on the USDA ERS-2010 labor-shed delineation.*
Clustered (City-level) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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

The results in Table 4.5 and Table 4.6 validate 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.

Industrial heterogeneity

In Table 4.7, I present the results for the Retail Trade and Accommodation and Food Industry. The results present a similar picture to the main results in Table 4.2. For the Retail Trade industry, Employee visits decrease by 4% when minimum wages increases by 10%. Controlling for the State-time trends in other words State-level policy changes across time we get higher negative results i.e. 7.5% decrease in employee visits when minimum wages increase by 10%.

Balanced and Unbalanced Panel

I have used zero to replace the missing values for the POIs visits in my main results. In Table 4.8, I present an unbalanced panel with missing values and a balanced panel by considering POIs which were tracked for all 24 months respectively. 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, Table 4.8 Model (4) presents a fully balanced panel with the POIs tracked for all 24 months, and Model (5) and Model (6) present a balance for the

Table 4.7. Minimum wages and duration visits in the Retail & Trade Industry and Accommodation & Food Industry with geographic trends

Model:	(1)	(2)	(3)	(4)	(5)
			Retail Industry		
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)
Fit statistics					
Observations	26,358,072	26,358,072	26,358,072	26,358,072	26,358,072
			Accommodation & Food		
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			
CD ×Date			Yes		
CR × 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*

Retail & Trade and Accommodation & Food industry respectively when the POIs are tracked for all 24 months. All estimates are clustered at the city level and present results close to the main results in Table 4.1.

Table 4.8. Minimum wages and duration visits for the balanced and unbalanced panel.

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

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

Normalization of visits

In Table 4.9, I present analysis with and without normalization of the visits to show that the change in population on January 2019 does not affect the change in visits at the POI. In model (1), I present the estimates from my main result table 4.2, Models (2) and (3) are the estimates when I normalize the visits at the POI using the total population of the state constant i.e using in the year 2018 and 2019 respectively as the numerator to have a better representation of the people by a number of devices identified in the Adavn data. In model (4), I present the non-normalized visits, these estimates show more variation as the number of devices identified by Advan across the study time period is not constant. Comparing models (1) with models (2) and (3) it is understood that jump in population on January 2019 does not have a significant effect on the estimates.

Table 4.9. Normalization of visits with the total population in the year 2018 and 2019.

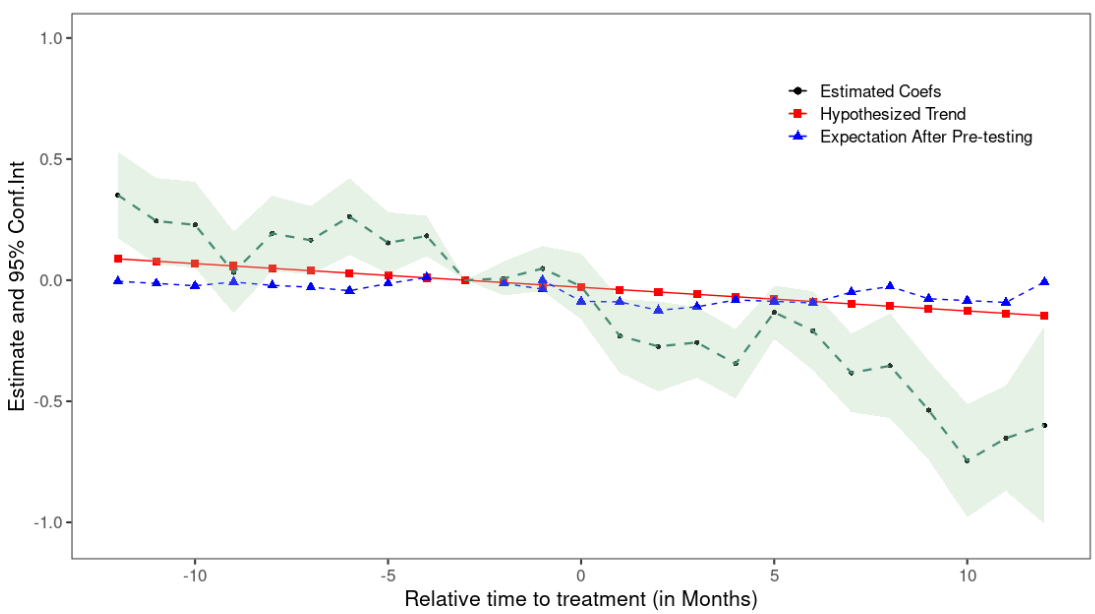
Model:	(1)	(2)	(3)	(4)
Employee Visits	-0.4623***	-0.4339***	-0.4334***	-0.5612***
	(0.0751)	(0.0757)	(0.0757)	(0.0608)
Customer Visits	-0.5387***	-0.5074***	-0.5069***	-0.7434***
	(0.0895)	(0.0898)	(0.0898)	(0.0908)
Fixed-effects				
POI	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	107,704,656	107,704,656	107,704,656	107,704,656

Clustered at city standard errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Pre-trend testing

