

City Minimum Wages and Spatial Equilibrium Effects

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Abstract

Local minimum wage laws are becoming common across U.S. cities, and their effects may be different from the effects of state or national minimum wage policies. This paper studies the effect of changes in the minimum wage on spatial equilibria in local labor markets. Using residence and workplace data for the United States, I analyze how commuting, residence, and employment locations change across city and state borders if the minimum wage changes on one side of the border. I find that areas in which the minimum wage increases receive fewer low-wage commuters. A 10 percent increase in the minimum wage reduces the inflow of low-wage commuters by about 2.5 percent. Rises in the minimum wage are also associated with employment relocation across borders toward areas that did not witness an increase in the minimum wage. I formulate a spatial equilibrium gravity model to explain the distribution of workers between low- and high-minimum wage areas. I calculate counterfactual equilibria with a higher minimum wage for U.S. counties with cities considering an increase, highlighting the role of commuting and migration responses. About two-fifths of the counties considering increases would receive fewer low-wage commuters. Employment relocation away from high-minimum wage areas drives the commuting losses.

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1 Introduction

Local minimum wage laws are becoming common across cities in the United States. The federal minimum wage has remained constant at \$7.25 an hour since 2009, leading city governments to raise the minimum wage themselves. Recently, Seattle and New York City increased their minimum wage to an unprecedented \$15 an hour. Political movements are pushing for rises in several other cities and an increase in the federal minimum wage.

A key feature of cities is the interaction of labor markets between the city and its surroundings. Cities attract migrants and commuters from surrounding areas. From a policy perspective, the effects of a higher city minimum wage may differ from a state- or country-wide policy effects because the former may alter the spatial equilibrium between the city and its surroundings. From the labor supply side, a higher minimum wage may induce additional workers to search for a job in the area, thereby expanding commuting, migration, and labor force participation. However, higher minimum wages may become exclusionary. They may translate into higher housing rents by raising households' income. From the labor demand side, a higher minimum wage makes workers more expensive for firms, possibly reducing labor demand and inducing firms to relocate towards low minimum wage areas.

This paper studies the reaction of city labor markets to minimum wage changes in a spatial equilibrium context. Through a reduced-form analysis and a structural model of location choice, I look at how employment, commuting, and migration into cities change if the city's minimum wage changes and how these changes relate to each local labor market's features. With the model, I build counterfactual equilibriums for U.S. cities considering minimum wage increases, thus highlighting commuting and migration responses.

In the first part of the paper, I undertake a reduced-form analysis to examine how commuting, migration, and employment change if the minimum wage changes. Because of the recent nature of city minimum wage policies, there is a limited sample of city policies to evaluate. I focus instead on borders between states in which labor markets are as well connected as they are in cities and in which the minimum wage has evolved differently on either side of the border because of state policy. I compare commuting flows and employment differences in adjacent crossborder areas in which the minimum wage has diverged with adjacent crossborder areas in which minimum wage differences have remained constant. I also compare cross-border commuting flows and crossborder employment differences that have been affected by minimum wage changes with the corresponding flows and differences in within-state counterparts that have not been so affected. I show that a higher minimum wage is associated with reductions in commuting. A 10 percent higher minimum wage is associated with a 1.9 to 2.5 percent reduction in commuting by low-wage workers to the

side of the border that increased the minimum wage. An examination of the drivers behind this effect reveals that low-wage employment shifts from the higher-minimum wage side of the border toward the lower-minimum wage side. My estimates for migration responses are imprecise but do not rule out emigration from higher minimum wage areas.

This reduced-form analysis is useful to highlight that the effect of the minimum wage in cities involves labor supply and demand responses. To disentangle these effects and study the mechanisms through which higher minimum wages affect the city equilibrium, I formulate a quantitative urban model of cities with a minimum wage in the second part of the paper. The model’s distinctive feature is the presence of unemployment in labor markets, which has been absent in recent urban economics models. I consider labor markets with employment rationing and matching frictions. By introducing this framework, I can analyze differences in employment probabilities across areas and how they react to the minimum wage. Higher minimum wages change expected wages, employment, and housing prices. Although higher minimum wages attract more low skill job-seekers to an area, they may reduce labor demand and reduce the number of vacancies. Therefore, the higher minimum wage may reduce the employment probability in equilibrium. The overall effect on commuting and migration depends on the relative strength of these effects. Through the lens of the model, I relate my empirical findings to the magnitude of these adjustment margins. The model allows me to study minimum wage effects beyond an average across cities and allows extrapolation to future minimum wage increases larger than past increases.

In the last part of the paper, I fit the model to commuting data for 51 U.S. cities in 28 counties considering minimum wage increases. To fit the model, I estimate the parameters that drive the relative strength of wage and employment effects and calibrate the remaining parameters to fit local labor market data. I estimate the parameters with two different strategies, first using the variation derived from cross-border differences in the minimum wage. Second, using the variation in commuting over time through a gravity equation estimation. I calculate how labor markets would react to a higher minimum wage. The counterfactual scenarios complement the reduced form analysis by highlighting the role of employment and migration responses. Eleven of the counties considered would experience commuting losses because of employment relocations, which is consistent with the reduced form results. Seventeen of the counties would experience commuting increases because employment effects are small compared with the increase in expected wages. Differences in search and employment probabilities drive the heterogeneity in the response across cities. Many cities experience increases in job-seeking and reductions in employment probabilities, translating into lower commuting and low-skill employment.

This paper contributes to the literature on the minimum wage and quantitative urban

models in three ways. First, it estimates the elasticities of commuting and migration to minimum wages at the local level and relates them to the minimum wage’s employment effects. It joins a broad literature on the effects of minimum wages on employment. [Belman and Wolfson \(2014\)](#) survey this literature and conclude that minimum wages do not have a substantial negative effect on employment. [Cengiz et al. \(2019\)](#) do not find evidence of disemployment effects from higher minimum wages in the U.S., except for some limited effects in tradeable sectors. Among the papers that find negative effects, the elasticity of employment to the minimum wage is around -0.1. The estimates of the elasticity of commuting to minimum wages shown here are larger, suggesting that employment effects may be larger for commuters or larger in cities.

Within the broad minimum wage literature, this paper joins a recent research branch that examines minimum wage effects in a spatial equilibrium. This literature tends to find larger negative employment effects and large negative elasticities of labor demand. [Cadena \(2014\)](#) shows that immigrants to the United States tend to migrate to states with a lower minimum wage. [Monras \(2019\)](#) builds a spatial equilibrium model with the minimum wage and shows how traditional state panel designs may understate a minimum wage’s employment effects if the spatial equilibrium is ignored. [Kuehn \(2016\)](#) shows that border designs may misstate the effects of minimum wages when there are commuting spillovers. [McKinnish \(2017\)](#) shows that workers are more likely to commute out-of-state when the minimum wage in their state increases. In contrast, [Shirley \(2018\)](#) finds that higher minimum wage differentials increase commuting probabilities modestly. Unlike [McKinnish \(2017\)](#) and [Shirley \(2018\)](#), this paper examines commuting flows explicitly and models the reaction of other groups of workers beyond low wage workers.

The paper’s second contribution is to provide evidence of local minimum wages’ effects beyond case studies, and to analyze upcoming minimum wage increases. [Dube et al. \(2007\)](#) find positive wage effects and negligible employment effects associated with San Francisco’s 2003 minimum wage increase. Regarding recent increases, [Jardim et al. \(2017\)](#) find large reductions in hours of work associated with Seattle’s 2016 minimum wage increase, and [Jardim et al. \(2018\)](#) find that workers made up lost hours by working outside of the city. [Leamer et al. \(2018\)](#) provide preliminary evidence of a large employment decrease in limited-service restaurants in California following the minimum wage increase starting in 2016. [Dube and Lindner \(2020\)](#) argue that the evidence on local minimum wages suggests their effects are similar to the effects of their state and national counterparts but do not analyze commuting explicitly. By using borders between states with labor markets that are as connected as cities, I provide evidence on a large sample. This paper explicitly models the migration and commuting responses to the minimum wage, which are more likely to be relevant in cities.

This paper’s last contribution is to introduce unemployment into a quantitative spatial equilibrium urban model with discrete choice (Redding and Rossi-Hansberg 2017). The paper is closely related to Monte et al. (2018) and Ahlfeldt et al. (2015). Monte et al. (2018) show how employment elasticities to productivity shocks may vary across locations depending on how commuting and migration respond. They also show how traditional designs for estimating the impact of productivity shocks that ignore this heterogeneity may be biased. However, these papers work in an environment of full employment wherein extra productivity fully translates into employment. Here, I use a search framework to model the response of employment and commuting to wage shocks in an environment of unemployment. Ahlfeldt et al. (2015) formulate a spatial equilibrium model of city structure and use the fall of the Berlin Wall as a natural experiment to estimate agglomeration effects. The present paper uses the variation in the minimum wage in an analogous fashion. Zhang (2018) formulates a spatial job search model to analyze local minimum wage hikes’ distributional effects. This paper focuses on the effects of cities that are in the process of increasing their minimum wage. Bilal (2020) proposes a theory of spatial equilibrium with unemployment and job search, where workers only search for jobs where they live.

This paper is divided into seven sections. Section 2 outlines the reduced form analysis to estimate the minimum wage effect on commuting and employment locally. Section 3 formulates an urban model with unemployment to highlight the effects of a minimum wage in spatial equilibrium. Section 4 shows how a minimum wage alters commuting, migration, and employment in the model’s context. Section 5 shows how this model can be fitted to commuting and employment data. Section 6 calculates counterfactuals for cities considering minimum wage increases. Section 7 concludes. Five appendixes illustrate details on data, the calculation of equilibriums and counterfactuals of the model, and additional results.

2 Reduced-Form Evidence

This section provides evidence on the effects of the minimum wage on worker locations. I look at how commuting flows, resident shares, and employment shares change in state border areas if the minimum wage changes on either side of the border. The analysis suggests that the minimum wage has a significant effect on local labor supply and demand and motivates the quantitative model that follows.

2.1 Data and Sample Construction

Commuting data. The main data source is the Longitudinal Employer-Household Dynamics Program’s Local Origin and Destination Employment Statistics (LODES) version 7.4 (2002-17).¹ For each pair of census blocks in the United States, the data count the number of workers who live in the first census block and work in the second census block. I refer to these as origin-destination pairs. The data come from administrative sources such as unemployment insurance claims, firm data from the Quarterly Census of Employment and Wages, and additional surveys.

An ideal empirical design would be comparing cities that experience a change in the local minimum wage and cities that do not experience such a change. However, relatively few cities have implemented local minimum wage laws, and most of these have only done so very recently. As of 2020, 42 localities had local minimum wage laws, and more than half of these laws were implemented after 2013. To overcome this sample limitation, instead of looking at cities, I focus on areas geographically close to state borders for the empirical analysis. This extended geographical focus gives a large number of locations and minimum wage changes.

I use the minimum wage variation in adjacent areas on either side of the borders to estimate the minimum wage change effects. The use of state borders minimizes the impact local labor market shocks may have in explaining shifts in commuting and migration. Any observed change in these variables must be attributed to policy changes that affect only one side of the border, such as the minimum wage.

This local approach has advantages over previous analyses of minimum wage effects in spatial equilibrium. [McKinnish \(2017\)](#) and [Shirley \(2018\)](#) study cross-state commuting and the minimum wage using public use microdata areas (PUMAs). Because PUMAs are generally larger than counties, this analysis may miss effects that emerge only in smaller local areas. [Manning and Petrongolo \(2017\)](#) show that local labor markets are relatively local in extent, so that job attractiveness substantially diminishes if jobs are more than one kilometer away.

Here, to examine effects on commuting, I calculate flows within and across states for all state borders in the United States.² Specifically, I look at a band that stretches 11 kilometers on each side of state borders. I choose this bandwidth because the average commute length in the United States is about 22 kilometers ([Kneebone and Holmes 2015](#)). However, for

¹For details on LODES data, see [U.S. Census Bureau \(2016\)](#) and [U.S. Census Bureau \(2019\)](#). The data’s public release contains some noise to avoid confidentiality issues because it is published at a fine geographical level. Appendix [A.2](#) provides details on the imputation process.

²I exclude counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data. I also exclude counties where the local minimum wage is higher than the state’s wage.

robustness, I also use larger bandwidths in some of the analyses. I then sum the flows in county pairs. This aggregation mitigates the workers’ residential locations imputation in census blocks in the LODES data and allows county covariates in the regression analysis. It also mitigates concerns about zero commuting between county-pairs and granularity (Dingel and Tintelnot 2021) that may affect both the reduced-form analysis and the model in section 3.

Extent of cross-border commuting. There are many low-wage cross border commuters every year. From 2002 to 2017, around 200,000 people commuted across state borders on trips shorter than 11 kilometers. By 2017, crossborder commuting accounted for around 10 percent of total commuting by low-wage workers in these areas every year.³

Sample selection. There are some potential issues involved in extrapolating from evidence on state borders to an analysis of future city policy. I select the sample to make state borders comparable with city borders and mitigate the differences between them. City borders may be more populated than state borders. Also, it may be easier for workers to commute or migrate across city borders. I choose a sample of border county pairs that exhibits high total cross-state commuting across the sample. This choice excludes borders with low population and borders across which workers do not commute (for example, the Nevada-Utah border). I divide the county pairs into five clusters according to total cross-border commuting using k-means cluster analysis. Then, I exclude the cluster with the lowest commuting from the sample. The exclusion amounts to omitting county pairs that have fewer than 150 commuters a year.⁴

Figure 1 shows the counties included in the sample. (All figures and tables follow the main text.) Most of these counties locate in cross-border metropolitan statistical areas or in densely populated borders. Figures G.4 and G.5 on appendix G show the amount of cross-border commuters these counties send and receive.

I focus on private-sector workers who commute for their primary jobs. The LODES data counts workers over three wage categories: below \$1,250 a month, between \$1,250 and \$3,333 a month, and over \$3,333 a month. These categories are labeled as low-, middle, and high-wage workers, respectively. Most minimum-wage workers fall among the low-wage category, although the minimum wage is sufficiently high in some states for the later years that they

³Figure G.2 in appendix G shows how commuting varies over time at different distances from state borders.

⁴The commuting and migration responses may be different in connected areas compared to non-connected areas. For example, workers may be more responsive to wage differences across space in connected areas. Differences in commuting costs should account for this heterogeneity.

could fall in the middle category.⁵

To examine migration and employment relocation effects, I use LODES data to compute residents' and employees' shares in each wage category for each location. Then, I focus on low-wage employees and residents.

Minimum wage data. For minimum wages, I use the average monthly state minimum wage from data compiled by [Neumark et al. \(2014\)](#) , and [Clemens et al. \(2018\)](#).⁶

Figure 2 shows differences in the minimum wage between neighboring states. If these differences were nonexistent because neighboring states always kept the minimum wage equal, it would be hard to attribute commuting changes to minimum wage policy. It turns out that the differences are substantial. Although the median difference is 0 for most of the time frame, it increases to about \$0.50 an hour in 2007 before slightly decreasing. There is also substantial heterogeneity in these differences across state pairs.⁷

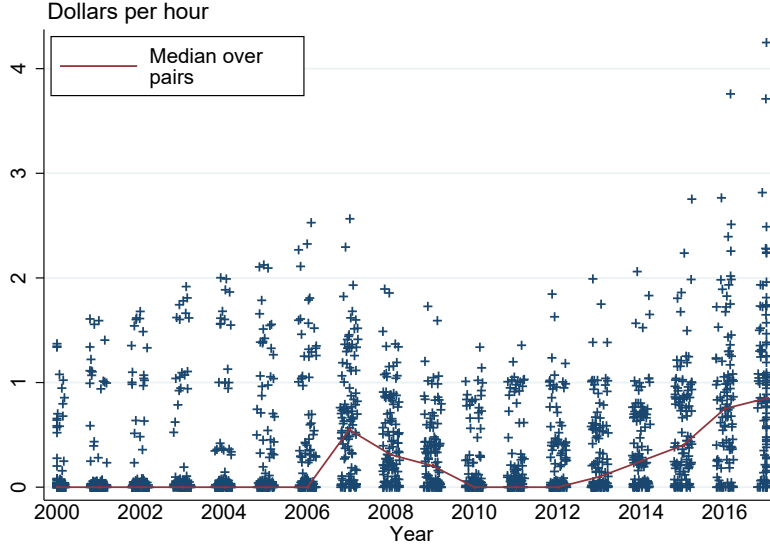
Additional data. I also compile a series of county-level controls that vary over time and may influence commuting behavior. Among these variables are total population across different age profiles, lags in county unemployment rates, county labor force, establishment

⁵Table G.1 of appendix G lists the states and years in which minimum wage workers would be in the second category. The results in section 2.3 are robust to excluding these observations or to a redefinition of minimum wage workers to include the second category in these states for all years.

⁶For robustness, I also use the data of [Vaghul and Zipperer \(2016\)](#). The main results of section 2.3 are robust to this change.

⁷Figure G.3 of appendix G plots the average minimum wage across states during the sample period. There has been a steady increase in the minimum wage across states. Most of the increase occurred between 2006 and 2010. The median minimum wage across states is equal to the federal minimum wage through most of the decade.

Figure 2: Difference in minimum wage between neighbor states



Source: Author's calculations based on data from [Neumark et al. \(2014\)](#) and [Clemens et al. \(2018\)](#). Points have been jittered to show that many state pairs have the same difference in minimum wages.

counts, corporate taxes, tax credits, and gas prices. Details on the sources are in appendix [A.1](#).