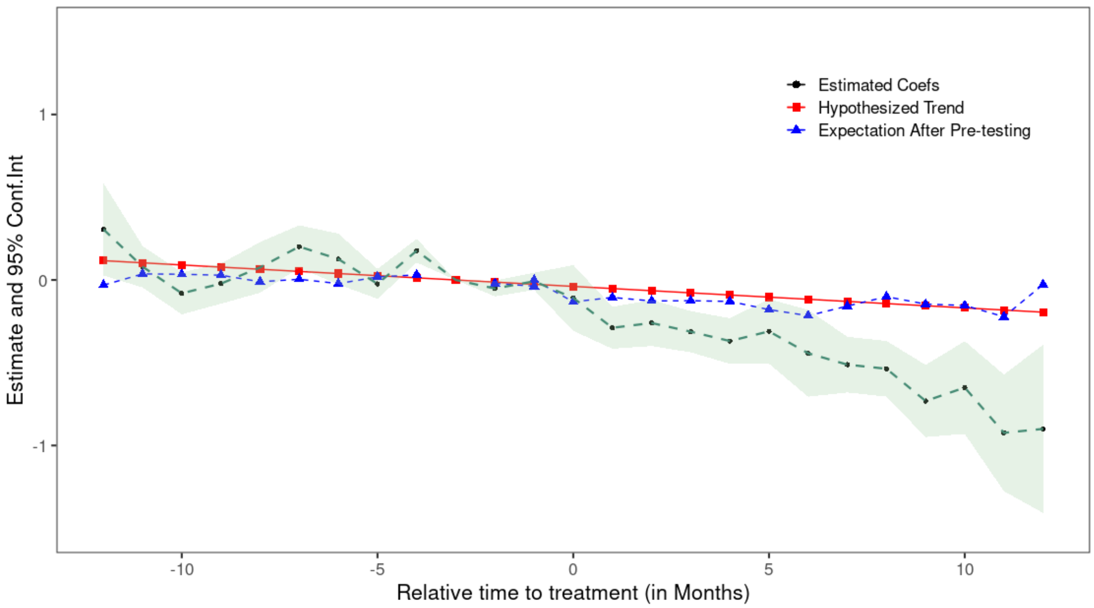
Since the policy change is announced months prior to the implementation, also some policies are programmatic in nature. It gives the firm the to adjust prices or employment and prepare for the treatment. I used the event study to understand how the duration of visits at a POI changes over time. However, In Figure 4.1, especially for the employee visits, I suspect a pre-trend i.e. a downward trend before the policy implementation. With the humongous amount of POIs there could be the possibility that due to the mean-reversion effect, the noise can mask the pre-existing trend and exacerbates bias in the treatment effect estimates.

Figure 4.2. Pre-trend and Effect of Minimum Wages on Employee visits



Also, due to the low power of the event study against the relevant violations of the parallel trends, there could be bias in the treatment estimates. 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) in Figure 4.2. I also construct a similar hypothesis for using pre-existing trends for Customer visits, Total visits, and Distance traveled in Figure 4.3, 4.4, and 4.5 respectively. I observe that the estimates from the dynamic DiD model present a negative relationship which is greater in magnitude than the expected estimates after pre-testing.

Figure 4.3. Pre-trend and Effect of Minimum Wages on Customer Visits



Staggered Treatment

In this study, I am looking at the minimum wage variations across the United States over the period of 2018 and 2019 at the state or sub-state level. The TWFE-equation 4.1 and event-study design equation 4.2 may not resolve the problem of staggered treatment problem raised by Callaway and Sant'Anna (2021) and Goodman-Bacon (2021). However, the new DiD methods available may also not provide the solution to the problem as there are treatment doses that once implemented increase annually or semi-annually over a period of time. For example, California enforces a state minimum

Figure 4.4. Pre-trend and Effect of Minimum Wages on Total Visitor

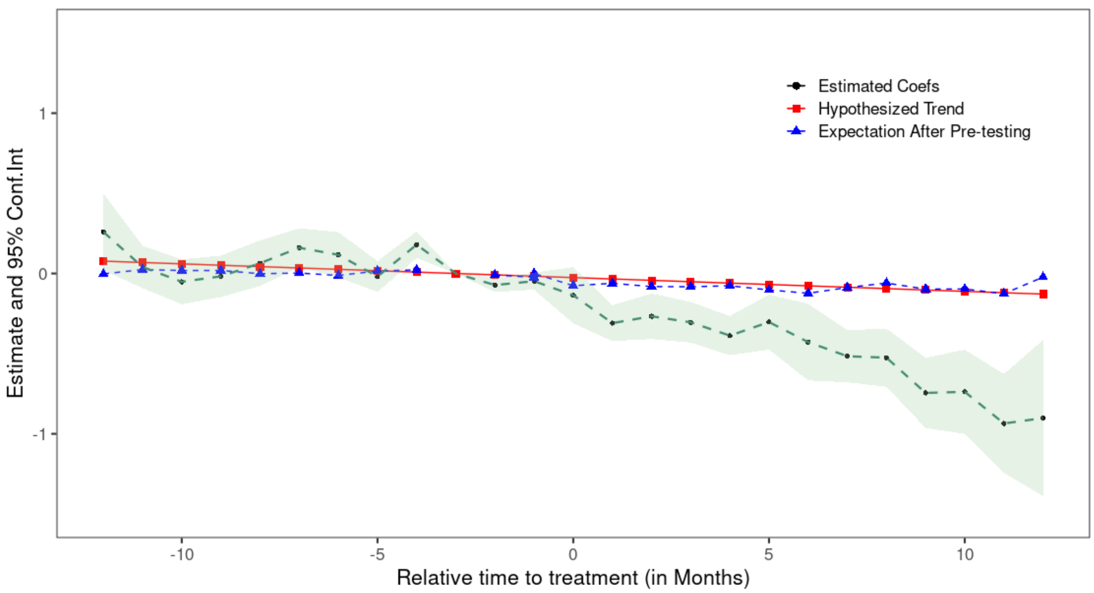
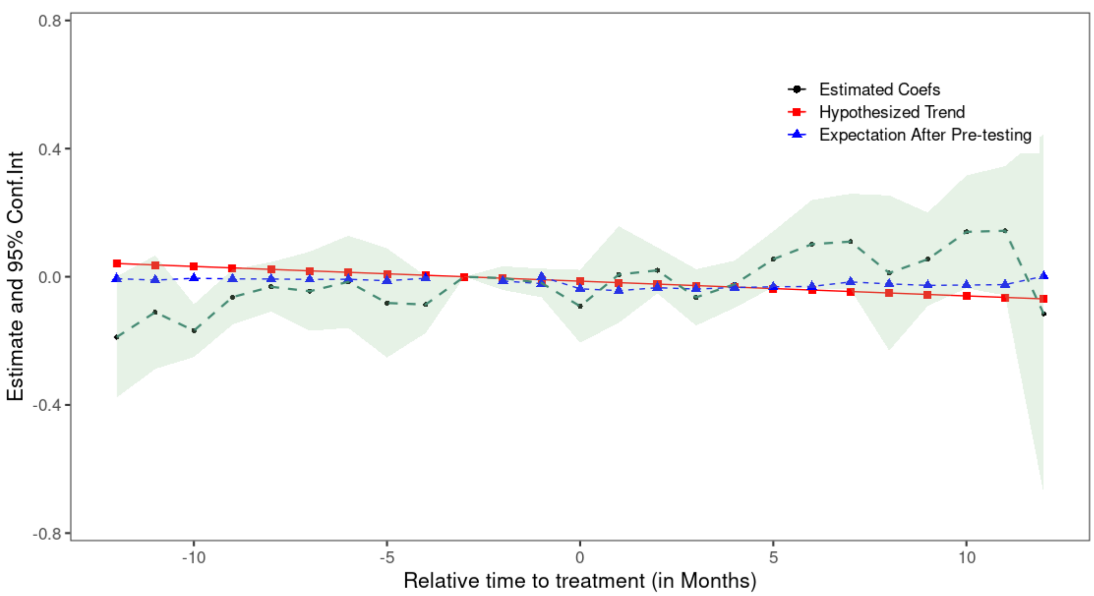