2.2 Empirical strategy

This subsection describes the regression strategy. The focus is on three local labor market outcomes. First is how commuting flows change if the minimum wage changes on either side of the border. Second is the difference in employment shares by wage categories across the border. Last is the difference in resident shares by wage categories.

These three outcomes provide a comprehensive view of how worker locations react to a minimum wage. I find that commuting shifts away from minimum wage increases so cross-border flows into higher minimum wage areas decrease. This commuting reduction could occur for several reasons. If employment decreases in the area that has raised the minimum wage, one would see fewer commuters into that area. In this case, low-wage employment shares should decrease. However, it may also be the case that employment is unaffected, and workers are moving into the area that increased the minimum wage. In that case, employment shares should be unaffected, while low-wage resident shares should increase.

Effects on commuting, panel design. The first step is the estimation of the effects on commuting. The unit of analysis is the county pair. I use n to index residence counties, i to index workplace counties, and C_{nit} to denote commuting from county n to county i at time

t . Because commuting goes in both directions, there are initially two observations in the sample for every pair of counties each year. These are restricted to the parts of the counties that are in a narrow distance band from the border. For the main analysis, I focus on places 11 kilometers from the border, but later I calculate coefficients for alternative bandwidths.

I examine how cross-border commuting flows change if the minimum wage changes on either side. I compare these flows with different counterfactuals using a difference-in-differences strategy. Figure 3a shows the first design, labeled the panel design. I compare flows between areas A and B with flows between C and D before and after a minimum wage change occurs in area B. This design is analogous to the state-panel design traditionally used in the minimum wage and employment literature (Neumark et al. 2014).

For this panel design, I estimate the following regression:

$$C_{nit} = \beta_0 + \beta_n \ln(\text{minwage}_{nt}) + \beta_i \ln(\text{minwage}_{it}) + \gamma_{ni} + \delta_t + \Phi_n X_{nt} + \Phi_i X_{it} + \epsilon_{nit} \quad (1)$$

The coefficients of interest are β_n and β_i , the effects of a minimum wage at the residence and the workplace. The residence-workplace pair effects, γ_{ni} , control for time-invariant differences in commuting between the pairs, while the time effects, δ_t , control for national changes in crossborder commuting over time. There is one fixed effect for every pair, so residence fixed effects and workplace fixed effects would be collinear with the pair effects.

Coefficients β_n and β_i are identified from changes in the minimum wage at residence and workplace locations. Using the data on both commuting directions allows identifying β_n and β_i separately.⁸

I include several control variables to address heterogeneity across local labor markets. X_{nt} and X_{it} are time-varying variables at the residence and workplace that may influence commuting across borders. I include state-specific linear time trends and pair-specific linear time trends in some specifications. In other specifications, I include census division effects interacted with year effects to compare only residence-workplace pairs within census divisions. In this case, identification requires multiple county pairs per state border and state border within a census division.⁹

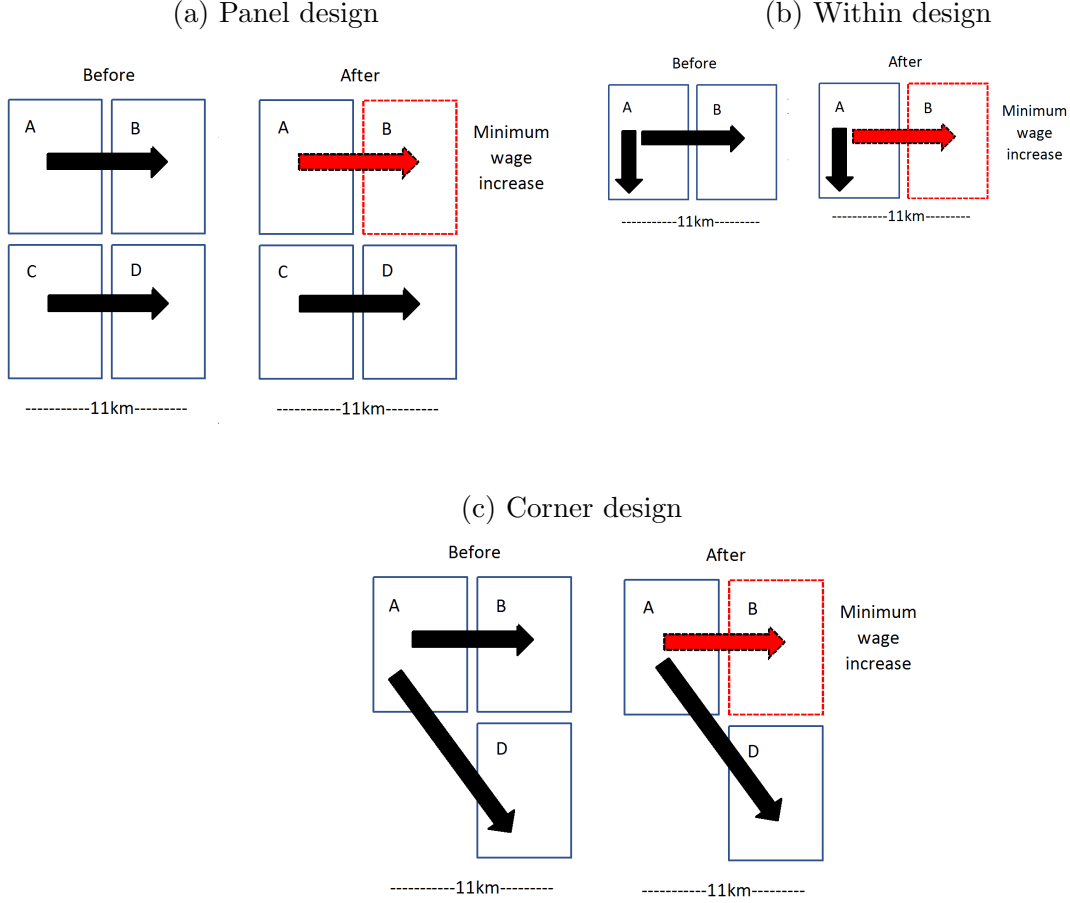
The effects of minimum wages β_n and β_i are identified here if

$$E(\epsilon_{nit} \times \ln(\text{minwage}_{nt})) = E(\epsilon_{nit} \times \ln(\text{minwage}_{it})) = 0, \quad (2)$$

⁸I use gross flows in both directions instead of net flows. The gross flows allow me to identify the effect of minimum wages in the workplace and the residence. In Appendix B, I show that regression with net flows would only allow me to identify the difference in these coefficients.

⁹Dube et al. (2010) show that these coarse time-varying trends are sufficient to dampen negative point estimates of the employment effect of minimum wages, and they attribute this to spatial heterogeneity.

Figure 3: Empirical strategy



This graph depicts the empirical strategies of section 2.2. Each rectangle represents an area in a state. The gap between the rectangles represents the state border, and the areas are in a bandwidth of 11km from the border. The minimum wage increases in area B. The top arrow represents the commuting flow from A to B. This flow is “treated” after the minimum wage increases in B. The treated flow is depicted with a red dashed arrow.

Panel (a) depicts the “panel” design. The flow from C to D, and the flow from A to B before the minimum wage change, are not treated and are represented by black arrows. This design compares the change in the flow from A to B when the minimum wage changes, to the change in the flow from C to D when the minimum wage changes.

Panel (b) depicts the “within” design. This flow within A is not treated and is represented by a black vertical arrow. This design compares the change in the flow from A to B when the minimum wage changes, to the change in the flow within A when the minimum wage changes.

Panel (c) depicts the “corner” design. The flows from A to B and A to D are not treated and are represented by black arrows. This design compares the change in the flow from A to B when the minimum wage changes, to the change in the flow from A to D when the minimum wage changes.

that is if minimum wage differences are uncorrelated with residual commuting. This condition requires that any unobservable differences in commuting across pairs are evolving in parallel over time. My estimation approach allows unobservables to exhibit different linear trends across states or vary systematically across census divisions by including state trends or census division-year effects. However, the estimates will be biased if there are time-varying differences in commuting across pairs that are not captured by these trends.

The usage of areas close to state borders controls for differences in covariates across counties. [Dube et al. \(2010, 2016\)](#) show that neighboring counties are similar in covariates' levels and trends. [Dube et al. \(2010\)](#) estimate the effects of minimum wages on employment using differences in neighboring counties across state borders. [Hagedorn et al. \(2016\)](#) highlight some limitations of using border designs in the context of evaluating the effects of unemployment insurance. First, they argue that border designs may fail to identify effects if policy differences across counties are not large and persistent. As shown in figure 2, cross-border differences in minimum wages can be as high as 50 percent of the federal minimum wage. These differences may not persist if states set minimum wages in response to their neighbor's policy. The lack of persistence in the differences may bias the estimates toward 0.

[Dieterle et al. \(2020\)](#) argue that border designs need to explicitly account for distance to the border when working with county-level data. My approach looks at pieces of counties usually closer to the border than county centroids, limiting the role of distance. In subsection 2.4, I show that commuting effects vary as I consider larger distances from the border.

Effects on commuting, within design. The second design, shown in figure 3b, is a within design. It involves comparing cross-border commuting flows from A to B and flows within county A before and after the minimum wage changes in B. All the identifying variation derives from workers who reside in the same area. As an alternative, I also compare flows originating across the border to flows in the same county. The regression specifications are as follows:

$$C_{nit} = \beta_0 + \beta_d(\ln(\minwage_{it}) - \ln(\minwage_{nt})) + \gamma_{nt} + \tau_i + \Phi_i X_{it} + \tilde{\epsilon}_{nit}, \quad (3)$$

where I include residence-time fixed effects, γ_{nt} , instead of the pair fixed effects of equation (1). Alternatively, I also compare commuting flows that end in the same workplace from residences with a different minimum wage. This is accomplished by including workplace-time fixed effects, γ_{nt} , as follows:

$$C_{nit} = \beta_0 + \beta_d(\ln(\minwage_{it}) - \ln(\minwage_{nt})) + \gamma_{it} + \tau_n + \Phi_n X_{nt} + e_{nit} \quad (4)$$

These specifications no longer identify the minimum wage effect at the origin or the

destination separately but identify the elasticity of low-wage commuting, β_d , to the minimum wage difference.

Effects on commuting, corner design. The final design, depicted in figure 3c, is a corner design, where I compare cross-border commuting flows to destinations with different minimum wage for counties that send workers to at least two states. The identifying variation in this approach is still derived only from workers who live in the same place. This approach combines the previous two by comparing cross-border flows that have the same origin or destination. The main drawback of this approach is the reduced sample size. To estimate this, I use equation (3), but I restrict the sample to residence counties with commuting flows to more than one state.

Effects on employment and migration. To look at employment responses and migration, I calculate the share of low-wage residents and the share of low-wage workers in each of the areas. I sort the pairs such that the “workplace” is the side that receives the most commuters. I then calculate the difference in shares by subtracting the “residence” share from the “workplace” share. Each county pair only enters the sample once every year. These differences then enter as dependent variables in specification (1). This design is analogous to a difference-in-differences design wherein the control counties are the neighboring counties, as in Dube et al. (2010).

Inference. To conduct inference, I use multi-way clustering (Cameron et al. 2011). Because county pairs that share an origin or a destination are correlated by construction, the error terms are allowed to be correlated if different county pairs share an origin or a destination. I also cluster at the state border to address spatial correlation and allow all pairs to be correlated over time.¹⁰

2.3 Main Results

Commuting. Table 1 shows estimates of the elasticity of low-wage commuting to the minimum wage using different panel specifications. Once location fixed effects are included, the elasticity of flows to the residence minimum wage is small and insignificant. However, the elasticity to the minimum wage in the workplace is significantly negative and stable across specifications, ranging from -0.19 to -0.25.

To put this elasticity into perspective, most studies that find negative employment effects of the minimum wage find an elasticity of about -0.1 (Neumark et al. 2014; Belman and

¹⁰An alternative to correct the mechanical correlation of both commuting directions across pairs is to use dyadic clustering (Aronow et al. 2015). However, this would not account for spatial correlation over the border segments. To estimate the models allowing for multidimensional clustering, I use the software provided by Correia (2017). In cases when the covariance matrix of the coefficients is not positive semi-definite, I apply the adjustment by Cameron et al. (2011).

Table 1: Effect of minimum wages on low wage commuting: Panel design.

Log Low Wage Commuters - 11 Km to Border						
	(1)	(2)	(3)	(4)	(5)	(6)
Log MW Residence	0.44 (0.35)	0.00 (0.11)	0.02 (0.10)	-0.02 (0.11)	0.02 (0.12)	-0.00 (0.12)
Log MW Workplace	-0.78* (0.40)	-0.25** (0.11)	-0.25** (0.10)	-0.22** (0.10)	-0.19* (0.11)	-0.25** (0.10)
Adj R sq.	0.002	0.965	0.967	0.969	0.968	0.976
N	7,610	7,603	7,603	7,603	7,603	7,603
Work counties	260	259	259	259	259	259
Res counties	295	290	290	290	290	290
Work, res effects		Yes	Yes	Yes	Yes	Yes
Year effects		Yes	Yes	Yes		Yes
Controls			Yes	Yes	Yes	Yes
State trends				Yes		
Census div x year effects					Yes	
Work, res trends						Yes
Mean dep. var.	395.2	395.5	395.5	395.5	395.5	395.5

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

The sample excludes 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work, county of residence and county pair level. Column 2 includes year effects and fixed effects at the workplace-residence county pair level. Column 3 also includes controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates. Columns 4 to 6 also include controls for spatial heterogeneity. Column 4 includes linear time trends interacted with state of residence and state of workplace dummies. Column 5 includes residence and work census division dummies interacted with year dummies. Column 6 includes pair-specific linear time trends.

Wolfson 2014). Most of these studies are panel designs, while border design studies tend to find insignificant effects. I find a negative commuting elasticity in a border design study. In principle, this elasticity should be higher than the employment elasticity if flows toward high-minimum wage areas are replaced with flows to low-minimum wage areas. This is indicative of the presence of spillovers of the minimum wage. These findings stand in contrast with those in Dube et al. (2010), who do not find significant county spillover effects. In narrow bands to state borders, these effects are much larger in magnitude.

Also, using a smaller sample and looking at commuting among PUMAs, McKinnish (2017) finds that a higher minimum wage is associated with lower commuting inflows in the PUMAs, with an elasticity of -0.02 to -0.04. The estimates here are significantly larger, suggesting that most of the decrease in commuting occurs at distances close to state borders.

The large magnitude of this elasticity compared with the negligible elasticity of employment to a minimum wage is worthy of interest. Kuehn (2016) and McKinnish (2017) analyze the existence of spillover effects of the minimum wage and how these bias employment elasticity estimates. These results confirm that estimates based on employment by residence may be biased toward zero.

Table 2 shows estimates of the commuting elasticity using only variations within residence counties. The elasticity remains negative and significant, with a value of -0.26 after including controls. Since these estimates are not affected by heterogenous shocks in the residence counties, they suggest that the findings are not being driven by heterogeneous trends.

Table 2: Effect of minimum wages on low wage commuting: Within design, same residence.

Log Low Wage Commuters - 11 Km to Border			
	Same Residence		
	(1)	(2)	(3)
Log MW - Workplace - Log MW Residence	-0.40 (0.93)	-0.24** (0.10)	-0.26*** (0.09)
Adj R sq.	0.000	0.304	0.303
N	12,416	12,136	12,136
Work counties	362	344	344
Res counties	316	288	288
Res effects x Year effects		Yes	Yes
Work effects x Year effects			
Res Effects			
Work effects		Yes	Yes
Controls			Yes
Mean dep. var.	2309.5	2273.6	2273.6
Within R sq.			0.000

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

The sample excludes 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work, and county of residence level. Column 2 includes residence-year effects and workplace effects. Column 3 also includes controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates.

The regression specification makes two implicit assumptions about the way the minimum wage affects low-wage commuting. For the panel design, I allow commuting to be influenced by the minimum wage at the residence and the workplace. From the residence county, the coefficient β_i captures changes in crossborder commuting if wages change on the other side of the border. The coefficient β_n captures substitution from cross-border commuting to

within-state commuting if the minimum wage changes in the residence location.

If only the difference in wages determined commuting, these coefficients would be equal in absolute value but have opposite signs, but this does not seem to be the case. If controls are included, the coefficient on the residence wage is close to zero. The coefficient on the difference of wages in the within design is similar to the panel design’s coefficient, which would be expected if the residence wage effect were negligible.

Tables G.2 and G.3 in appendix G also estimate this elasticity using only variation within workplace counties and using only counties in state corners, after comparing cross-border flows originating in the same county. The within-workplace estimates are small and unprecise. If the minimum wage reduces employment among employees commuting from within and across the state in a similar magnitude, these estimates should be small. The corner estimates are still negative, although imprecise because of the small sample used.

Employment and resident shares. Table 3 shows results on the difference of low-wage employment shares across neighboring county pairs. The results show a significant decrease in low-skill employment shares if the minimum wage goes up at the workplace relative to the neighboring county. A ten percent higher minimum wage reduces the low wage employment share by around thirty percentage points, relative to the adjacent county in the neighboring state. This finding reinforces the view that lower employment plays a significant part in the decrease in commuting because of the higher minimum wage.

Table 4 shows analogous results for residence shares. If workers migrate away from minimum wage increases, one should see negative coefficients in this regression. There is also a potential for heterogeneity in the effects across counties because of the link between areas and their surroundings. However, all the estimates are imprecise and do not allow any inferences to be made on migration effects. The finding here contrasts with Cadena (2014), who finds that workers migrate away from minimum wage increases in states. However, the incentive for migrating instead of commuting in response to the wage change is much smaller in this sample because commuting costs are much lower. Nevertheless, the estimates do not rule out negative migration responses.

2.4 Robustness Tests

This subsection describes an array of robustness tests to the results above. These tests suggest that the results are not driven by preexisting trends in commuting, nor by a shift of employment to other categories. They also vary little if one looks at areas farther away from state borders.

Pre-trends and dynamics. To test for preexisting trends and lagged effects, I follow

Table 3: Effect of minimum wages on low wage employment shares.

Difference in low wage employment shares: Workplace - residence

	(1)	(2)	(3)
	11 Km	11 Km	11 Km
Log MW Residence	0.02 (0.01)	0.03* (0.01)	-0.00 (0.02)
Log MW Workplace	-0.02* (0.01)	-0.03* (0.01)	-0.03* (0.02)
Adj R sq.	0.838	0.846	0.864
N	4,973	4,660	4,660
Work counties	189	188	188
Res counties	208	207	207
Work, res effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Controls		Yes	Yes
Census div x year effects			Yes
Mean dep. var.	-0.01	-0.01	-0.01

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

The sample excludes 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work, and county of residence level. Column 1 includes year effects and fixed effects at the workplace-residence county pair level. Column 2 also includes controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates. Column 3 also includes residence and work census division dummies interacted with year dummies.

Schmidheiny and Siegloch (2020) and Freyaldenhoven et al. (2019) and estimate a panel event study analog of equation (3), including leads and lags of up to three years of the difference in minimum wages between workplace and residence. The specification is:

$$\begin{aligned}
C_{nit} = & \beta_0 + \delta_{-4} [1 - (\ln(\min wage_{i,t-4}) - \ln(\min wage_{n,t-4}))] \\
& + \sum_{k=-3}^3 \delta_{-k} (\ln(\min wage_{i,t+k}) - \ln(\min wage_{n,t+k})) \\
& + \delta_4 (\ln(\min wage_{i,t-4}) - \ln(\min wage_{n,t-4})) + \gamma_{nt} + \tau_i + \Phi_i X_{it} + \varepsilon_{nit}
\end{aligned} \tag{5}$$

The coefficients $\delta_k, k = -4, -3, \dots, 3$ measure lead and lag effects of the increase in the difference in minimum wages between a residence and a workplace county on the pairwise

Table 4: Effect of minimum wages on low wage residence shares.

Dependent variable: Difference in low wage resident shares: Workplace - residence

	(1)	(2)	(3)
	11 Km	11 Km	11 Km
Log MW Residence	0.00	0.01	-0.02
	(0.01)	(0.02)	(0.02)
Log MW Workplace	0.04	0.03	0.03
	(0.04)	(0.04)	(0.04)
Adj R sq.	0.797	0.796	0.836
N	4,978	4,664	4,664
Work counties	189	188	188
Res counties	208	207	207
Work, res effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Controls		Yes	Yes
Census div x year effects			Yes
Mean dep. var.	-0.00	-0.00	-0.00

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

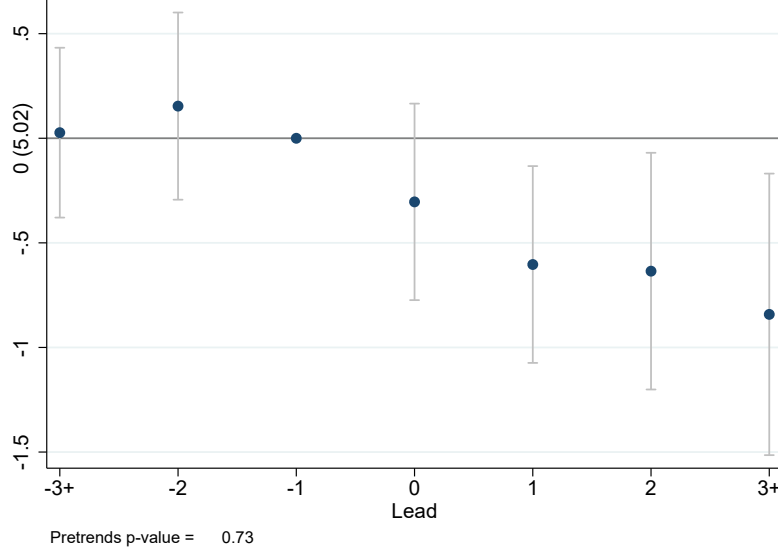
The sample excludes 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage. Column 1 includes year effects and fixed effects at the workplace-residence county pair level. Column 2 also includes controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates. Column 3 also includes residence and work census division dummies interacted with year dummies.

low-wage commuting flows. Suppose the coefficients δ_k were different from zero for $k < 0$. Then, the identification assumptions behind the estimates of equation (3) would be suspect because there would be differences in the flows before the difference in minimum wages changed. The coefficients δ_k for $k > 0$ measure contemporaneous and lagged effects of the difference in minimum wages on commuting.

The results are shown in figure 4. These indicate that the elasticity of commuting to the difference in minimum wages only becomes negative and significant after such difference increases. The coefficients on the leads are not significant and do not display a time pattern, and the coefficient on the contemporaneous effect is not attenuated. The coefficients grow over time, and the point estimate for the low-wage commuting elasticity is around -0.5 after two years. However, lagged effects display substantial uncertainty, since differences in

minimum wages between neighboring counties need not be persistent.¹¹

Figure 4: Effect of minimum wages on low-wage commuting: Panel event study for within-residence design



This figure depicts estimates of the coefficients δ_k from equation (5), a panel event study specification of equation (3). The vertical bars are 95% confidence intervals, calculated from a regression with robust standard errors, calculated with multidimensional clustering at border segment, county of work, and county of residence level. The regression is analogous to that of column 3 of table 2, and includes controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates. The horizontal axis label at 0 shows the mean of the dependent variable at $k = -1$. The “pretrends p-value” comes from a test of $\delta_{-3} = \delta_{-2} = \delta_{-1} = 0$.

Other wage categories. Workers may be keeping their jobs but switching to a higher wage category because of their wage increase. I test this by estimating the same regressions for mid-wage and high-wage commuters. The results are in Appendix table G.4. The lack of a positive effect in the mid and high-wage categories indicates a change in categories is not the driver behind the commuting and employment results.

Distance from state borders. Appendix Figure G.1 shows commuting elasticities at different distances from the state border. The effect remains similar as one looks farther away from the state boundaries, suggesting that differences in commuting flows remain even when considering wider control groups.

Overall, this reduced-form analysis suggests that a larger minimum wage would reduce low-wage commuting to cities and induce employment relocation toward areas that did not

¹¹In the sample, about 15 percent of cross-border differences in minimum wages are eliminated after one year, and about 60 percent of the differences are reduced after one year. When the differences are reduced, the remaining differences are about 30 percent of the original differences.

increase the minimum wage. However, the reduced-form analysis has a few limitations. First, it is restricted to state borders where there is a history of minimum wage changes. To the extent that state borders are different from the cities considering minimum wage increases, cities' effects may be different. Cities are also considering wage changes that are larger than those observed in the sample.

The next section describes a new model that allows an extrapolation to cities.

3 A Quantitative Model of the Minimum Wage and Local Commuting and Migration

This section specifies a location choice model to study how the minimum wage alters commuting and migration in general equilibrium. The reduced-form results suggest that a higher minimum wage reduces commuting inflows and induces some employment sorting. The model enriches this analysis in several directions. First, it sheds light on the different margins of adjustment behind the reduced form results. Reductions in commuting may arise from employment, migration, or labor supply responses (see above). Second, the model allows me to elicit expectations on how future local minimum wage increases will affect cities by allowing producing counterfactual changes in employment, commuting, and migration.

I build a quantitative urban model in the spirit of [Ahlfeldt et al. \(2015\)](#) and [Monte et al. \(2018\)](#). I consider an economy with N locations indexed by n and i . n indexes residence locations, while i indexes work locations. The economy can be a metropolitan area that straddles city or state borders. Each location can be thought of as a county along the border. There are three types of workers with different skill levels, $s = \ell, m, h$ with measures L^ℓ, L^m, L^h . The metropolitan area is a closed city, and the city's total measures of workers are exogenous. Each worker decides on a location to live and to search for work.

3.1 Consumers and Firms.

Preferences. Workers have heterogeneous preferences over locations and choose their locations and consumption optimally given the choices of other agents. Workers are indexed by ω . They may live and work in any location. Following [Ahlfeldt et al. \(2015\)](#) and [Redding and Rossi-Hansberg \(2017\)](#), the indirect utility function of a worker i who lives and consumes in r and works in w is Cobb-Douglas¹²:

¹²This form for the utility function has a particular implication in terms of risk preferences. It implies that the worker values income and commuting costs separately in a risk-neutral fashion. Income enters as an expectation in the numerator. Commuting costs enter as an expectation in the denominator.

$$u_{ni\omega} = \frac{z_{ni\omega}^s \tilde{w}_{ni}^s}{(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}}. \quad (6)$$

The variable \tilde{w}_{ni}^s is expected income if the worker lives in n and works in i . This equals the wage in i , w_i , times the probability of finding a job in location i for a worker of type s , ρ_i^s , plus a residence-based unemployment benefit, R_n^s , in case of unemployment:

$$\tilde{w}_{ni}^s = \rho_i^s w_i^s + (1 - \rho_i^s) R_n^s. \quad (7)$$

The variable Q_n is the price of housing in n . The parameter β is the consumption share of income. The variable κ_{ni} is the commuting cost from n to i . Variable $z_{ni\omega}^s$ is a preference heterogeneity parameter that reflects the taste for living and working in particular locations.¹³ Each worker ω gets a draw for each residence workplace pair ni . Following [Eaton and Kortum \(2002\)](#) and [Ahlfeldt et al. \(2015\)](#), I assume these preference heterogeneity parameters follow a Fréchet distribution:

$$G_{ni}^s(z) = e^{-T_n^s X_i^s z^{-\epsilon}} \quad T_n > 0, X_i > 0, \epsilon > 1. \quad (8)$$

The variables T_n^s and X_i^s are scale parameters that reflect the average taste that each worker type has for living in n and working in i , respectively. ϵ is a dispersion parameter common to all locations. Larger ϵ implies less dispersion of preferences and lower gains from commuting.

Production. Each region has a representative firm that uses workers of all types to produce a single, numéraire consumption good. This good is consumed locally and is not traded. The firm's production function is CES with constant returns to scale ([Card and Lemieux 2001](#); [Ottaviano and Peri 2012](#)):¹⁴

$$Y_i = [A_i^\ell (L_{Mi}^\ell)^\sigma + A_i^m (L_{Mi}^m)^\sigma + A_i^h (L_{Mi}^h)^\sigma]^\frac{1}{\sigma}, \quad (9)$$

where L_{Mi}^s is the total number of workers of type s in location i . Denoting L_{ni}^s as the number of workers of type s who live in n and are employed in i , then employment by workplace is the sum of employees across residence locations. Similarly, L_{Rn}^s denotes employment by residence and is the sum of employees across workplace locations:

$$L_{Mi}^s \equiv \sum_{n=1}^N L_{ni}^s; \quad L_{Rn}^s \equiv \sum_{i=1}^N L_{ni}^s. \quad (10)$$

¹³Since these parameters multiply the wage, they also have an interpretation as worker-specific productivity measures for every residence workplace pair.

¹⁴Here, I focus on substitution between labor at different skill levels and treat the capital stock as fixed. This focus assumes that the effects of wage changes are short term or that capital stocks adjust slowly.

The parameter σ governs the elasticity of substitution between different types of labor. The A_i^s terms are productivity terms specific to each type of labor and each location. (I drop the upper limits of the summations in the remainder of the text for convenience.)

3.2 Labor Markets.

Labor demand. I model labor demand using the approach of [Michaillat \(2012\)](#) and [Michaillat and Saez \(2015\)](#). At a given wage, firms do not hire all the workers searching for a job in each area for two reasons. First, there are matching frictions, and not all workers who search for a job are matched. Second, firms may post fewer vacancies in response to higher wages, which induces job rationing. In equilibrium, there is unemployment in every area. The modeling of unemployment contrasts with existing quantitative urban models without unemployment ([Redding and Rossi-Hansberg 2017](#)), where productivity shocks fully translate into employment. I describe the matching process and the labor market equilibrium in a steady state.

Each firm chooses an optimal amount of labor of every type $s \in \{\ell, m, h\}$ to maximize profits according to the production function of equation (9), taking wages as given. Then, they post vacancies, V_i^s , in every region. There is a recruiting mark-up, τ_i^s , per vacancy filled, so every worker of skill level s costs the firm $w_i(1 + \tau_i^s)$.

Labor market equilibrium. Vacancies are randomly matched to unemployed workers, U_i^s , with a matching function $\mu^s(U_i^s, V_i^s)$ with constant returns to scale. There is a matching market for every type of labor s . Define labor market tightness as $\theta_i^s \equiv \frac{V_i^s}{U_i^s}$. The probability of finding a job in each region is $f^s(\theta_i^s) = \mu^s(U_i^s, V_i^s)/U_i^s$, and the probability of filling a vacancy is $q^s(\theta_i^s) = \mu^s(U_i^s, V_i^s)/V_i^s$.

Let O_{ni}^s be the number of people of type s who search for a job in i and live in n . The number of searchers in location i by type is $O_{Mi}^s = \sum_{n=1}^N O_{ni}^s$. Unemployment by type and place of search is

$$U_{Mi}^s = O_{Mi}^s - L_{Mi}^s. \quad (11)$$

Labor supply for skill s in area i , equals the number of job-seekers times the probability of finding a job:

$$L_{Mi}^s = f(\theta_i^s) O_{Mi}^s \quad (12)$$

Firms take wages and recruiting mark-ups as given; then they choose employment, L_{Mi}^s , to maximize profits. The first-order conditions are

$$Y^{1/\sigma_1-1} (L_{Mi}^s)^{\sigma-1} = w_i^s (1 + \tau_i^s(\theta_i^s)), \quad s = \ell, m, h \quad (13)$$

These equations implicitly define labor demand functions $L_i^s(\theta_i^s, w_i^s)$. In equilibrium, labor demand equals employment in each location, so $L_i^s(\theta_i^s, w_i^s) = L_{Mi}^s$.

Following [Michaillat \(2012\)](#), I assume that recruiting mark-ups are wages paid to recruiters within the firm. Each vacancy requires r^s recruiters to be filled. The amount of recruiters required does not vary by location. The number of filled vacancies is $q^s(\theta_i^s)V_i^s$, which requires $r^s V_i^s$ recruiters. Therefore, each vacancy has a mark-up of

$$\tau^s(\theta_i^s) = \frac{r^s}{q^s(\theta_i^s)} \quad (14)$$

To operationalize this matching model, I choose specific functional forms for the matching function and the recruiting mark-up. I adopt a standard Cobb-Douglas matching function

$$\mu^s(U_i^s, V_i^s) = \Omega^s (U_i^s)^\eta (V_i^s)^{1-\eta}, \quad (15)$$

where I allow matching efficiency, Ω^s , to vary by skill, but not by location.¹⁵ η is the elasticity of the matching function, which is assumed constant across skills and locations. With this functional form, the job finding probability is $f^s(\theta_i^s) = \Omega^s (\theta_i^s)^{1-\eta}$ and the vacancy filling probability is $q^s(\theta_i^s) = \Omega^s (\theta_i^s)^{-\eta}$. Because $q^s(\theta_i^s)$ is decreasing in tightness θ_i^s , recruiting mark-ups $\tau^s(\theta_i^s)$ in equation (14) are increasing in θ_i^s . This implies that vacancies are harder to fill if there are fewer job-seekers available.

Minimum wages. There is a binding minimum wage, w_i , in each location. This minimum wage applies to workers of the lowest skill level ℓ . With a binding minimum wage, firms reduce their hiring if the minimum wage rises and jobs become rationed in each region, reducing the number of matches. Simultaneously, the minimum wage alters the number of people who search for a job in the region, changing OM_i . Together, equations (12) and (13) determine an equilibrium value of θ_i^s and L_{Mi}^s in each location, given a number of searchers, OM_i^s , and a wage.

Labor mobility. Workers choose where to live and search for work to maximize their utility in (6). Following [Monte et al. \(2018\)](#), utility is Fréchet distributed and the workplace-residence probabilities are given by:¹⁶

¹⁵The Cobb-Douglas matching function has constant returns to scale, homogeneous of degree 1, and its value equals 0 if either of its arguments is 0. See [Petrongo and Pissarides \(2001\)](#) for details on assumptions behind matching functions.