Figure 4.5. Pre-trend and Effect of Minimum Wages on Distance traveled



wage ordinance during the study period at the same time many cities in California also increase city minimum wages by a higher magnitude. Using a binary treatment for 0 or 1 may not work. Moreover, there is variation in the magnitude of the doses, Figure 3.9 presents the variation in state minimum wages with the highest increase in New York State of \$1.5 followed by California by a \$1. Similarly, other states and cities also increased minimum wages by different dollar amounts. To provide a robust analysis for the estimates, I compare the POIs treated in January 2019 to the POIs which are never treated with minimum wage ordinances in my study period which means only one treatment across the study period.

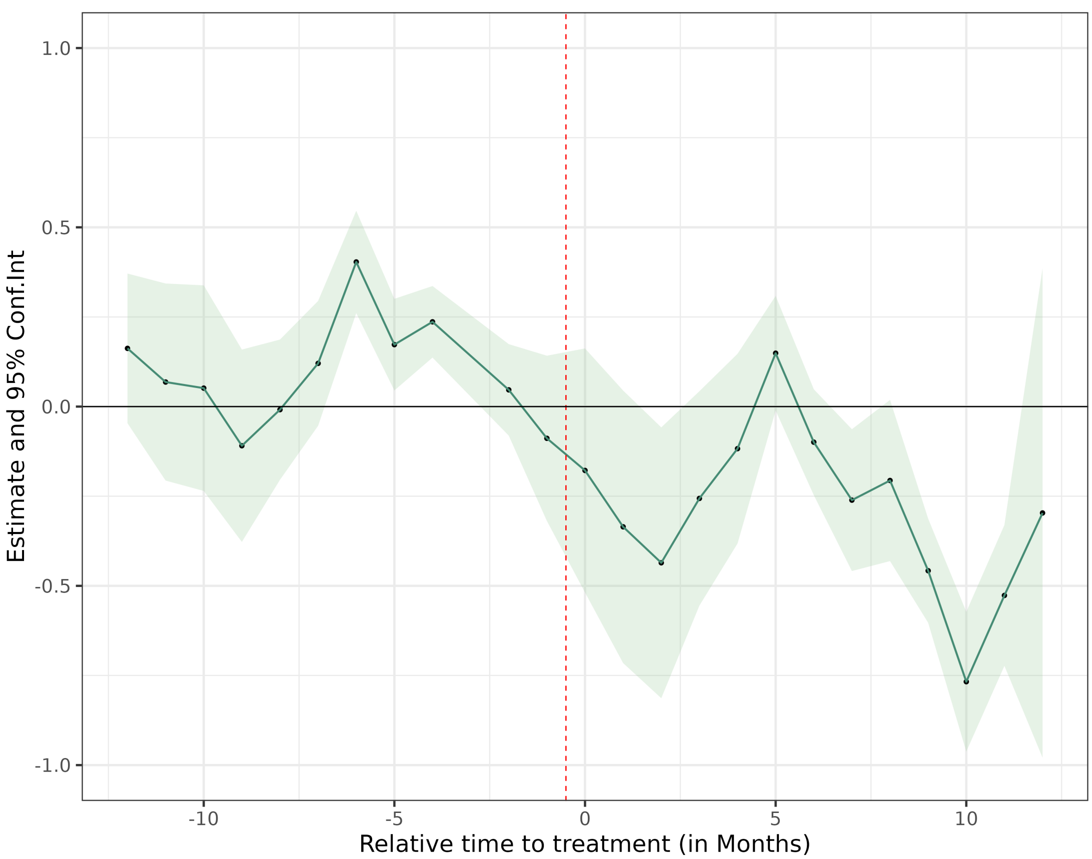
Table 4.10. Duration visits at a POI and Minimum wages for POIs treated in January 2019

Model	Full Sample (1)	Sample w/o short-term lodging (2)	Retail Trade Industry (3)	Acc. & Food Industry (4)
Dependent Variables(log)				
Employee Visit	-0.5016***	-0.5028***	-0.4902***	-0.6633***
	(0.0971)	(0.0973)	(0.0817)	(0.1314)
Customer Visit	-0.6601***	-0.7932***	-0.6528***	-0.9861***
	(0.1177)	(0.1180)	(0.1309)	(0.1593)
Visit > 240 mins	-0.5442***	-0.5455***	-0.5495***	-0.7564***
	(0.0967)	(0.0968)	(0.0804)	(0.1277)
Visit < 5 mins	-1.029***	-1.029***	-1.387***	-1.559***
	(0.1216)	(0.1938)	(0.1751)	(0.2616)
Total visits	-0.5302***	-0.6523***	-0.7627***	-0.9505***
	(0.1765)	(0.1203)	(0.1253)	(0.1548)
Fixed-effects				
POI	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Observations	96,696,864	95,481,288	23,728,200	14,461,440