¹⁶Details are in appendix C.

$$o_{ni}^s = \frac{\psi_{ni}^s}{\sum_n \sum_i \psi_{ni}^s}, \quad (16)$$

$$\psi_{ni}^s \equiv T_n^s X_i^s [(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}]^{-\epsilon} (\tilde{w}_{ni}^s)^\epsilon.$$

From these bilateral probabilities, one may obtain the marginal probabilities of living in n and searching in i , as follows:

$$o_{Rn}^s = \sum_i o_{ni}^s; \quad o_{Mi}^s = \sum_n o_{ni}^s. \quad (17)$$

These probabilities, multiplied by the exogenous measures of workers of each type, give the number of residents, O_{Rn}^s , and job-seekers, O_{Mi}^s , in each location. From the job-seeker amounts, equilibrium in the labor market from equations (12) and (13) gives an amount of employment, L_{Mi}^s , and unemployment, U_{Mi}^s , for each type at each location. In equilibrium, the employment probabilities that workers perceive are consistent with the ratios of employment to job-seekers at each location:

$$\rho_i^s = \frac{L_{Mi}^s}{O_{Mi}^s} = f^s(\theta_i^s). \quad (18)$$

To determine employment at the residence level and commuting flows, I assume that the employment probabilities at each workplace do not depend on where the job-seekers reside. This assumption implies that the number of people employed in location i coming from n is proportional to the number of job-seekers from n .¹⁷

$$L_{ni}^s = O_{ni}^s \rho_i^s. \quad (19)$$

Define global commuting probabilities as $l_{ni}^s \equiv \frac{L_{ni}^s}{L^s}$. Equation (19) implies that

$$l_{ni}^s = o_{ni}^s \rho_i^s = o_{ni}^s \frac{L_{Mi}^s}{O_{Mi}^s}. \quad (20)$$

The probability of living in n while employed, and the probability of being employed in i are then given by:

$$l_{Rn}^s = \sum_i l_{ni}^s; \quad l_{Mi}^s = \sum_n l_{ni}^s. \quad (21)$$

¹⁷While tractable, this assumption may fail to hold if employers care about commuting distance and its effects on productivity. For example, [Diaz and Salas \(2020\)](#) show that firms discriminate against workers that live further away from firms.

3.3 Housing Markets and General Equilibrium.

Housing Market. Land supply is inelastic and given by D_n . Because of the Cobb-Douglas specification in (6), workers spend a fraction, $1 - \beta$, of their income on housing. This fraction is paid to absentee landlords. The price of housing equals the amount spent on it in each location, divided by the supply of housing, as follows:

$$Q_n = \frac{(1 - \beta)v_n O_{Rn}}{D_n}, \quad (22)$$

where v_n is the average expected income in each location:

$$v_n = \sum_s \left(\frac{O_{Rn}^s}{\sum_t O_{Rn}^t} \sum_b o_{nb|n}^s \tilde{w}_{nb}^s \right). \quad (23)$$

General Equilibrium An equilibrium in the model is a vector of housing prices, Q_n , income, v_n , residents, O_{Rn}^s , workers, L_{Mi}^s , and job-seekers, O_{Mi}^s , of each worker type at each location such that:

1. Residence-search probabilities satisfy equation (16).
2. Equations (12) and (13) are satisfied so the labor market is in equilibrium.
3. Employment probabilities are consistent with ratios of search to employment and satisfy equation (18).
4. Equation (22) is satisfied so the housing market clears.

Turnover. Dube et al. (2016) show that minimum wage jobs are characterized by high turnover. To allow for the possibility of differences in turnover across low- and high-wage jobs, I allow for the possibility of different separation rates. I assume that workers may be dismissed from their jobs but always search in the same location. Jobs are lost according to an exogenous separation rate ξ^s that varies by job type. I then assume job markets are in the steady-state of this hiring and separation process, so the model remains static. In this steady-state, the number of jobs lost by separations has to equal the number of jobs found from unemployment. Equation (12) becomes

$$\xi^s L_{Mi}^s = f(\theta_i^s)(O_{Mi}^s - L_{Mi}^s), \quad (24)$$

and equation (18) becomes

$$\rho_i^s = \frac{L_{Mi}^s}{O_{Mi}^s} = \frac{f^s(\theta_i^s)}{\xi^s + f^s(\theta_i^s)}. \quad (25)$$

Appendix D.1 describes an algorithm to compute equilibriums in the model, allowing for turnover. In equilibrium, employment probabilities must be consistent with commuting patterns. The algorithm starts from an initial value of employment probabilities and housing prices and updates commuting patterns and employment probabilities until they are mutually consistent.

4 Effects of the Minimum Wage

This section examines the effects of changes in the minimum wage on low-wage commuting, migration, and employment in the model. I show that the effects depend on the relative strength of wage effects, employment effects, and housing price changes. I relate the effects found in the model to the elasticities estimated in the reduced form analysis.

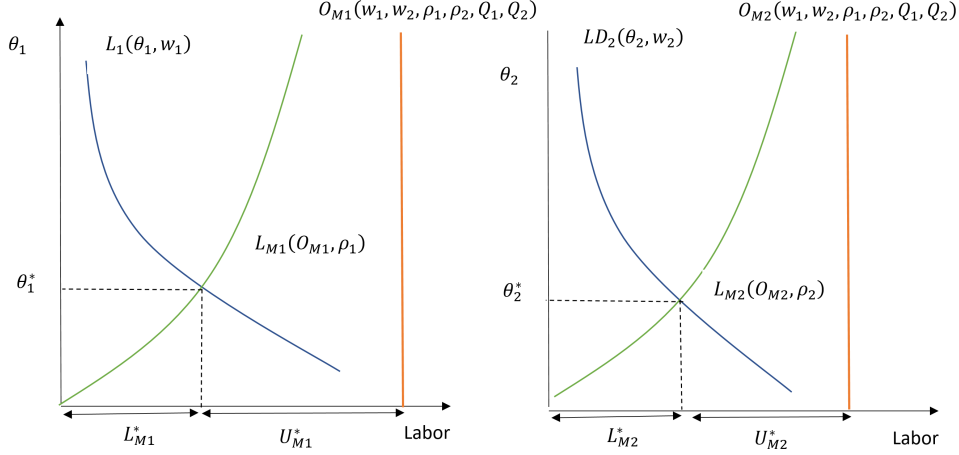
A simple illustration of the minimum wage effects. I illustrate the minimum wage effects in a model of two regions and a single labor type. Figure 5 shows an initial equilibrium of the model. Job-seekers in each region, O_{M1} and O_{M2} , are determined by wages, w , employment probabilities, ρ , and housing prices, Q , in each region. The number of job-seekers and the steady-state equilibrium conditions of each labor market in equation (24) determine labor supply curves, L_{M1} and L_{M2} . Firms in each location have labor demand curves, L_1 and L_2 , that depend on tightness and wages. The intersection of labor supply and demand curves determines equilibrium employment, L_{M1}^* and L_{M2}^* , and unemployment, U_{M1}^* and U_{M2}^* .

Consider an increase in the wage in market 1. This increase changes equilibriums in these locations through three effects.

1. A positive wage effect on the number of job-seekers, since larger wages make location 1 more attractive.
2. A negative employment effect: larger wages reduce labor demand by firms in location 1, reducing employment probabilities and making location 1 less attractive for searchers.
3. A housing prices effect: larger wages increase expected income and housing prices unless the wage change causes a large share of workers to become unemployed, in which case average income and housing prices decrease.

The overall change in employment in these locations depends on the relative strength of these effects. Figure 6a shows a new equilibrium with increased employment. Dashed lines depict new labor supply and demand curves. In this equilibrium, the increase in wages increases the search in location 1 and reduces the search in location 2. Employment and

Figure 5: Labor market equilibrium for a model with two locations



The figure depicts an equilibrium in labor markets for a model with two locations $i, n = 1, 2$, and a single labor type. The variables O_{M1} and O_{M2} are the supply of searchers in each market, which depend on wages w_i , employment probabilities ρ_i , and housing prices Q_n . The curves L_{M1} and L_{M2} are labor supply curves that are upward sloping in market tightness θ_i since more workers are hired as tightness increases. The curves L_1 and L_2 are labor demand functions decreasing in market tightness since higher tightness implies higher recruiting costs. The quantities L_{M1}^* and L_{M2}^* are equilibrium employment levels. The quantities U_{M1}^* and U_{M2}^* are equilibrium unemployment levels. The values θ_1^* and θ_2^* are equilibrium market tightness levels.

unemployment are now greater in location 1 and lower in location 2, although labor demand has decreased in location 1.

Figure 6b shows a new equilibrium with lower employment. In this equilibrium, the increase in wages reduces the search in location 1 and increases the search in location 2. The search reduction in location 1 occurs because the employment effect is large and negative, overcoming the positive wage effect. Employment is now lower in location 1 and higher in location 2. Unemployment in location 2 increases, but the effect on unemployment in location 1 is ambiguous.

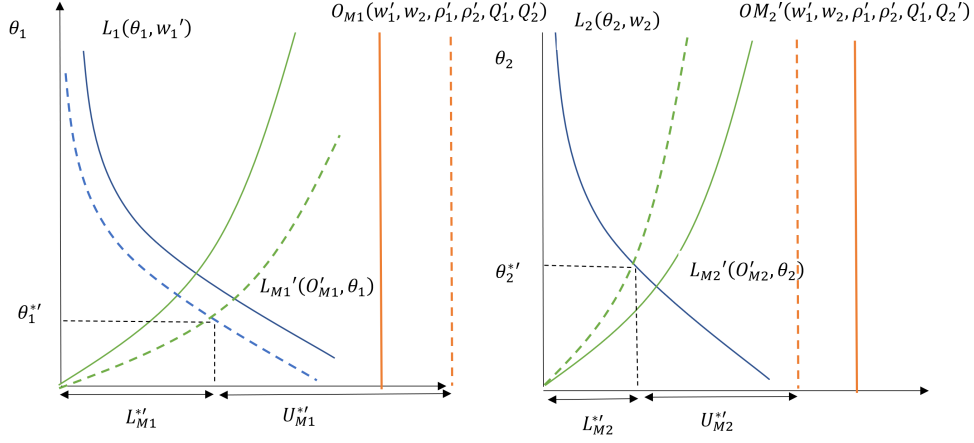
The effects on commuting and migration depend on how the search changes in location 1 are distributed between commuters and migrants. As location 1 becomes more attractive, some residents from location 2 may decide to search for a job in location 1, increasing commuting. In contrast, other individuals may decide to migrate to location 1, increasing the search, but decreasing commuting from 2 to 1.

Elasticity of low-wage commuting to the minimum wage. The model allows me to examine the determinants of the commuting and migration elasticities to minimum wage increases estimated in the reduced-form analysis.

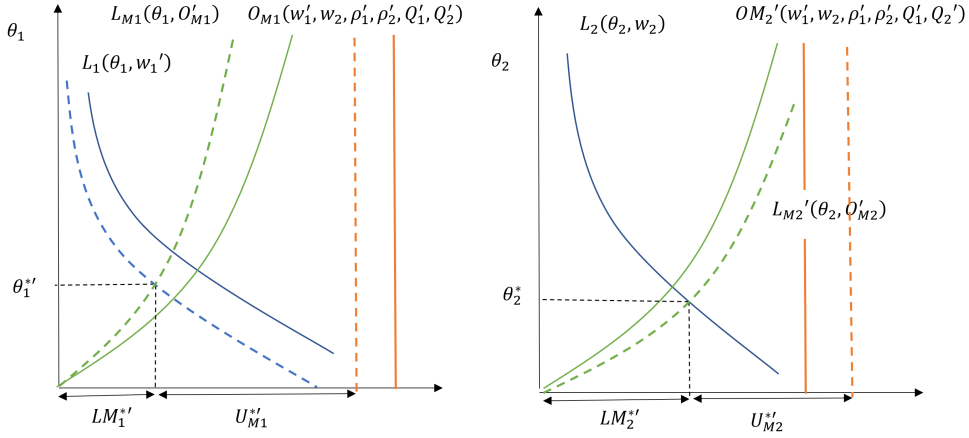
Consider the probability of commuting from n to i among low-wage workers from equation (20):

Figure 6: Changes in labor market equilibrium when the minimum wage increases in location 1

(a) Increase in employment in location 1



(b) Decrease in employment in location 1



The figure depicts how equilibrium changes after a wage increase in a single market, for a model with two locations $i, n = 1, 2$ and a single labor type. Solid lines depict the initial equilibrium and dashed lines depict the new equilibrium. The wage increases in location 1 from w_1 to w_1' .

Panel (a) depicts a case where employment increases in location 1. The number of searchers in location 1 increases to $O_{M1}(w_1', w_2, \rho_1', \rho_2', Q_1', Q_2')$, and decreases search in location 2. Employment in location 1 increases to L_{M1}' , and unemployment increases to U_{M1}' . Employment and unemployment in location 2 decrease.

Panel (b) depicts a case where employment decreases in location 1. The number of searchers in location 1 decreases to $O_{M1}(w_1', w_2, \rho_1', \rho_2', Q_1', Q_2')$, and increases in location 2. Employment in location 1 decreases to L_{M1}' , and unemployment decreases to U_{M1}' . Employment and unemployment in location 2 increase.

$$l_{ni}^\ell = o_{ni}^\ell \rho_i^\ell. \quad (26)$$

The change in this probability depends on how search probabilities and employment probabilities change. Define the partial equilibrium elasticity of low-wage commuting to the minimum wage, $\eta_{w_i^\ell}^{l_{ni}^\ell}$, as the log change in commuting over the log change in the minimum wage keeping endogenous variables constant in locations that are not analyzed. That is, for the commutes from n to i , commuting across other residence-workplace pairs remain fixed. From equation (20), this elasticity is:

$$\eta_{w_i^\ell}^{l_{ni}^\ell} = \eta_{w_i^\ell}^{\rho_i^\ell} + \eta_{w_i^\ell}^{o_{ni}^\ell}. \quad (27)$$

The first term, $\eta_{w_i^\ell}^{\rho_i^\ell}$, summarizes how the employment probability changes as the minimum wage changes. The second term, $\eta_{w_i^\ell}^{o_{ni}^\ell}$, summarizes how the search probability changes with the change in wages. This second term may depend on how the employment probability changes, since o_{ni}^ℓ is a function of ρ_i^ℓ .

In Appendix E, I derive the elasticities of search probabilities to changes in the minimum wage, and obtain the following decomposition for the partial equilibrium commuting elasticity:

$$\eta_{w_i^\ell}^{o_{ni}^\ell} = \underbrace{(\epsilon - \epsilon o_{ni}^\ell) \left[\theta_{ni}^\ell - (1 - \theta_{ni}^\ell) - \frac{1}{\tilde{w}_{ni}^\ell} - \kappa_{ab}^s \right] \eta_{w_i^\ell}^{\rho_i^\ell}}_{\text{Employment effect}} + \underbrace{(\epsilon - \epsilon o_{ni}^\ell) \theta_{ni}^\ell}_{\text{Wage effect}} - \underbrace{(\epsilon - \epsilon o_{ni}^\ell) (1 - \beta) \eta_{w_i^\ell}^{Q_n}}_{\text{Housing prices effect}}. \quad (28)$$

where $\theta_{ni}^\ell \equiv \frac{\rho_i^\ell w_i^\ell}{\rho_i^s w_i^\ell + (1 - \rho_i) R_n^\ell}$ is the fraction of wages in expected income, and $\kappa_{ni}^s = \frac{\kappa_{ni}^s}{1 + \rho_i \kappa_{ni}^s}$.

The wage effect is positive and increases with the share of wages in expected income. The housing price effect grows with the housing share of expenditure. In partial equilibrium, this effect is negative because it increases v_n and leaves LR_n unchanged. The sign of the employment effect is ambiguous. If the elasticity of the search probabilities to the wage is negative, and the wage share in income is sufficiently large, this effect is negative.

The dispersion parameter ϵ plays a crucial role in determining the value of this elasticity. As ϵ grows, wage effects are larger. Larger ϵ implies lower gains from commuting and lower initial commuting in equilibrium. If commuting is lower in an initial equilibrium, then commuting is more sensitive to higher expected wages. Larger ϵ also increases the magnitude of the other effects.

Based on equation (28), the commuting elasticity becomes

$$\eta_{w_i^\ell}^{\ell_{ni}} = \underbrace{(\epsilon - \epsilon o_{ni}^\ell) \left[\theta_{ni}^\ell - (1 - \theta_{ni}^\ell) - \frac{1}{\tilde{w}_{ni}^\ell} - \kappa_{ab}^s \right] \eta_{w_i^\ell}^{\rho_i^\ell} + \eta_{w_i^\ell}^{\rho_i^\ell}}_{\text{Employment effect}} + \underbrace{(\epsilon - \epsilon o_{ni}^\ell) \theta_{ni}^\ell}_{\text{Wage effect}} - \underbrace{(\epsilon - \epsilon o_{ni}^\ell) (1 - \beta) \eta_{w_i^\ell}^{Q_n}}_{\text{Housing prices effect}} \quad (29)$$

which is similar to the effect on search probabilities except for an extra term $\eta_{w_i^\ell}^{\rho_i^\ell}$ in the employment effect. If $\eta_{w_i^\ell}^{\rho_i^\ell} < 0$ then the employment effect becomes more negative overall.

The reduced-form analysis in section 2 above showed an average negative effect of minimum wages on commuting and employment relocation toward the side that did not increase the minimum wage. The average negative effect implies that, for the average county pair in the sample, employment effects are negative and larger in absolute value than the sum of wage and housing price effects.

Elasticities of low-wage residents to the minimum wage. I now examine the effects on the share of low-wage residents, which reflects migration. Define the share of low-skill residents as

$$\Lambda_{Rn}^\ell = \frac{l_{Rn}^\ell}{l_{Rn}^\ell + l_{Rn}^m + l_{Rn}^h}. \quad (30)$$

The semi-elasticity of the share of low-skill residents is given by $\varepsilon_{w_n^\ell}^{\Lambda_{Rn}^\ell} \Lambda_{Rn}^\ell$. This elasticity equals

$$\varepsilon_{w_n^\ell}^{\Lambda_{Rn}^\ell} \Lambda_{Rn}^\ell = \Lambda_{Rn}^\ell \left(\varepsilon_{w_n^\ell}^{l_{Rn}^\ell} - \Lambda_{Rn}^\ell \varepsilon_{w_n^\ell}^{l_{Rn}^\ell} - \Lambda_{Rn}^m \varepsilon_{w_n^\ell}^{l_{Rn}^m} - \Lambda_{Rn}^h \varepsilon_{w_n^\ell}^{l_{Rn}^h} \right), \quad (31)$$

which is a function of the initial resident shares by skill and the elasticity of residents for each skill level. These total resident elasticities can be written as sums of commuting elasticities over workplaces, as follows:

$$\varepsilon_{w_n^\ell}^{l_{Rn}^s} = \sum_b \varepsilon_{w_n^\ell}^{l_{nb}^s}. \quad (32)$$

In general, the effect on migration is ambiguous because this sum could take any sign. A comparison with the estimated reduced form effect is not informative because these effects have been imprecisely estimated.

Extrapolating to cities considering minimum wage changes. The analysis in this section shows how to analyze the effects of minimum wages in the model and decomposes the elasticities into several effects arising through different channels. It shows that the overall effects are ambiguous and depend on the relative strength of these channels. To suggest how minimum wage policies affect cities that increase their minimum wage, one could quantify

these channels for each city separately.

One way of achieving this would be to quantify the elasticity components in equation (29). The key would be to obtain reduced-form estimates of the elasticities of employment and housing prices to the change in the minimum wage, as well as an estimate of the dispersion parameter ϵ . This exercise would be limited, however. The decomposition of equation (29) is only valid for a partial equilibrium elasticity. Besides, a reduced-form estimate of the effect on housing prices would require detailed rental price data.

Instead, I focus on the policy’s general equilibrium effects, which I calculate by fitting the model to data for the cities considering increases and obtaining counterfactuals with a higher minimum wage from the model.

5 Fitting the Model

This section shows how to implement the model on commuting data and calculate counterfactual equilibria when exogenous variables such as the minimum wage change. Table 5 shows the parameters of the model grouped into three categories. The section shows how to obtain these parameters and model counterfactuals in four parts.

Table 5: Model parameters

Type	Parameters
Observed location-specific	$w_i^s, R_n^s, D_n, \kappa_{ni}$
Unobserved location-specific	$\rho_i^s, T_n^s, X_i^s, A_i^s$
Constant across locations	$L^s, \epsilon, \beta, \sigma, \Omega^s, \eta, r^s, \xi^s$

1. I describe how to obtain location-specific parameters of the model from data and values associated with the other parameters.
2. I show how to calibrate non-location specific parameters in the model.
3. I outline a strategy for estimating ϵ , which governs the strength of commuting responses.
4. I describe an algorithm to calculate model counterfactuals.

Computation of location-specific parameters. I fit the model at the county level. The first group of parameters are location-specific but may be observed in the data. The wage among the low-skill group is the minimum wage used in section 2. Wages for the other skill groups are exogenous, and they are calculated from average wages in the American

Community Survey (ACS) by location and industry. Unemployment benefits are residence-based and obtained from the Bureau of Labor Statistics. Land areas come from the census. Details on these variables are in appendix A.1. Unemployment benefits are residence based and obtained from BLS data. Land areas are observed from the census. Details on these variables are in Appendix A.1.¹⁸

I calculate commuting costs as a function of the distance between county centroids. Using driver data, Couture et al. (2018) calculate average commuting costs as a function of distance as follows:

$$\ln(avgcommutingcost_{ni}) = -0.394\log(distance_{ni}) + \log(1.352) + e_{ni}. \quad (33)$$

Here, *avgcommutingcost* is the cost in minutes per kilometer for a commuting trip, and e_{ni} is an error term. This scales to a cost of about four minutes per kilometer traveled. Using this relationship, I calculate commuting costs as the loss in hourly wages from commuting:

$$\kappa_{ni} = \frac{hours}{hours - (2 \times avgcommutingcost_{ni} \times distance_{ni})/60}, \quad (34)$$

where *hours* are hours of work per day. For the baseline estimates, I assume 8 hours of work a day.

The second group of parameters in table 5 are location-specific but are unobserved and have to be recovered from data. These are employment probabilities, ρ_i^s , residential amenities, T_n^s , workplace amenities, X_i^s , and productivity, A_i^s , by worker type.

Appendix F.1 describes how to obtain employment probabilities using unemployment data by wage category across counties. Details on the unemployment data are in appendix A.1. Unemployment is observed only by residence. I obtain unemployment at the workplace level using a random-matching assumption, which implies that unemployment data by residence are weighted averages of unemployment data by workplace.

For the computation of unobserved amenities and productivity, I assume that the data are a model equilibrium and recover the parameter values that rationalize the data as an equilibrium. Given data on commuting, L_{ni} , unemployment, U_{Mi} , and the observed location-specific parameters, there exist unique values of the unobserved parameters T_n^s , X_i^s , and A_i^s that are consistent with the data as an equilibrium of the model, up to a normalization (Ahlfeldt et al. 2015; Monte et al. 2018). Appendix sections F.2, F.3 and F.4 show how to calculate these parameters given values of the parameters that are constant across loca-

¹⁸Wages in other categories may react to the minimum wage, in which case they would not be exogenous. The evidence on the extent of these spillovers in the United States is limited. (Autor et al. 2016) finds that, while there are spillovers from increased minimum wages to higher percentiles of the wage distribution, they may be due to measurement error.

tions and the observed data on commuting and location-specific parameters. Here, I briefly describe how these parameters are obtained.

- Based on employment probabilities, ρ_i^s , and wages, I calculate expected wages, \tilde{w}_i^s . Conditional on residence and given the expected wages, places that receive more commuters must have higher workplace amenities. This allows the identification of workplace amenities, X_i^s . Details are in appendix F.2.
- Given these workplace amenities, places that have more residents must have higher residential amenities or lower housing prices. This relationship allows the identification of residential amenities, T_n^s , adjusted by housing prices. Details are in appendix F.3.
- Given the wages, unemployment, and labor market tightness, the firm’s first-order conditions imply values of productivity by type, A_i^s . Equilibrium market tightness can be obtained from data on job finding probabilities related to the spatial distribution of employment through equation (25). Details are in appendix F.4.

Calibration of parameters that do not vary by location. To obtain counterfactuals for cities that are considering minimum wage increases, I calibrate many of the parameters of the model to fit commuting and labor market data for these cities and the U.S. as a whole. Table 6 summarizes the calibrated parameters.

Table 6: Calibrated parameters

Parameter	Value	Source
β	0.4	Monte et al. (2018) matching housing share of expenditure from the Consumer Expenditure Survey
σ	2	Lower end of estimates from Ottaviano and Peri (2012)
Ω^s	varies by city	To match a vacancy filling rate of 1.3 (Landaïs et al. 2018)
η	0.5	Petrongolo and Pissarides (2001)
ξ^s	varies by city	Separation rates by city and wage category from Quarterly Workforce Indicators (QWI)
r^s	varies by city	To match a recruiting cost of 2.5 percent of wage (Landaïs et al. 2018)

I set β as the housing share of expenditure from the Consumer Expenditure Survey following Monte et al. (2018). Davis and Ortalo-Magne (2011) estimate the parameter at around 0.24 for renters in the United States. Combes et al. (2019) estimate this share at 0.2 to 0.4 from a sample of French cities.

I set the parameter σ at 2, in the lower end of estimates from [Ottaviano and Peri \(2012\)](#). Using a CES production function analogous to (9), they estimate this parameter using U.S. census data on employees by educational attainment and place of birth, among other variables. Here, I use the lower end of their estimates for the substitutability across educational levels. In the counterfactuals, some of the employment losses from an increased minimum wage arise because of substitution for other labor types. If σ is higher than this estimate, employment losses in the counterfactuals should be a lower bound.

The parameters Ω^s and r^s are set to match a recruiting cost of 2.5 percent of a workers wage and a vacancy filling rate of 1.3, following [Landais et al. \(2018\)](#). There is relatively little evidence on the extent of recruiting costs or how these costs vary across types of jobs. [Landais et al. \(2018\)](#) estimate the costs based on the size of the recruiting industry. Their vacancy filling rate comes from data from the Job Openings and Labor Turnover Survey.

The matching function's elasticity η is set at 0.5 following a survey by [Petrongolo and Pissarides \(2001\)](#) that finds constant returns to scale on matching functions and elasticities close to 0.5 across a wide range of studies. Separation rates, ξ^s , are set using data on separations by industry from the Quarterly Workforce Indicators and averaged across wage categories. Details are in appendix A.1.

Estimating ϵ . As shown in section 4, ϵ governs the strength of commuting and migration responses to changes in wages. I outline two strategies to estimate ϵ based on commuting data. The first strategy is a gravity equation estimation using the function of commuting flows implied by the data. The second is a structural estimation strategy assuming that changes in residential and workplace amenities are uncorrelated with changes in wages.

The first strategy is a gravity equation estimation. From equations (C.3) and (20), the probability of commuting from n to i among workers of type s equals:

$$\begin{aligned} l_{ni}^s &= \rho_i^s o_{ni}^s \\ &= \rho_i^s \frac{T_n^s X_i^s [(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}]^{-\epsilon} (\tilde{w}_{ni}^s)^\epsilon}{\sum_{ab} T_a^s X_b^s [(1 + \rho_b^s \kappa_{ab}) Q_a^{1-\beta}]^{-\epsilon} (\tilde{w}_{ab}^s)^\epsilon}. \end{aligned} \quad (35)$$

By taking logs on both sides of the previous equation, I decompose commuting probabilities into workplace fixed effects, residence fixed effects, and effects of employment probabilities, wages, and commuting costs:

$$\begin{aligned}
\ln(l_{ni}^s) = & \underbrace{-\ln(\psi^s)}_{\text{Constant}} + \underbrace{+\ln(X_i^s)}_{\text{Workplace F.E.}} \\
& \underbrace{+\ln(T_n^s) - \epsilon(1 - \beta)\ln(Q_n)}_{\text{Residence F.E.}} + \ln(\rho_i^s) \\
& - \epsilon \ln(1 + \rho_i^s \kappa_{ni}) + \epsilon \ln(\tilde{w}_{ni}^s).
\end{aligned} \tag{36}$$

I estimate this equation using the commuting data in section 2 for each city. I combine all labor types and years in a single regression and estimate:

$$\begin{aligned}
\ln(l_{nit}^s) = & \beta_0 + \gamma^s + \gamma_{it}^s + \gamma_{nt}^s + \gamma_t \\
& + \ln(\rho_{it}^s) - \epsilon \ln(1 + \rho_{it}^s \kappa_{ni}) + \epsilon \ln(\rho_{it}^s w_{it}^s + (1 - \rho_{it}^s) R_{nt}) + \tilde{e}_{nit}^s.
\end{aligned} \tag{37}$$

Here, the error term, \tilde{e}_{nit}^s , arises from the error in measuring commuting costs from equation (33). The time and skill fixed effects, γ^s and γ^t , capture the changes in the constant $-\ln(\psi^s)$ across years and types of labor. The residence and workplace fixed effects, γ_{it}^s and γ_{nt}^s , capture the variation in the amenity terms.

I implement a constrained least squares estimation and set the coefficient on $\ln(\rho_i^s)$ at 1 and the coefficients on $\ln(1 + \rho_i^s \kappa_{ni})$ and $\ln(\rho_i^s w_i^s + (1 - \rho_i^s) R_n)$ equal in absolute value, but with opposite signs. The identifying assumption is that the error term is not correlated with wages or commuting costs.

The second strategy is a generalized method of moments (GMM) estimation using the minimum wage variation across borders used to estimate the results in section 2. I can only do this for border cities in which the minimum wage varies by location, and I only use low-wage commuting data in the estimation. Following Ahlfeldt et al. (2015), I consider X_i^ℓ and T_i^ℓ to be structural errors of the model. The identifying assumption is that changes over time in these structural errors are uncorrelated with changes over time in the minimum wage, as follows:¹⁹

$$\Delta X_{it}^\ell \Delta w_{it}^\ell = 0 \tag{38}$$

$$\Delta T_{nt}^\ell \Delta w_{nt}^\ell = 0. \tag{39}$$

¹⁹This is equivalent to assuming that X_i^ℓ and T_i^ℓ have a fixed component and a time-varying shock, as in Ahlfeldt et al. (2015). Also, note that X_i^s and T_i^s are measured up to a normalization. Normalizing cancels out components that are constant across locations.

The border design of section 2 makes this identification assumption plausible because it reduces the impact of local shocks that may be correlated with changes in the minimum wage.

Using my commuting and unemployment data, and values of the calibrated parameters, I obtain values of X_{it}^ℓ and T_{it}^ℓ with the algorithms of sections F.2 and F.3, for every city and year in my sample. I then obtain sample analogs of equations (38) and (39) and estimate ϵ through the generalized method of moments. The estimated ϵ solves the following minimization problem:

$$\hat{\epsilon} = \underset{\epsilon}{\operatorname{argmin}} \frac{1}{NT} \sum_{i,t} \begin{bmatrix} \Delta X_{it}^\ell \Delta w_{it} & \Delta T_{nt}^\ell \Delta w_{nt}^\ell \end{bmatrix} W \begin{bmatrix} \Delta X_{it}^\ell \Delta w_{it} \\ \Delta T_{nt}^\ell \Delta w_{nt}^\ell \end{bmatrix}, \quad (40)$$

where N is the number of locations in a city, T is the number of years, and W is a weighting matrix. I use a two-step efficient GMM estimator and set W equal to the inverse of the variance of each of the moments.

Computing counterfactuals. With the values of the constant and location-specific parameters, the model can be used to calculate counterfactual equilibriums if the minimum wage has increased in a location. Unlike the reduced-form analysis of section 2 and the partial equilibrium elasticities of section 4, the counterfactual exercises allow me to obtain commuting and employment in general equilibrium after the minimum wage changes.

Appendix D.2 describes an algorithm to compute counterfactual equilibriums based on Monte et al. (2018). Given the observed data on commuting and employment and the values of the parameters, ϵ , β , σ , Ω^s , η , r^s and ξ^s , the counterfactuals of the employment probabilities, $f(\theta_i^s)$, and the search probabilities, σ_{ni}^s , can be obtained.

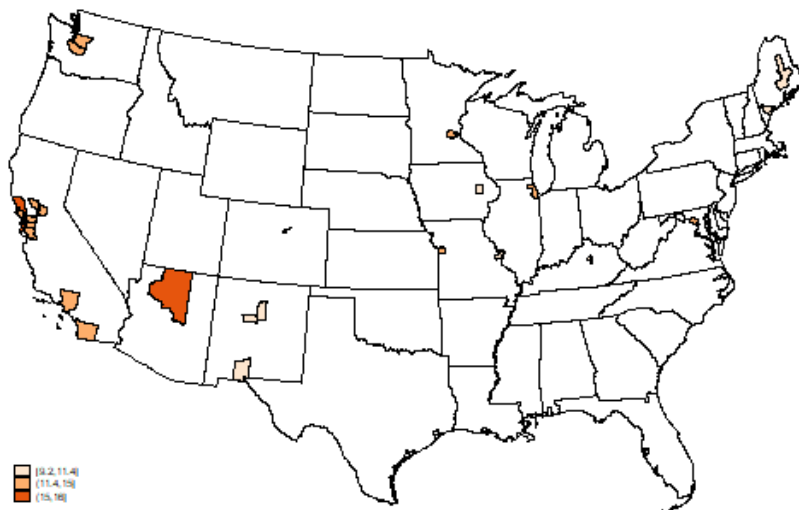
6 Counterfactuals for City Data

This section calculates counterfactual scenarios for cities that are considering minimum wage increases. I show some descriptive data on commuting and low-wage employment in these cities. Then I show estimates of ϵ derived from the methods described in the previous section. With these estimates of ϵ and other calibrated parameters, I calculate commuting, migration, and employment elasticities by comparing counterfactuals with minimum wage changes against the initial equilibriums. I show that the effects are heterogeneous across cities. Two-fifths of the counties with cities that are considering minimum wage increases would experience reductions in low-wage commuting. Furthermore, there is a nonlinear effect of the minimum wage on low-wage commuting.

City-level minimum wage policies. Figure 7 shows counties with cities that are

considering minimum wage increases. I consider all increases that would take place from 2018 onward since the LODES data ends in 2017. There are 50 cities in 28 counties considering increases, ranging from \$9.05 to \$16.00 an hour.²⁰ The counties are in 20 commuting zones, 8 of which span state borders.²¹

Figure 7: Counties for cities with proposed minimum wage increases



Source: Author's calculations based on [National Employment Law Project \(2016\)](#) and [Dube and Lindner \(2020\)](#). The colors indicate the maximum minimum wage proposed. Target years for minimum wage increases differ across counties.