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

In Table 4.10, I present results estimated using equation 4.1 with only one treatment i.e January 2019 minimum wage policy change across the United States; the treatment units are all the POIs treated due to January 2019, Minimum Wage Ordinances, and the control group are all the POIs which are not treated over the study period. Around 1,732,312 POIs are treated in January 2019 due to state-level minimum wage ordinance at the same time only 178,732 POIs are treated due to sub-state minimum wage increase. I compare all these treated units with 2,117,992 POIs which are "clean controls" across the United States. The estimates of employee visits in Table 4.10 are

Figure 4.6. Employee visits and Minimum wages for POIs treated in January 2019



statistically significant at a 99% confidence interval. Estimate for employee visits in Model (1) can be interpreted as a 10% increase in minimum wage decreases employee visits by around 5% which is close to 4.6% from Table 4.1. Moreover, the estimates in Model (2) are statistically significant and close to the estimates from Model (1), it can also be interpreted as, around a 5% decrease in employee visits when minimum wage increases by 10%. Similar to Table 4.1, I present results for the POIs related to Retail trade and Accommodation & Food Industry in Models (3) and (4) respectively. All the estimates present a negative minimum wage elasticity for duration visits similar to Table 4.1 with a slight variation i.e. the estimates are greater in magnitude than the results presented in Table 4.1. I also estimate the minimum wage elasticity for the employee visits using equation 4.2 in order to understand the change in employee visits over the period of time. Since I am estimating the effect of the treatment by comparing treatment units that were treated in January 2019 to the units which never saw treatment in the period 2018 and 2019, I may not face the problem of staggered treatment. However, the event study in Figure 4.6 presents a trend similar to the trend in Figure 4.1, I take 3rd month before the treatment month as the reference period assuming the POIs would adjust wages and employment starting from the previous quarter. Moreover, there is an increase in long-duration visits(Employee Visits) in the summer months after the minimum wage ordinances are enforced though there is an overall decrease in employee visits. There could be two reasons, first, there might be an increase in summer employment when more young workers join the labor force; Second, these are customers staying longer at a POI. The latter has less possibility as the sample eliminates public parks or short-term lodging facilities. In the next chapter, I will explore how the visits at the destination POI changes conditioned on the home census block group. Further, in Chapter 6, I will summarise the effect of the minimum wage ordinances enforced in the year 2019 and 2018.

Chapter 5: Cross-Border visits

"Carly Lynch, who dreams of one day competing on the professional rodeo circuit, currently works as a waitress in a small city in eastern Oregon, a 20-mile commute from her home in Idaho" reported by The New York Time (2014), recounting experiences of minimum wage workers who cross state boundaries for higher minimum wage workers. The local or state minimum wage ordinances implemented by the respective governments apply to the employees working within the geographic boundaries of the state or city or county[1]. However, the labor markets are stretched beyond the administrative boundaries. In this chapter, I discuss how variation in minimum wages within a labor market change commuting patterns using mobile-device location.

The prior literature found no negative effect of an increase in minimum wages on employment outcomes when compared to contiguous regions, overturning the prediction of the competitive labor market model i.e. higher minimum wages reduced employment among low-skilled workers. Card and Krueger (1993) and Dube et al. (2010) are among the most cited studies that used the strategy to compare nearby areas to study minimum wage variation within local economic areas by controlling for economic conditions that may correlate with the minimum wages. This strategy could create a measurement bias especially when studying a local policy change within a

[1] Alameda City Minimum Wage Ordinance, implemented on July 2019

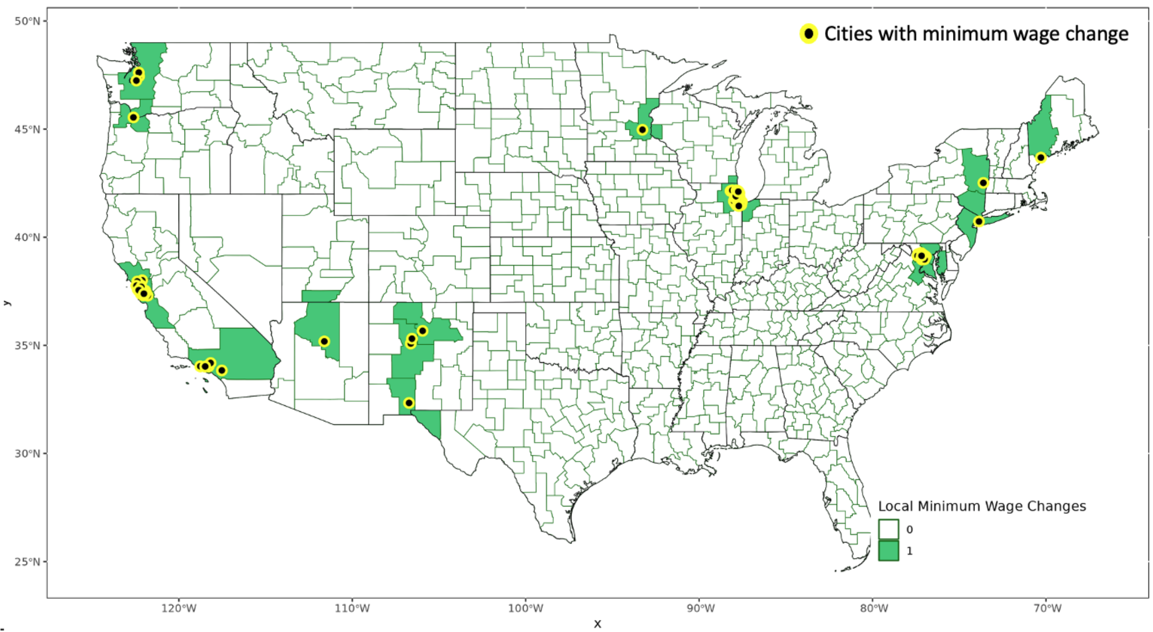
small geographic area. Neumark et al. (2014) also pointed out that if a minimum wage increase attracts individuals to and from the administrative periphery, then cross-border comparisons can create a bias in the disemployment affect. To understand the restructuring of the labor market when the minimum wage increases especially sub-state level changes, I analyze commuting patterns using mobile-device location.