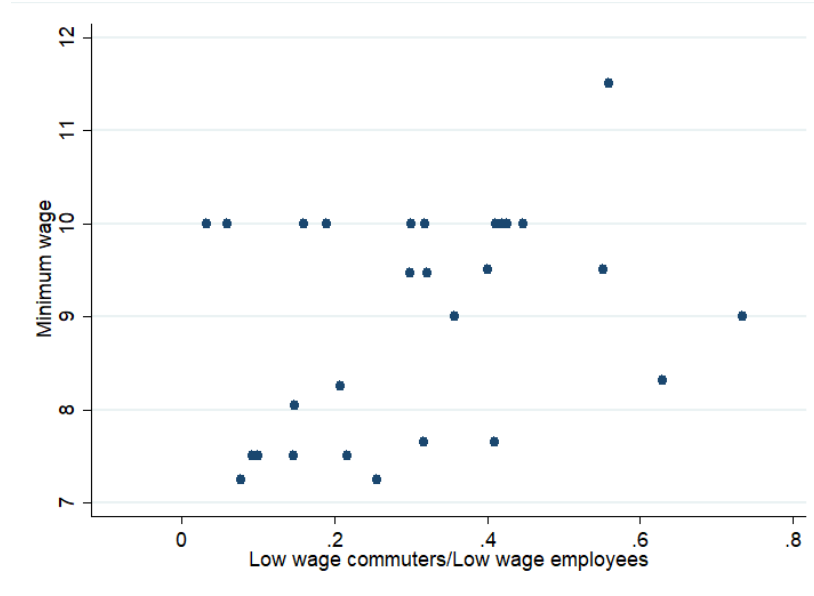
Figure 8 shows the relationship between commuting and the minimum wage in the associated counties in 2017, the latest year in the sample. It illustrates a weak positive relationship between higher minimum wages and the fraction of low wage commuters, which would be expected if the higher wages attract them. The positive association appears even though places with a higher minimum wage tend to have lower shares of low-wage employment, as shown in figure G.7 of appendix G.

Figure 9 shows the initial state of low-wage commuting and employment probabilities. A substantial share of low-wage employees in these areas are commuters, ranging from 3 percent to 73 percent. Employment probabilities range from 70 percent to 96 percent. As a share of low-wage employment, low-wage commuting tends to be higher in places with high employment probabilities. Larger employment probabilities (over job-seekers) on the vertical axis do not necessarily imply a large share of low-wage employment (over total employment).

²⁰I exclude Albuquerque, NM from these calculations because the ACS data did not report any high-wage unemployment there in 2017.

²¹The cross-border commuting zones are: Washington DC-MD-VA, Flagstaff, AZ-Kane City UT, Kansas City KS-MO, Las Cruces NM-El Paso TX, Los Angeles CA-La Paz AZ, Minneapolis-St. Paul MN-WI, Sacramento CA-Douglas City CO, and St. Louis MO - IL.

Figure 8: Low wage commuting and minimum wages. 2017.



Source: Author's calculations based on LODES. Counties that include cities with approved proposals for minimum wage increases.

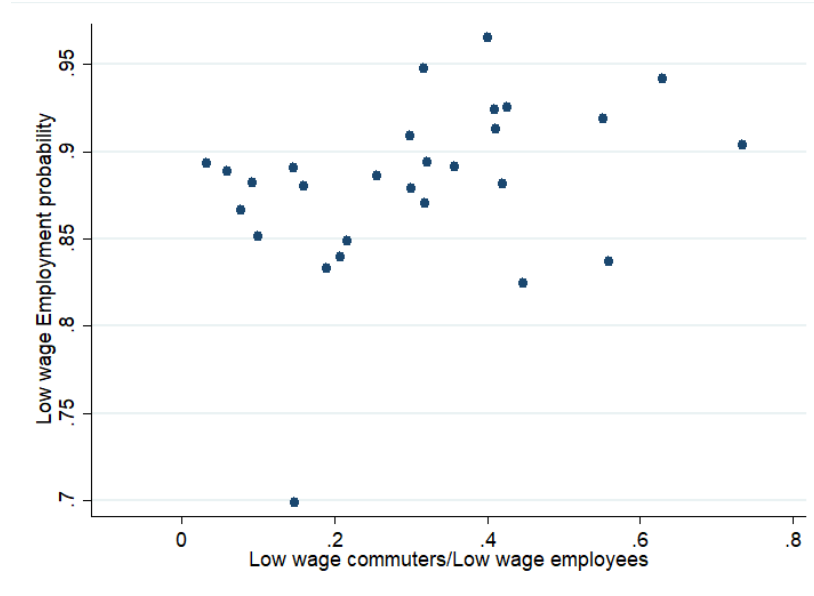
In figure G.6 of appendix G, I show that in fact, counties with higher low-wage employment tend to have fewer low-wage commuters as a share of employees. This last observation highlights the relevance of considering differences in search when examining commuting.

Estimates of ϵ . To fit the model, I consider the counties together with their commuting zones. The commuting zone acts as a city, and each county in the commuting zone is a location. I obtain counterfactual commuting and migration data for each commuting zone. I do this to obtain an operational definition of the closed city in the model. This definition disregards commuting and migration responses that may occur across commuting zones. There are 20 commuting zones in which one or more counties are considering increases in the minimum wage.²²

Based on the gravity equation in section 5, I calculate estimates of epsilon for each of the commuting zones using the commuting data described in section 2. Unemployment data from the ACS have only been available since 2005, so the sample runs from 2005 to 2017. Figure 10 shows the distribution of estimates across the commuting zones. These estimates range from around 5 to around 13. The lowest estimate corresponds to the Santa Fe, NM commuting zone, while the largest estimate is from Hennepin County in MN. The estimate of Monte et al. (2018) is around 3.5 based on commuting data for all workers and the entire

²²Figure G.8 of appendix G shows these commuting zones, the counties they include, and the target minimum wage.

Figure 9: Low wage commuting and employment probabilities. 2017.



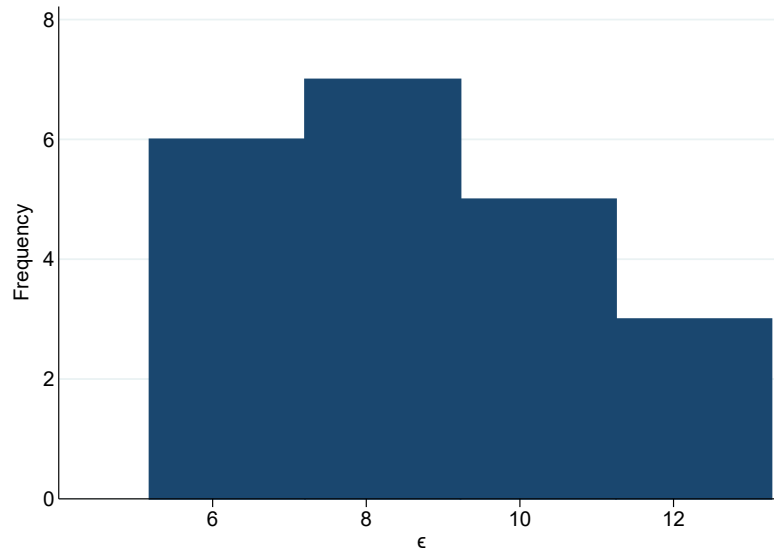
Source: Author's calculations based on LODES. Employment probabilities are calculated using unemployment data and the algorithm described in section F.1. Counties that include cities with approved proposals for minimum wage increases.

country. The estimates here are much larger. Ahlfeldt et al. (2015) estimate coefficients between 8 and 12 for blocks in Berlin after the fall of the Berlin Wall. This latter range of estimates is closer to the ones presented here for U.S. cities.

I also estimate ϵ through GMM for seven of the commuting zones that span state borders and in which the minimum wage varies. Figure 11 shows estimates of ϵ for these cities. In general, GMM estimates tend to be lower than gravity estimates. While gravity equation estimates rely on commuting information for all labor types, GMM estimates use only data on low-wage commuting and the variation in the minimum wage. This pattern of estimation suggests that low-wage commuting may react less than high-wage commuting to wages. For consistency across cities, I use gravity equation estimates for the analysis across all the cities. Higher values imply larger wage effects.

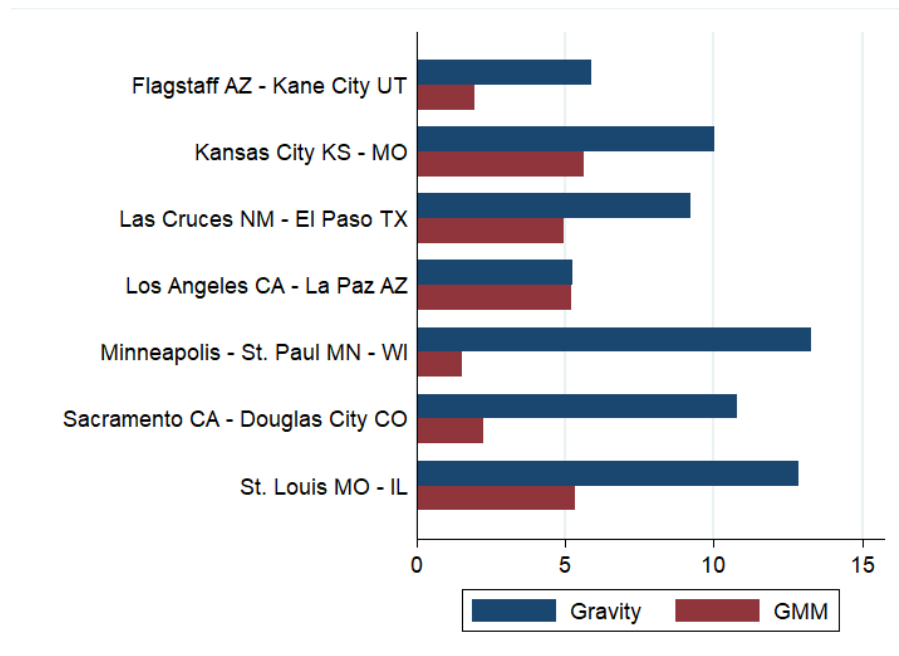
Counterfactual scenarios for all cities. Counterfactuals are calculated based on a computation of new equilibriums of the model involving increases in the minimum wage in the areas proposing changes. To make comparisons across cities, I increase the minimum wage by the same percentages in all these areas. This way, heterogeneity across areas in terms of response will be derived from differences across cities and not because of differences in the target minimum wage. For the baseline estimates, I increase the minimum wage by 5 percent. To keep this in perspective, one of the largest increases in the sample, the Min-

Figure 10: Distribution of estimated ϵ : Gravity equation



Source: Author's calculations. Observations are 20 commuting zones with cities considering minimum wage increases. Values of ϵ are estimates using equation (37) with commuting data from section 2. Sample goes from 2005 to 2017.

Figure 11: Estimates of ϵ for border cities.

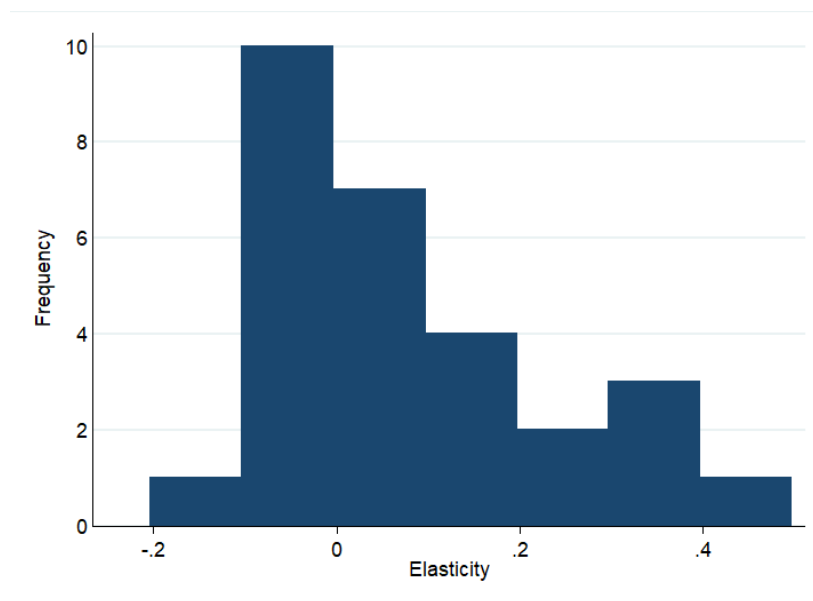


Source: Author's calculations. Observations are 7 commuting zones on state borders with cities considering minimum wage increases. Gravity estimates of ϵ are estimated using equation (37) with commuting data from section 2. GMM estimates are obtained using the strategy in section 5. Sample goes from 2005 to 2017.

neapolis minimum wage proposal for 2022, corresponds to an increase of 33 percent. I report elasticities of employment, commuting, and migration to these minimum wage increases.

The first step is to check if the areas that increase the minimum wage become more attractive for low-wage job-seekers in the city. Figure 12 shows the elasticity of low-wage job searchers, O_{Mi}^ℓ , to the minimum wage increase. 17 out of 28 cities experience increases in job searches. Hennepin and Ramsey counties in MN experience the largest increases. The rest of the cities experience modest decreases in the number of job searchers, with elasticities below 0.25 in absolute value. For the cities that experience job search increases, the model implies that the increase in job searches associated with a higher minimum wage if a job is found offsets the decrease in job searches associated with lower employment probabilities.²³

Figure 12: Elasticity of low wage searchers O_{Mi}^ℓ



Source: Author's calculations. Observations are 28 counties considering minimum wage increases. Values are elasticities of the number of low wage searchers O_{Mi}^ℓ to an increase in the minimum wage, calculated from comparing an initial equilibrium to a model counterfactual with a minimum wage increase. In the counterfactuals, minimum wages were increased by 5 %.

After establishing that more than half of the cities would experience higher job search rates and the others would experience decreases in job search, and after showing that this depends on the size of the employment effects, I focus on commuting and migration. The

²³I also examine the effects on total employment in the appendix. Figure G.9 shows that the places in which employment losses are the largest experience the largest reductions in job searches, as expected in the model. All counties experience reductions in employment probability. For most of the cities, the low-wage employment probability elasticity to the minimum wage is between -1.3 and -1.5. Figure G.10 of appendix G shows how employment probabilities change for other types of labor. Because of substitution away from low-wage employment, these probabilities increase slightly.

aim is to examine if areas that increase minimum wages attract more commuters from other areas or induce workers to move to the former areas.

Figure 13a shows the estimated elasticities of low-wage commuting, calculated as total low-wage employment, minus low-wage employment among nonresidents. 12 out of 28 counties would experience decreases in commuting, with an average elasticity of around -0.4. Twelve cities would experience commuting increases, with an average elasticity of around 0.5.

Figure 13b shows that low-wage workers would migrate away from most of the relevant counties. The average elasticity is around -0.4. The negative elasticity shows that the commuting losses are not because of low-wage workers moving to areas with an increased minimum wage. The losses arise, instead, because of employment losses and relocation.

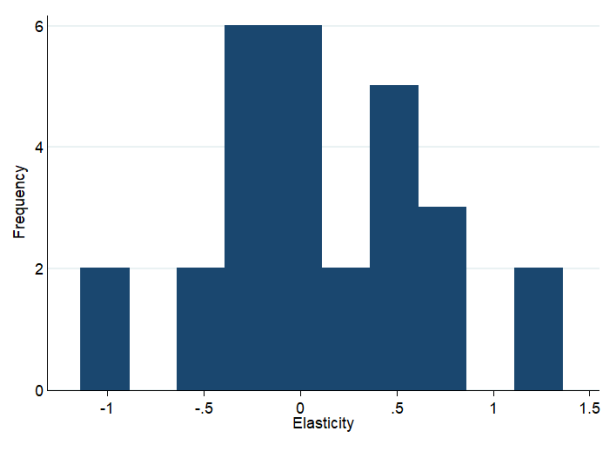
The differences in the magnitude of the wage effects explain a great deal of commuting and migration responses' heterogeneity. I show this in figure 14, which illustrates the relationship between ϵ and the elasticities of low-wage commuting and migration. As shown in section 4, ϵ governs the size of the wage effects. As these wage effects increase, areas tend to experience increases in commuting. The relationship between ϵ and the migration elasticity is negative, with areas with higher values of ϵ exhibiting more negative migration elasticities, possibly due to housing price effects.

Elasticities and the size of minimum wage increases. One of the concerns about upcoming minimum wage policies is that the proposed increases are more considerable than historical increases of the federal or state minimum wage. Jardim et al. (2017) argue that Seattle's employment responses are more negative than what might be expected from current estimates in the minimum wage literature. The study here indicates the possibility of larger effects on commuting if the minimum wage increases are more extensive than historical. Figure 15 shows the average low-wage commuting elasticity for increases of 1 percent, 5 percent, and 10 percent in the minimum wage across areas. The commuting elasticity becomes more negative as the minimum wage increase becomes larger. Although in the model (from equation 20), commuting probabilities are a nonlinear function of expected wages, they have a constant elasticity to expected wages. The nonlinear response arises from other channels in the model, such as stronger employment responses.

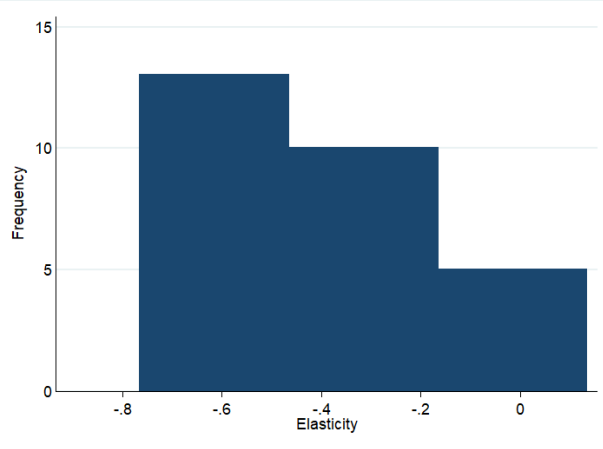
Alternative estimates of ϵ from figure 11 imply smaller wage effects, which would imply that commuting elasticities would be more negative if we were to use the estimates from this subset of cities. The counterfactual scenarios based on gravity equation estimates of ϵ should be interpreted as a lower bound on the negative elasticity of commuting to the minimum wage if one prefers the smaller estimates.