5.1 Data

To have a spatial measure of the local labor market, the Economic Research Services (ERS) defined Labor Market Zones (LMZs) as geographic areas where workers have a high probability of commuting to jobs. LMZs are delineated using a hierarchical cluster analysis of county-to-county commuting flows. Fowler and Jensen (2020) updated LMZs by using ERS commuting pattern identification to form clusters of counties that have strong commuting ties and aggregated them into 2020 LMZs. I use these LMZs to understand the cross-jurisdiction visits and changes in minimum wages on either side of the border. In Figure 5.1, I present the Labor Market Zones affected by the local minimum wage change in 2018 and 2019 across the United States.

The dots represent the cities that experienced an increase in minimum wage either due to the city or county minimum wage ordinance. I use these local areas represented by dots in the LMZs to study the variation in the minimum wage when compared with surrounding areas within LMZs. The labor markets are said to be relatively local to the extent that job attractiveness substantially diminishes if jobs are more than a few miles away (Manning & Petrongolo, 2017). Moreover, I use the neighborhood pattern dataset by Advan, which provides information on the unique visitor count aggregated at the destination Census Block Group (CBG) from an origin CBG. This is

Figure 5.1. Minimum wage change in the Labor Market Zones(ERS-LMZs) in 2018 and 2019 across the U.S.



different from the POI-level dataset which I used in the previous chapter. In the Advan neighborhood pattern dataset the origin CBGs or the home location are identified by using the mobile-device location at non-working hours i.e. by tracking(by GPS pings) a device during night hours(between 6 pm to 7 am) for more than 6 weeks. Moreover, if a device is pinged for more than 1 minute at a location it is counted as a visitor which is lower than the threshold of 4 minutes used in the monthly pattern dataset used in chapter 4. I used these neighborhood patterns tracked on monthly bases over the period of 2018 and 2019 to study the effect of minimum wages on the cross-visits.

To preserve privacy, Advan's data is introduced with noise at the CBG level. Also, it considers CBG which has at least 2 devices. If there are between 2 and 4 visitors it is reported as 4[2]. The introduction of noise at the CBG level may under or over-represent

[2]Advan documentation for Neighborhood pattern dataset.

the visitors at the destination CBG "i" from a home CBG "r". I use the county-level population and the number of unique devices aggregated at the county level as a normalization factor similar to Coston et al. (2021). I use the normalized visit at the destination "i" Census Block Group i.e. V_{irt} from home CBG "r" for a month "t" for the analysis in this chapter. R_k is the set of CBGs in a origin county "k".

$$Normalized\ V_{irt} = V_{irt} \times \frac{Total\ Population_{kt}}{\Sigma_{r' \in R_k} Number\ of\ Unique\ Devices_{r't}} \tag{5.1}$$

I use the proportion of the total population in the home county "k" for the home CBG "r" at the time "t" to the total number of unique devices identified by Advan in the county "k" for the home CBG "r" at the time "t" as a normalization factor. This normalization method provides a balance for the representation of people(visitors) at a CBG, as the number of visitors at the destination from a CBG in a county is equal to the total number of devices identified at the home CBG in the county. I used a similar normalization method for the visitor count in Equation 4.1. I use the NBER distance dataset[3] to merge on the Advan data to identify the distance between the CBG-pairs. For computational effciency, I construct CBG-pairs with 5 miles bins i.e. "0-5 miles", "5-10 miles", "10-15 miles", "15-20 miles", "20-25 miles", "25-30 miles", "30-35 miles", "35-40 miles", "40-45 miles", and "45-50 miles". I balanced this panel data by introducing zeros for no visit for that month between CBG pairs that ever have a positive flow. In the next sections, I discuss the research design and main results for the cross-visits when the minimum wage changes.

[3]NBER Files for the distance between CBGs up to 50 miles

5.2 Research Design

In this section, I will present an analysis at the Census Block Group(CBG) level, first, to understand the elasticity of minimum wages; second, to understand the flow of visits at the destination when minimum wages changes.

I use a model similar to Pérez (2022) by comparing the minimum wage elasticity at home and destination visits at the destination. In Equation 5.2, "r" is the home CBG and "i" is the Destination CBG. I used the $asinh$ of minimum wage for the month "t" at the home "MW_{rt}" and the destination "MW_{it}" CBGs. I also use the log for visits "V_{irt}" at a destination CBG "i" from a home CBG "r" for a month "t". I also use the distance(in miles) "$Distance_{ir}$" between the CBG pairs.

$$log(V_{irt}) = \beta_1 log(MW_{rt}) + \beta_2 log(MW_{it}) + \zeta_d Distance_{ir} + \mu_i + \lambda_r + \rho_t + \epsilon_{irt} \quad (5.2)$$

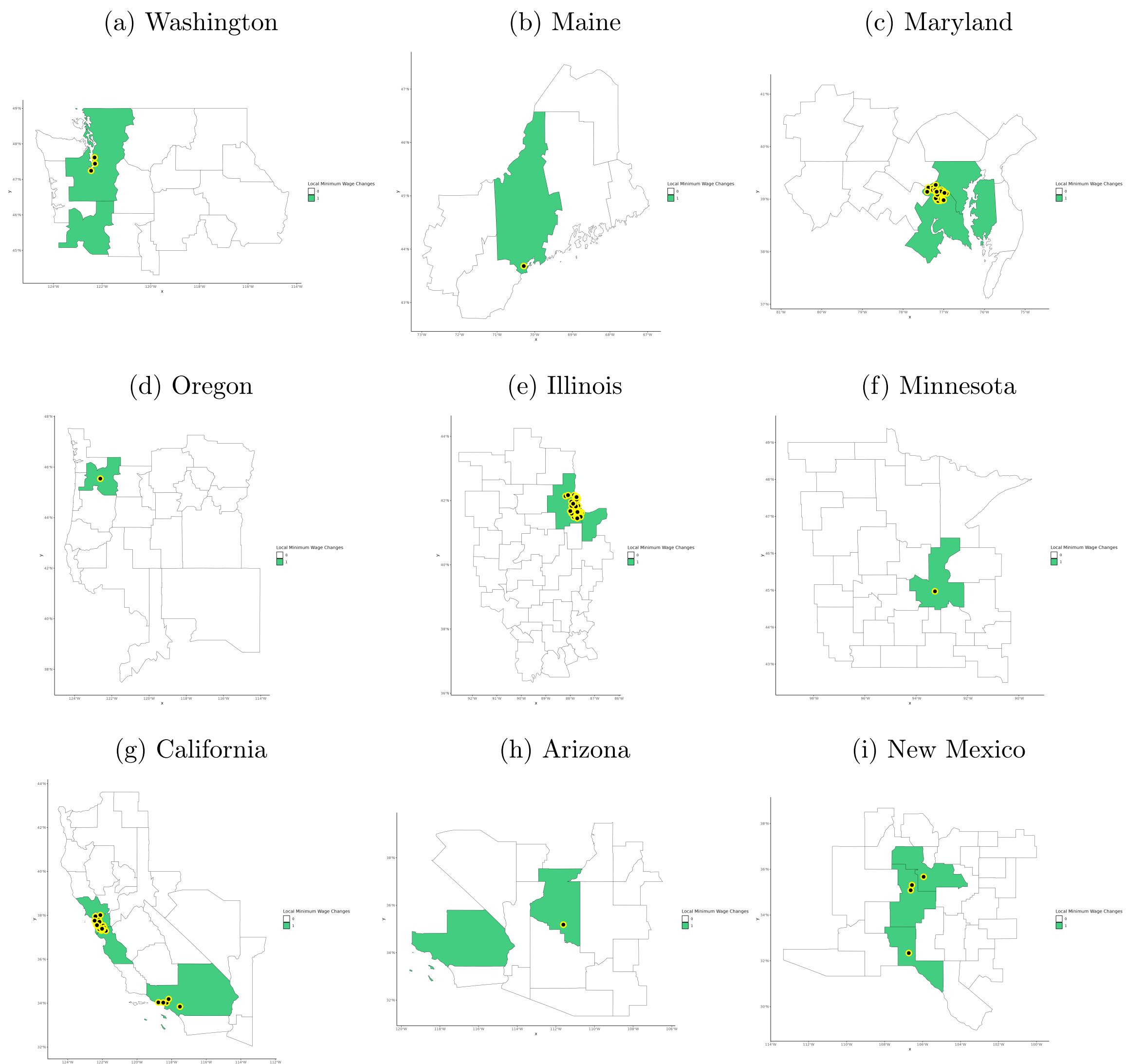
β_1 and β_2, measure the minimum wage elasticity at residence and workplace or destination Census Block Group(CBG) respectively. ζ_d presents the percentage change in visitors when the distance between the CBGs increases by a mile. I use the destination "i" and the residence "r" CBGs fixed effect to capture the time-invariant characteristics like terrain or proximity to the water bodies or major highways or roads. These characteristics tend to change at a slower rate, especially over 2 years. I use monthly time "ρ_t" fixed effects to control for the time-invariant shocks that may influence the visits and the location. In the next section, I present the results for equation 5.2 in Table 5.1 and discuss them in detail. To understand the flow of visits, I used the Census Block Groups within the Labor Market Zones to identify the effect of changes in local minimum wage ordinances on visits to destinations conditional on the home CBGs and the distance between them. Figure 5.2, presents the Labor Market Zones in the states that experienced an increase in destination based sub-state minimum wage increase in 2018-2019, the dots are cities that experienced an increase in minimum wages. The green-shaded area is the labor market zone that contains these cities. The other regions in the state are never treated with the local minimum wage increase in the two-year time period. As part of my identification strategy, I use the census block groups within these green-shaded labor market zones as my sample. There are CBGs within these green-shaded labor market zones that are not treated by the minimum wage increase as they are outside the county or city administrative boundaries, I use them are control to compare with the treated CBGs which lie within the city limits.

Since the control and the treated CBGs belong to the same ERS-LMZs they cater to the same labor market thus the assumption of a parallel trend suffices. I use $\omega_{it} \in \{0, 1\}$ in equation 5.3 to identify the destination CBGs that experience an increased minimum wage due to sub-state ordinance. $\omega_{it} = 0$ if there is no increase in minimum wages at the destination CBG "i" at a time "t" and switches to $\omega_{it} = 1$ if they experience change due to local minimum wage ordinance in a month "t". ω_{it} is always zero for the destination CBGs within LMZs which are never treated over the study period i.e. 2018-19. These never treated CBGs belong to the LMZ but never experience an increase in minimum wage due to sub-state level minimum wage ordinance. I use the $Distance_{ir}$ between the CBG pairs similar to the equation 5.2.

$$log(V_{irt}) = \beta_1\omega_{it} + \beta_2(\omega_{it} \times Distance_{ir}) + \zeta_d Distance_{ir} + \mu_i + \lambda_{rt} + \rho_t + \epsilon_{irt} \quad (5.3)$$

In the equation 5.3, β_1, is the percentage change in visitors at the destination

Figure 5.2. Labor Market Zones(LMZs) and the local minimum wage changes in 2018 and 2019 by State.



CBG when minimum wages increase at the destination due to sub-state minimum wage ordinance. ζ_d, identifies the percentage change in the visitors when the distance between the CBG pairs increases by a mile. I also use the unit and time fixed effects to control for the destination CBG "i" and for the month in a year "t" to control for unit and time-invariant shocks. Moreover, I used home-CBG-by-time fixed effects

"λ_{rt}" to control for the changes in commuting patterns to other destinations from the home "r" over the period of time "t" assuming that an individual may change its commuting pattern over a period of time. In the next section, first I present the results for equation 5.2 to discuss the effect of the elasticity of minimum wages at home and destination on the visits at the destination. Later, I present results from equation 5.3 to understand the direction of the visits.