Figure 13: Elasticities of commuting and migration to changes in the minimum wage

(a) Elasticities of low wage commuting $L_{Mi}^\ell - L_{ii}^\ell$



(b) Elasticities of low wage residents O_{Rn}^ℓ

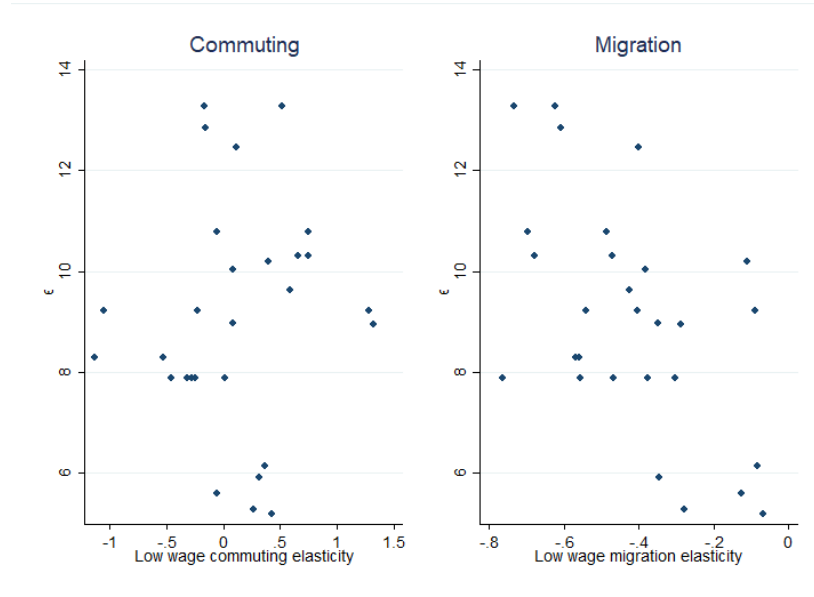


Source: Author's calculations. Observations are 28 counties considering minimum wage increases. Values are elasticities calculated by comparing an initial equilibrium to a model counterfactual with a minimum wage increase. In the counterfactuals, minimum wages were increased by five percent.

Panel (a) shows elasticities of low wage commuting $L_{Mi}^\ell - L_{ii}^\ell$ to an increase in their minimum wage. Low wage commuting is low-wage employment coming from areas different from the area that experiences the minimum wage increase.

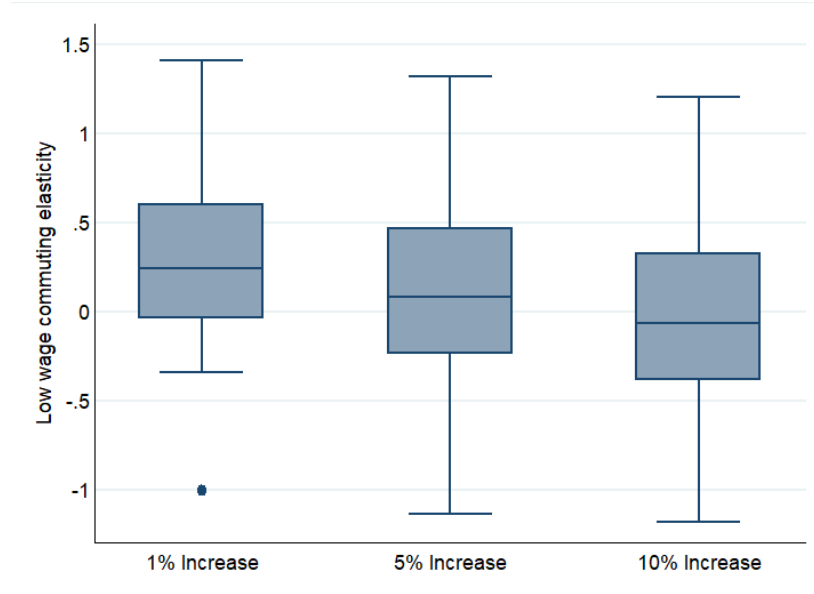
Panel (b) shows elasticities of low wage residents O_{Rn}^ℓ to an increase in the minimum wage.

Figure 14: Low wage commuting and migration elasticities and value of ϵ



Source: Author's calculations. Observations are 28 counties considering minimum wage increases. The left panel shows values of the elasticity of low wage commuting $L_{Mi}^\ell - L_{ii}^\ell$ to an increase in the minimum wage against values of the dispersion parameter ϵ . The right panel shows values of the elasticity of low wage residents O_{Rn}^ℓ to an increase in the minimum wage against values of the dispersion parameter ϵ . Elasticities are calculated from comparing an initial equilibrium to a model counterfactual with a minimum wage increase. Low wage commuting is low-wage employment coming from areas different from the area that experiences the minimum wage increase. In the counterfactuals, minimum wages were increased by five percent.

Figure 15: Low wage commuting elasticity and size of the minimum wage increase



Source: Author's calculations. Observations are low-wage commuting elasticities for minimum wage increases of 1, 5, and 10 % in counties considering minimum wage increases. Elasticities are calculated from comparing an initial equilibrium to a model counterfactual with a minimum wage increase. Low wage commuting is low-wage employment coming from areas different from the area that experiences the minimum wage increase.

7 Concluding Remarks

To analyze the effects of a higher city minimum wage, I estimate the reduced form elasticity of low-wage commuting, low-wage employment, and low-wage residents to changes in the minimum wage in adjacent border areas in the United States. I find a negative association between the minimum wage and commuting in cities adjacent to U.S. state borders. I find that commuting responses can be explained by employment relocation.

To clarify the drivers behind these results and extrapolate to U.S. cities considering an increase in the minimum wage, I propose a structural model of commuting, migration, and employment. The model extends standard quantitative urban models to allow for unemployment. I describe how to obtain equilibriums and counterfactuals for this model. I fit the model to data on U.S. cities.

In the counterfactual scenarios, areas considering larger minimum wage increases experience commuting and low-wage employment losses. Several other channels (not analyzed here) may change this elasticity. Two significant margins are the relocation of firms from high-minimum wage to low-minimum wage areas, which changes labor demand and the responses in the labor supply of low-skill workers. More research on these topics might explore the spatial variation of these demand and supply responses.

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Online Appendix - Not for Publication

A Data appendix

A.1 Details on data sources

This section describes the additional data sources used for the reduced-form analysis and the model in detail.

- **Wages for mid and high wage categories:** Estimates from ACS data 2005-2017. I assign workers into categories based on their reported monthly income. For unemployed workers, I impute their income category as the modal income category on their PUMA, industry, race, age and education. I calculate their hourly wages by dividing their monthly income over 4 times the reported usual weekly hour of work. I then calculate the average wage across industries and PUMA. To obtain county-level wage data, I use the PUMA - County crosswalks based on the American Fact Finder by the University of Michigan Population Studies Center.
- **Population:** County-level population estimates from the U.S Census Bureau from 2000 to 2017. I combine information from the 2000-2010 estimates and 2010-2017 estimates. I use the July estimates. I use total population and population younger than 30 grouped in age bins of 4 years.
- **Unemployment rate and labor force:** For the reduced form analysis, I use data from the Local Area Unemployment Statistics from the BLS. I calculate yearly averages of the monthly non-seasonally adjusted unemployment rate. Then I use lags of these yearly state-level unemployment rate as controls.
For the model I need unemployment rates by wage level for each county. I get unemployment rates for workers in the age and wage categories of the LODES from the yearly ACS at the puma level. I then match these unemployment rates to the county level using the crosswalks provided by the Michigan Population Studies Center.
- **Establishment counts:** I use Annual Average Establishment counts from the QCEW high level county files.
- **Corporate taxes:** I use average corporate taxes compiled by [Suárez Serrato and Zidar \(2016\)](#).
- **EITC:** I use state EITC data from the Center of Budget and Policy Priorities

- **Gas prices:** I use data from the State Energy Data System of the US Energy Information Administration
- **Unemployment benefits:** I use BLS data on the percentage of the wage that can be claimed as unemployment benefits by state.
- **Land:** I use county areas from the 2010 Census geography files.
- **Separations:** County level separation data from the Quarterly Workforce Indicators (QWI). I use earnings and the separations rate at the beginning of the quarter. I assign wage categories based on industry averages for NAICS industries at the highest level of disaggregation available for every state. Then I average across quarters, earnings categories and locations.

A.2 Details on imputation in LODES data

This section is heavily based on [Hayward \(2014\)](#) and [Graham et al. \(2014\)](#). LODES employment totals have noise infusion. Job counts are multiplied by random factors specific to each employer and establishment. The LODES dataset does not suppress job counts, as opposed to the QWI. Residential locations of workers are synthesized using a method described in [Machanavajjhala et al. \(2008\)](#). For each workplace cell, residential locations are drawn from a distribution based on the data. This distribution is the posterior distribution produced by combining the data distribution with a prior that is based on the previous year of data. For the initial year in LODES, priors are taken from the CTPP. For later years, the prior is the previous sample of LODES. There is a different distribution for each breakdown of jobs. If the sample taken is not representative of the original data, new samples are redrawn until the data satisfies representability criteria. Each job gets a residential location synthesized at least at the Super-PUMA level, and these are then decoarsened to the census tract and block level using the population distribution from the Census. LODES 7 is based on PUMAs and population from the 2010 Census.

B Regressions with gross flows and regressions with net flows

In this section I show that a regression with net flows only identifies minimum wage effects if they are symmetric at the workplace and residence levels. Assume that commuting from n to i at time t depends on the differences in minimum wages between n and i in both directions:

$$C_{nit} = \alpha_{ni} + \beta(\min wage_{it} - \min wage_{nt}) + \varepsilon_{nit} \quad (\text{B.1})$$

$$C_{int} = \alpha_{in} + \beta(\min wage_{nt} - \min wage_{it}) + \varepsilon_{int} \quad (\text{B.2})$$

Then a regression of net flows overestimates the coefficient:

$$C_{nit} - C_{int} = (\alpha_{ni} - \alpha_{in}) + 2\beta(\min wage_{nt} - \min wage_{it}) + \varepsilon_{nit} - \varepsilon_{int} \quad (\text{B.3})$$

Now assume that commuting depends on minimum wages both at the workplace and residence, β_r is associated with the residence minimum wage, and β_w is associated with the workplace minimum wage:

$$C_{nit} = \alpha_{ni} + \beta_r \min wage_{nt} + \beta_w \min wage_{it} + \varepsilon_{nit} \quad (\text{B.4})$$

$$C_{int} = \alpha_{in} + \beta_r \min wage_{it} + \beta_w \min wage_{nt} + \varepsilon_{int} \quad (\text{B.5})$$

Then a regression with net flows as the dependent variable does not identify the coefficients, only their differences :

$$C_{nit} - C_{int} = (\alpha_{ni} - \alpha_{in}) + (\beta_r - \beta_w) \min wage_{nt} + (\beta_w - \beta_r) \min wage_{it} + \varepsilon_{nit} - \varepsilon_{int} \quad (\text{B.6})$$

A regression with net flows would also fail to identify the coefficients if they are different in each commuting direction, for example, if the flows towards and away from central business district react to minimum wages differently.

C Residence and workplace probabilities

Here, I derive the expression for the residence and workplace probabilities. Workers choose where to live and search for work to maximize their utility in (6). The distribution of utility for a worker of type s that lives in n and searches in i is

$$\begin{aligned} G_{ni}^s(u) &= \Pr(u_{niw}^s \leq u) \\ &= \Pr\left(\frac{z_{niw}^s \tilde{w}_{ni}^s}{(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}} \leq u\right) \\ &= \Pr\left(z_{niw}^s \leq \frac{u (1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}}{\tilde{w}_{ni}^s}\right) \\ &= e^{-\psi_{ni}^s u^{-\epsilon}}. \end{aligned} \quad (\text{C.1})$$

So, worker utility is Fréchet distributed with a residence-workplace specific shape parameter given by

$$\psi_{ni}^s \equiv T_n^s X_i^s [(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}]^{-\epsilon} (\tilde{w}_{ni}^s)^\epsilon. \quad (\text{C.2})$$

From the properties of the Fréchet distribution ([Monte et al. 2018](#)), one may obtain the joint probabilities of living in n and searching in i , as follows:

$$\begin{aligned} o_{ni}^s &= \frac{\psi_{ni}^s}{\psi^s} \\ \psi^s &= \sum_n \sum_{i1} \psi_{ni}^s. \end{aligned} \quad (\text{C.3})$$

These probabilities are the expression in equation (16) in the text.

D Algorithms for computing equilibria and counterfactuals

D.1 Computing equilibria

The following fixed-point algorithm can be used to calculate equilibria in the model. Start from conjectured initial values of housing prices $(Q_i)^t$ and employment probabilities $(\rho_i^s)^t$. Then proceed as follows:

1. Compute search probabilities $(o_{ni}^s)^t$ according to (C.3).
2. Compute searchers by residence and workplace $(O_{Mi}^s)^t$ and $(O_{Ri}^s)^t$ according to (17)
3. Compute equilibrium tightness and recruitment mark-ups with a fixed-point algorithm
 - (a) Set the recruiting mark-up $(\tau^s(\theta_i^s))^t = 0$. Compute equilibrium values of θ_i^s using (24) and (13)
 - (b) Update $(\tau^s(\theta_i^s))^t$ using (14)
 - (c) Iterate until convergence in $(\tau^s(\theta_i^s))^t$. Obtain $(\theta_i^s)^t$
4. Compute equilibrium employment by workplace $(L_{Mi}^s)^t$ using (24) and (13) given the equilibrium mark-ups.
5. Compute unemployment as $(U_{Mi}^s)^t = (O_{Mi}^s)^t - (L_{Mi}^s)^t$
6. Compute employment by residence workplace pair $(l_{ni}^s)^t$ using (20)

7. Update employment probabilities ρ_i^s using (25)

$$(\rho_i^s)^{t+1} = \frac{f^s((\theta_i^s)^t)}{\xi^s + f^s((\theta_i^s)^t)} \quad (\text{D.1})$$

8. Calculate expected income $(v_n)^t$ using (23)

9. Update housing prices using (22)

$$(Q_n)^{t+1} = \frac{(1 - \beta)(v_n)^t (L_{Rn})^t}{D_n} \quad (\text{D.2})$$

10. Iterate until convergence in ρ_i^s and Q_n

D.2 Computing counterfactuals

Given a cross section of commuting data, wages, unemployment benefits, commuting costs, land supply and unemployment, and values of the parameters ϵ , β , σ , Ω^s , η , r^s and ξ^s , counterfactuals changes for the job finding probability $f(\theta_i^s)$ and the search probabilities o_{ni}^s can be obtained. Changes in the other endogenous variables can be obtained from these.

Denote by x' the value of a variable on a counterfactual equilibrium and by $\hat{x} = \frac{x'}{x}$ the counterfactual change in this variable. From the initial data, obtain values of the unobserved location-specific parameters T_n^s , X_i^s , A_i^s and ρ_i^s using the algorithms of sections F.1, F.2, F.3 and F.4.