5.3 Main Results

In Table 5.1, I discuss the results of my analysis of the elasticity of minimum wages at the home and destination to the visits at the destination using equation 5.2. I used the log value of the minimum wages prevailing in Home "r" and Destination "i" CBGs for a month "t" and divided CBG-pairs by 5 miles distance bins. For instance, in Column (1), the minimum wage elasticity for the visitors at the destination CBG if the home CBG is within a distance of 0-5 miles of the destination. I find that when the destination CBG minimum wage increases by 10% in this bin, the number of visitors at the destination decreases by 3.6%. Similarly, when the minimum wage at home CBG increases by 10%, the number of visitors at the destination decreases by 2.1%. Additionally, I find that if the distance between the home and destination increases by a mile, the number of visitors at the destination decreases by around 50% i.e $e(-0.69) - 1 = -0.50 \times 100$.

This pattern changes when I compare the higher-distance CBG pairs. The elasticity of home minimum wage has a higher negative magnitude on the number of visitors at the destination than the elasticity of destination minimum wage. For example, when comparing home and destination CBGs in Column (6) i.e. within 20 to 25 miles, if

Table 5.1. Elasticity of Home and Destination minimum wages on normalized visitors for CBG pairs within 50 miles distance.

Model:	(1) 0-5 miles	(2) 5-10 miles	(3) 10-15 miles	(4) 15-20 miles	(5) 20-25 miles
Destination MW	-0.3560***	-0.2995***	-0.2975***	-0.2887***	-0.2747***
	(0.0177)	(0.0118)	(0.0106)	(0.0103)	(0.0107)
Home MW	-0.2186***	-0.2981***	-0.3316***	-0.3546***	-0.3531***
	(0.0157)	(0.0093)	(0.0083)	(0.0081)	(0.0091)
Miles b/w CBGs	-0.6966***	-0.1810***	-0.0963***	-0.0637***	-0.0459***
	(0.0010)	(0.0005)	(0.0003)	(0.0002)	(0.0002)
Fit statistics					
Observations	481,756,296	639,351,312	541,433,640	429,350,688	347,087,952
R^2	0.504	0.399	0.326	0.269	0.222
Within R^2	0.167	0.021	0.007	0.003	0.00195
	(6) 25-30 miles	(7) 30-35 miles	(8) 35-40 miles	(9) 40-45 miles	(10) 45-50 miles
Destination MW	-0.2479***	-0.2164***	-0.1974***	-0.1650***	-0.1974***
	(0.0123)	(0.0132)	(0.0126)	(0.0127)	(0.0126)
Home MW	-0.3302***	-0.2751***	-0.2425***	-0.2121***	-0.2425***
	(0.0108)	(0.0120)	(0.0112)	(0.0113)	(0.0112)
Miles b/w CBGs	-0.0330***	-0.0253***	-0.0190***	-0.0140***	-0.0190***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Fit statistics					
Observations	284,873,760	235,939,080	198,640,416	170,721,072	198,640,416
R^2	0.18271	0.15112	0.12561	0.10764	0.12561
Within R^2	0.00111	0.00071	0.00044	0.00026	0.00044
Fixed-effects					
Destination	Yes	Yes	Yes	Yes	Yes
Home	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes

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

the minimum wage increases at the home CBG by 10%, the number of visitors at the destination decreases by 3.5%. However, an increase in the minimum wage at the destination by 10% only decreases visitors by 2.7%. Moreover, if the distance between the CBGs increases by a mile in this large distance bin, the visits at the destination decrease by only 4.6%. A similar pattern is seen when I compare longer-distance CBG pairs. An increase in the minimum wage at home by 10% decreases visits at the destination by 2.4% for CBGs that are 45-50 miles away, and an increase in the minimum wage at the destination CBG by 10% only decreases visitors by around 1.9%. However, an increase in distance between the CBGs by a mile decreases visits at the destination by only 2%. These results suggest that an increase in the minimum wage can have a negative impact on the number of visitors to a destination. The impact is more pronounced for destinations that are located further away from the home CBG. This is likely because an increase in the minimum wage makes it more expensive for people to travel to the destination. The results also suggest that the elasticity of minimum wages to visits is not the same for all destinations. The elasticity is higher for destinations that are located further away from the home CBG. This is likely because people are more likely to be sensitive to the cost of travel for destinations that are located further away.

In Table 5.2, I present results using the equation 5.3, I analyze the change of visitors to the destination when the minimum wage at the destination CBG increases. I only use CBG-pairs that lie within the Labor Market Zones which experienced an increase in local minimum wage increase across the United States. In column (1) of Table 5.2, I find that if the destination CBG experienced an increase in minimum wages, the visitors at the destination CBG decreases by 34% i.e $e(-0.40) - 1 = (0.33) \times 100$. This could be because an increase in the minimum wage can lead to an increase in the cost of living in the destination CBG, which can make it more expensive for people to visit. Additionally, an increase in the minimum wage can lead to a decrease in the number of jobs available in the destination CBG, which can also make it less attractive for people to visit.

Table 5.2. Effect of local minimum wage change on the direction of distance traveled for CBG pairs within 50 miles distance.

Model:	(1)	(2)	(3)	(4)	(5)
	0-5 miles	5-10 miles	10-15 miles	15-20 miles	20-25 miles
City Binded	-0.4024***	-0.4218***	-0.2605***	-0.2069***	-0.0817***
	(0.0087)	(0.0111)	(0.0109)	(0.0114)	(0.0141)
Miles	-0.7425***	-0.1570***	-0.0669***	-0.0375***	-0.0253***
	(0.0018)	(0.0010)	(0.0006)	(0.0004)	(0.0003)
Miles × City Binded	0.1154***	0.0536***	0.0204***	0.0117***	0.0037***
	(0.0025)	(0.0014)	(0.0008)	(0.0006)	(0.0006)
Fit statistics					
Observations	212,354,256	261,732,432	210,120,648	156,713,952	117,068,184
Model:	(6)	(7)	(8)	(9)	(10)
	25-30 miles	30-35 miles	35-40 miles	40-45 miles	45-50 miles
City Binded	-0.0805***	0.1214***	-0.0559*	0.0452	0.0718
	(0.0162)	(0.0254)	(0.0276)	(0.0313)	(0.0457)
Miles	-0.0161***	-0.0112***	-0.0083***	-0.0063***	-0.0044***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Miles × City Binded	0.0031***	-0.0036***	0.0009**	-0.0005	-0.0012
	(0.0006)	(0.0008)	(0.0007)	(0.0007)	(0.0010)
Fit statistics					
Observations	89,453,208	67,464,648	51,435,912	39,799,200	31,022,544
Fixed-effects					
Destination	Yes	Yes	Yes	Yes	Yes
Home × Date	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes

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

I also find that as the distance between the Home and Destination CBG increases by a mile, the visitors at the destination CBG decrease by 52% i.e $e(-0.74) - 1 = -0.52 \times 100$. This could be because it might be more expensive and time-consuming to travel to a destination that is further away. Additionally, people may be less likely to visit a destination that is further away if they are not familiar with it. Interestingly, I find that if the distance between the home and destination CBG increases by a mile and the destination is treated with minimum wage ordinance, there is an increase in visitors by 12% for destination and home CBGs within 0-5 miles distance. This could mean that a higher minimum wage CBG attracts people from further distances. Overall, my findings suggest that an increase in the minimum wage at the destination CBG can lead to a decrease in the number of visitors to that CBG. However, the effect of an increase in the distance between the home and destination CBG on the number of visitors is more complex. The effect is negative if the destination is not treated with the minimum wage ordinance, but the effect reduces and moves towards the positive side if the destination is treated with the minimum wage ordinance. For CBG-pairs at greater distances, I find that this effect of increased distance and city treatment becomes statistically insignificant and approaches zero as we compare longer distance CBG pairs, for instance in columns (9) and (10) in Table 5.2 there no statistically significant effect of an increase in the minimum wage. To summarise, the results from equation 5.2 and 5.3, the increase in minimum wage attract more visitors to the treated CBGs within Labour Market Zones but the minimum wage elasticity for visitors at the destination remains negative. Moreover, I cannot differentiate between the visits by a customer and an employee. The results from chapter 4 and chapter 5 provide us enough evidence that minimum wages have a negative effect on employment, also it attracts visitors from outside the administrative boundaries when minimum wage increases.

Chapter 6: Discussion

This study contributes to the debate on the relationship between employment and minimum wages by exploring two broad arguments. First in Chapter:4 I study, the effect of minimum wages on employment when the workers can commute to nearby areas to arbitrage the variation in local minimum wages? Later, in Chapter:5, I explore how the labor markets restructure when there is variation in wages within a small geographical area. Before that in Chapter:2, I provide a background of the literature and discuss about drawbacks of the administrative dataset when studying a local policy issue; In Chapter:3, I provide a description of the novel mobile-device location data by Advan and how can we use it to study the labor markets and other local policy issues.

I use the visit duration at establishments [POIs] as a proxy for employment to explore the variation in minimum wages at the establishment level using the geo-locations. I argue, similar to McKinnish (2017) that the place of residence for a worker might be different from the place of work, especially for low-wage workers. Thus, using residential-based administrative data i.e. Public Use Microdata Areas(PUMAs) from ACS can not provide us with the correct estimates. Moreover, even the data from payroll at the county level may also not work when studying variation within a county. To the best of my knowledge, Jardim et al. (2022) is the only other study apart from mine that uses the establishments' geo-location to identify the effect of minimum wages to study Seattle's minimum wage increase. However, I use the geo-locations of establishments across the United States to study the variation in minimum wages at state and sub-state levels. I find that when minimum wages increase by 10% the employee visits decreases by 4.6%. According to the literature (Card & Krueger, 1993; Dube et al., 2007; Neumark et al., 2014), the Accommodation & Food Industry and Retail Industries are more likely to employ minimum-wage workers. The minimum wage elasticity to employee visits in these two industries is negative and greater in magnitude than the main sample with no POI related to public parks or short-term lodging facilities. Moreover, I find that the POIs which are bounded by the local minimum wage change experience around 7% more decline in employee visits than the POIs which are bound to state minimum wage change. It is important to note here that the state minimum wage binding on the POIs is less negatively elastic in terms of magnitude than the local minimum wage. This brings us to the argument of restructuring labor markets, in smaller areas, workers are more likely to be mobile i.e. work likely to switch jobs. This complements the competitive market structure. In chapter 5, I control the visitor's home location along with destination CBG. I find that the visits at the destination are more negatively elastic to the minimum wage locations when the CBG pairs are far from each other i.e. more than 10 miles from each other. I also observe that the further the home location from the destination greater the negative magnitude of elasticity of visits at the destination. Interestingly, I find that though there is an overall decline in visits at the destination CBG, if the local minimum wage is binding on the destination CBG, it attracts more visitors. These empirical findings take us back to Figure 2.3 from chapter 2, which explains that more skilled workers are like to be attracted to the higher minimum wage areas, though there is an overall decrease in employment due to increasing the minimum wage. This is the first study, to use the high-frequency dataset to understand the commuting pattern when there is an income shock in the labor market.

There are certain limitations to the study which also provide scope for future exploration. I use the total visits at the destination CBG to study the cross-visit when the minimum wage change. In the future, I will use other dataset by Advan to combine with the neighborhood pattern data to differentiate between the home location of an employee and a customer. For instance, spending data at a POI along with other information about the consumer visits. I do not observe individual-device-level data, which makes it difficult to ascertain whether there is a decrease in the duration of work hours or a decrease in the number of workers. My future research will address the minimum wage "bite", by identifying commuting patterns using CBG demographic characteristics by linking the CBGs with ACS demographic characteristics. In this study, I used the Economic Research Services defined Labor Market Zones based on commuting patterns. However, the literature has expanded on the definition of Labor Market Zones. Benmelech et al. (2022) and Azar et al., 2022 used the industrial and occupational concentration along with the commuting pattern to identify the labor market zones. For instance, some areas might see more employee visitors from Information Technology or Banking sector which may not be affected by the increase in the minimum wage. In my future studies, I may concentrate on the visitors to the food and retail industry visitors from lower income and education level CBGs to get a better understanding of the effect of minimum wage changes in smaller areas. Moreover, 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, this 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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