Given counterfactual changes in exogenous variables $\{\hat{w}_i^s, \hat{R}_n, \hat{T}_n^s, \hat{X}_i^s, \hat{\kappa}_n^s\}$, I can solve for counterfactual changes $\{\hat{f}_i^s, \hat{o}_{ni}^s\}$ using the following fixed-point algorithm. Start from an initial value of these changes, $\left\{(\hat{f}_i^s)^0, (\hat{o}_{ni}^s)^0\right\}$. Then proceed as follows:

1. Find the change in employment probabilities using equation (25)

$$(\hat{\rho}_i^s)^t = \frac{(\hat{f}_i^s)^t (\xi^s + f_i^s)}{\xi^s + f_i^s (\hat{f}_i^s)^t} \quad (\text{D.3})$$

2. Find the new number of searchers by workplace and residence using equation (17)

$$(o_{ni}^s)^t = o_{ni}^s (\hat{o}_{ni}^s)^t \quad (\text{D.4})$$

$$(O_{Mi}^s)^t = \sum_n L^s (o_{ni}^s)^t \quad (\text{D.5})$$

$$(O_{Rn}^s)^t = \sum_i L^s (o_{ni}^s)^t \quad (\text{D.6})$$

3. Find counterfactual changes in expected wages using equation (7)

$$\left(\hat{w}_{ni}^s\right)^t = \frac{\rho_i^s w_{ni}^s \hat{w}_{ni}^s + (1 - \rho_i^s) R_n \hat{R}_n}{\tilde{w}_{ni}^s} \quad (\text{D.7})$$

4. Find counterfactual changes in expected income using equation (23)

$$\begin{aligned} (\hat{v}_n^s)^t &= \frac{1}{v_n^s} \sum_i \frac{o_{ni}^s (1 + \rho_i^s \kappa_{ni})^\epsilon \left[1 + \rho_i^s (\hat{\rho}_i^s)^t \kappa_{ni}\right]^{-\epsilon} \hat{T}_n^s \hat{X}_i^s \left(\hat{w}_{ni}^s\right)^t}{\sum_b o_{ab}^s (1 + \rho_b^s \kappa_{nb})^\epsilon \left[1 + \rho_b^s (\hat{\rho}_b^s)^t \kappa_{nb}\right]^{-\epsilon} \hat{T}_n^s \hat{X}_b^s \left(\hat{w}_{nb}^s\right)^t} \tilde{w}_{ni}^s \left(\hat{w}_{ni}^s\right)^t \quad (\text{D.8}) \\ (\hat{v}_n)^t &= \frac{1}{v_n} \sum_s \frac{(O_{Rn}^s)^t}{O_{Rn}^s} \hat{v}_n^s \end{aligned}$$

5. Find counterfactual changes in housing prices using equation (22)

$$\left(\hat{Q}_n\right)^t = (\hat{v}_n)^t \frac{\sum_s (O_{Rn}^s)^t}{\sum_s O_{Rn}^s} \quad (\text{D.9})$$

6. Compute new changes in search probabilities using (C.3)

$$(\hat{o}_{ni}^s)^{t'} = \frac{(1 + \rho_i^s \kappa_{ni})^\epsilon \left[1 + \rho_i^s (\hat{\rho}_i^s)^t \kappa_{ni}\right] \left[\left(\hat{Q}_n\right)^t\right]^{-\epsilon(1-\beta)} \hat{T}_n^s \hat{X}_i^s \left[\left(\hat{w}_{ni}^s\right)^t\right]^{-\epsilon}}{\sum_a \sum_b (1 + \rho_b^s \kappa_{ab})^\epsilon \left[1 + \rho_b^s (\hat{\rho}_b^s)^t \kappa_{ab}\right] \left[\left(\hat{Q}_a\right)^t\right]^{-\epsilon(1-\beta)} \hat{T}_a^s \hat{X}_b^s \left[\left(\hat{w}_{ab}^s\right)^t\right]^{-\epsilon}} \quad (\text{D.10})$$

7. Compute new searchers by workplace using (17)

$$(O_{Mi}^s)^{t+1} = \sum_n L^s o_{ni}^s (\hat{o}_{ni}^s)^{t+1} \quad (\text{D.11})$$

8. Compute equilibrium tightness, recruitment mark-ups and labor demand with a fixed-point algorithm

- (a) Set the recruiting mark-up $\tau^s(\theta_i^s) = 0$. Compute equilibrium values $(\theta_i^s)^t$ and $(LM_i^s)^t$ using (24) and (13)
 - (b) Update $\tau^s(\theta_i^s)$ using (14)
 - (c) Iterate until convergence in $\tau^s(\theta_i^s)$
9. Compute new counterfactual changes in search probabilities

$$\left(\hat{f}_i^s\right)^{t'} = \frac{f_i^s \xi^s (LM_i^s)^t}{(O_{Mi}^s)^{t+1} - (LM_i^s)^t} \quad (\text{D.12})$$

10. Update changes in search and employment probabilities with an adjustment factor ζ

$$(\hat{o}_{ni}^s)^{t+1} = \zeta (\hat{o}_{ni}^s)^{t'} + (1 - \zeta) (\hat{o}_{ni}^s)^t \quad (\text{D.13})$$

$$\left(\hat{f}_i^s\right)^{t+1} = \zeta \left(\hat{f}_i^s\right)^{t'} + (1 - \zeta) \left(\hat{f}_i^s\right)^t \quad (\text{D.14})$$

11. Iterate until convergence

E Computing elasticities

In this appendix I compute general and partial equilibrium elasticities of commuting to minimum wage changes.

I consider two types of elasticities, following [Monte et al. \(2018\)](#). The general equilibrium elasticity ε_x^y considers the change in endogenous variable y given a change in x from initial to a final equilibrium of the model where all endogenous variables change. The partial equilibrium elasticity η_x^y considers the change in y keeping other endogenous variables constant.

From equation (20), the elasticity of commuting to a minimum wage change is

$$\varepsilon_{w_i^\ell}^{l_{ni}^\ell} = \varepsilon_{w_i^\ell}^{\rho_i^\ell} + \varepsilon_{w_i^\ell}^{o_{ni}^\ell} \quad (\text{E.1})$$

The first term $\varepsilon_{w_i^\ell}^{\rho_i^\ell}$ summarizes how the employment probability changes as the minimum wage changes. The second term summarizes how the search probability $\varepsilon_{w_i^\ell}^{o_{ni}^\ell}$ changes with the change in wages.

First, I calculate the general equilibrium elasticity of search o_{ni}^s to a change in wages. From equation (C.3), the elasticity of the residence-search probability o_{ni}^s to changes in the minimum wage in area j , w_j^ℓ is

$$\begin{aligned}
\varepsilon_{w_j}^{o_{ni}^s} &= \varepsilon_{w_j}^{\psi_{ni}^s} - \varepsilon_{w_j}^{\psi} \\
&= \varepsilon_{w_j}^{\psi_{ni}^s} - \frac{d\psi}{dw_j^\ell} \frac{w_j^\ell}{\psi} \\
&= \varepsilon_{w_j}^{\psi_{ni}^s} - \sum_{a,b} \frac{d\psi_{ab}^s}{dw_j^\ell} \frac{w_j^\ell}{\psi_{ab}^s} \frac{\psi_{ab}^s}{w_j^\ell} \frac{w_j^\ell}{\psi} \\
&= \varepsilon_{w_j}^{\psi_{ni}^s} - \sum_{a,b} \varepsilon_{w_j^\ell}^{\psi_{ab}^s} o_{ab}^s
\end{aligned} \tag{E.2}$$

To solve for $\varepsilon_{w_j^\ell}^{\psi_{ni}^s}$, take logs of 16 and differentiate to get

$$\begin{aligned}
\ln(\psi_{ni}^s) &= \ln(T_n^s) + \ln(X_i^s) - \epsilon \ln(1 + \rho_i^s \kappa_{ni}) - \epsilon(1 - \beta) \ln(Q_n) + \epsilon \ln(\rho_i^s w_i^\ell + (1 - \rho_i^s) R_n) \\
\varepsilon_{w_j^\ell}^{\psi_{ni}^s} &= -\frac{\epsilon}{1 + \rho_i^s \kappa_{ni}} \left(\frac{d\rho_i^s}{d \ln(w_j^\ell)} \kappa_{ni} \right) - \epsilon(1 - \beta) \varepsilon_{w_j^\ell}^{Q_n} \\
&\quad + \frac{\epsilon}{\rho_i^s w_i^\ell + (1 - \rho_i^s) R_n} \left(\frac{d\rho_i^s}{d \ln(w_j^\ell)} w_i^s + \rho_i^s \frac{dw_i^s}{d \ln(w_j^\ell)} - \frac{d\rho_i^s}{d \ln(w_j^\ell)} R_n \right) \\
&= -\frac{\epsilon}{1 + \rho_i^s \kappa_{ni}} \left(\varepsilon_{w_j^\ell}^{\rho_i^s} \rho_i^s \kappa_{ni} \right) - \epsilon(1 - \beta) \varepsilon_{w_j^\ell}^{Q_n} \\
&\quad + \frac{\epsilon}{\rho_i^s w_i^s + (1 - \rho_i^s) R_n} \left(\varepsilon_{w_j^\ell}^{\rho_i^s} \rho_i^s w_i^s + \rho_i^s w_i \varepsilon_{w_j^\ell}^{w_i^s} - \rho_i^s \varepsilon_{w_j^\ell}^{\rho_i^s} R_n \right) \\
&= \varepsilon_{w_j^\ell}^{\rho_i^s} \left[\frac{\epsilon \rho_i^s (w_i^s - R_n)}{\tilde{w}_{ni}^s} - \frac{\epsilon \rho_i^s \kappa_{ni}}{1 + \rho_i^s \kappa_{ni}} \right] + \frac{\epsilon \rho_i^s w_i \varepsilon_{w_j^\ell}^{w_i^s}}{\tilde{w}_{ni}^s} - \epsilon(1 - \beta) \varepsilon_{w_j^\ell}^{Q_n}
\end{aligned} \tag{E.3}$$

Define

$$\theta_{ni}^s \equiv \frac{\rho_i^s w_i^s}{\tilde{w}_{ni}^s}; \quad \kappa_{ni}^s = \frac{\rho_i^s \kappa_{ni}}{1 + \rho_i^s \kappa_{ni}} \tag{E.4}$$

This is the share of wages in expected income. Rewrite the elasticity as

$$\frac{\varepsilon_{w_j^\ell}^{\psi_{ni}^s}}{\epsilon} = \varepsilon_{w_j^\ell}^{\rho_i^s} \left[\theta_{ni}^s - (1 - \theta_{ni}^s) - \frac{1}{\tilde{w}_{ni}^s} - \kappa_{ni}^s \right] + \theta_{ni}^s \varepsilon_{w_j^\ell}^{w_i^s} - (1 - \beta) \varepsilon_{w_j^\ell}^{Q_n} \tag{E.5}$$

Plugging in the previous expression and simplifying

$$\frac{\varepsilon_{w_j^\ell}^{o_{ni}^s}}{\epsilon} = \varepsilon_{w_j^\ell}^{\rho_i^s} \left[\theta_{ni}^s - (1 - \theta_{ni}^s) - \frac{1}{\tilde{w}_{ni}^s} - \kappa_{ni}^s \right] + \theta_{ni}^s \varepsilon_{w_j^\ell}^{w_i^s} - (1 - \beta) \varepsilon_{w_j^\ell}^{Q_n} - \sum_{a,b} o_{ab}^s \left\{ \varepsilon_{w_j^\ell}^{\rho_b^s} \left[\theta_{ab}^s - (1 - \theta_{ab}^s) - \frac{1}{\tilde{w}_{ab}^s} - \kappa_{ab}^s \right] + \theta_{ab}^s \varepsilon_{w_j^\ell}^{w_b^s} - (1 - \beta) \varepsilon_{w_j^\ell}^{Q_a} \right\} \quad (\text{E.6})$$

To decompose this elasticity into wage, employment and housing prices effects, it is simpler to focus on a partial equilibrium elasticity, that assumes away effects on employment and prices in other locations. Denote the partial equilibrium elasticity as $\eta_{w_i^\ell}^{l_{ni}^\ell}$. The partial equilibrium elasticity of commuting to the minimum wage is an analog of the general equilibrium elasticity:

$$\eta_{w_i^\ell}^{l_{ni}^\ell} = \eta_{w_i^\ell}^{\rho_i^\ell} + \eta_{w_i^\ell}^{o_{ni}^\ell} \quad (\text{E.7})$$

I focus on commuting from a given region n to a given region i and assume that wages, employment probabilities and housing prices do not react in places other than n and i . That is, assume $\varepsilon_{w_j^\ell}^{\rho_b^s} = 0$ for $b \notin (n, i)$, $\varepsilon_{w_j^\ell}^{w_b^s} = 0$ for $b \neq i$ and $\varepsilon_{w_j^\ell}^{Q_a} = 0$ for $a \notin (n, i)$. The partial equilibrium elasticity of the fraction of low wage searchers coming from n , o_{ni}^ℓ to the minimum wage in i , w_i^ℓ , becomes:

$$\eta_{w_j^\ell}^{o_{ni}^s} = \eta_{w_j^\ell}^{\rho_i^\ell} \left(\epsilon \Theta_{ni} - \sum_a \epsilon o_{ai}^\ell \Theta_{ai}^\ell \right) - \eta_{w_i^\ell}^{\rho_n^\ell} \sum_a \epsilon h_{an}^\ell \Theta_{an}^\ell + \epsilon \theta_{ni}^\ell - \sum_a \epsilon o_{ai}^\ell \theta_{ai}^\ell - \epsilon (1 - o_{Rn}^\ell) (1 - \beta) \eta_{w_j^\ell}^{Q_n} + \epsilon o_{Ri}^\ell \eta_{w_i^\ell}^{Q_i} \quad (\text{E.8})$$

where $\Theta_{ab}^s = \left[\theta_{ab}^s - (1 - \theta_{ab}^s) - \frac{1}{\tilde{w}_{ab}^s} - \kappa_{ab}^s \right]$. For partial equilibrium, I assume that all search probabilities remain unchanged except for o_{ni}^s . This is equivalent to assuming $\varepsilon_{w_i^\ell}^{\rho_n^\ell} = 0$, $\varepsilon_{w_i^\ell}^{Q_i} = 0$ and making all the terms in the summations equal to 0 unless $a = n$. The elasticity becomes

$$\eta_{w_j^\ell}^{o_{ni}^s} = (\epsilon - \epsilon h_{ni}^\ell) \left[\theta_{ni}^\ell - (1 - \theta_{ni}^\ell) - \frac{1}{\tilde{w}_{ni}^\ell} - \kappa_{ab}^s \right] \eta_{w_i^\ell}^{\rho_i^\ell} + (\epsilon - \epsilon h_{ni}^\ell) \theta_{ni}^\ell - (\epsilon - \epsilon o_{ni}^\ell) (1 - \beta) \eta_{w_i^\ell}^{Q_n} \quad (\text{E.9})$$

Replacing $s = \ell$ for low skilled labor yields equation (29) in the main text.

The search probability elasticity is a combination of three effects: the change in employment probabilities, $\eta_{w_i^\ell}^{\rho_i^\ell}$, the change in wages and the change in housing prices $\eta_{w_j^\ell}^{Q_n}$. I call these effects wage effect, employment effect and housing prices effect in the main text.

F Computing unobserved location-specific parameters

F.1 Computing search and employment probabilities

We observe data on employment by workplace l_{Mi}^s and unemployment by workplace UR_n^s . Unemployment at the workplace level U_{Mi}^s is unobserved, since I do not see how many workers searched in each location. Under random matching, unemployment at the workplace level is an employment-weighted average of employment at the residence level

$$U_{Rn}^s = \sum_b \frac{L_{nb}^s}{L_{Mb}^s} U_{Mb}^s \quad (\text{F.1})$$

This linear system can be solved for unique values of U_{Mi}^s . Given this data on unemployment by workplace and employment by workplace L_{Mi}^s , the number of searchers in each workplace is

$$O_{Mi}^s = U_{Mi}^s + L_{Mi}^s \quad (\text{F.2})$$

Given this data, under the assumption of random matching, the number of searchers per residence-workplace pair is

$$O_{ni}^s = \frac{L_{ni}^s O_{Mi}^s}{L_{Mi}^s} \quad (\text{F.3})$$

From these we can obtain residents as:

$$O_{Rn}^s = \sum_b O_{nb}^s \quad (\text{F.4})$$

Search probabilities are then

$$o_{ni}^s = \frac{O_{ni}^s}{\sum_a \sum_b O_{ab}^s} \quad (\text{F.5})$$

And employment probabilities are

$$\rho_i^s = \frac{O_{Mi}^s}{L_{Mi}^s} \quad (\text{F.6})$$

F.2 Computing workplace productivities

Given data on residents per residence location O_{Rn}^s , searchers per workplace O_{Mi}^s , wages w_i^s , employment probabilities ρ_i^s , unemployment benefits R_n^s , a dispersion parameter ϵ and commuting costs κ_{ni} , there is a unique (up to a normalization) vector of search costs X_i^s

consistent with the data being an equilibrium of the model. From the commuting equilibrium

$$\begin{aligned} O_{Mi}^s &= \sum_a o_{ai|a} O_{Ra} \\ &= \sum_a \frac{X_i^s (1 + \rho_i^s \kappa_{ni})^{-\epsilon} \tilde{w}_{ni}^\epsilon}{\sum_b X_b^s (1 + \rho_b^s \kappa_{nb})^{-\epsilon} \tilde{w}_{nb}^\epsilon} O_{Rn}^s \end{aligned} \quad (\text{F.7})$$

Where $\tilde{w}_{ni}^s = \rho_i^s w_i + (1 - \rho_i^s) R_n^s$. From Lemmas S.6. and S.7 of [Ahlfeldt et al. \(2015\)](#), this system has a unique solution for X_i^s , up to a normalization,

F.3 Computing residential amenities

Given productivities X_i^s , data on residents per location O_{Rn}^s , wages w_i^s , employment probabilities ρ_i^s , unemployment benefits R_n^s ; and a dispersion parameter ϵ , there is a unique (up to a normalization) vector of amenities T_n^s that is consistent with the data being an equilibrium of the model. From (17) and (16)

$$\begin{aligned} o_{Rn}^s &= \frac{T_n^s (Q_n^{1-\beta})^{-\epsilon} \sum_b X_b^s \tilde{w}_{ns}^\epsilon (1 + \rho_b^s \kappa_{ns})^{-\epsilon}}{\psi} \\ \frac{(T_n^s)^{\frac{1}{\epsilon}} Q_n^{-(1-\beta)}}{\psi} &= \frac{(o_{Rn}^s)^{\frac{1}{\epsilon}}}{(\sum_b X_b^s \tilde{w}_{ns}^\epsilon (1 + \rho_b^s \kappa_{ns})^{-\epsilon})^{\frac{1}{\epsilon}}} \end{aligned} \quad (\text{F.8})$$

So T_n^s can be identified up to a normalization by ψ^s and housing prices Q_n . Using (22), housing prices can be identified using data on land D_n and expected income v_n , which can be calculated using equation (23). This allows us to identify T_n^s up to a normalization.

F.4 Computing productivities

From the first order conditions of the firm

$$Y^{1/\sigma_1-1} (L_{Mi}^s)^{\sigma-1} = w_i^s (1 + \tau_i^s(\theta_i^s)), \quad s = \ell, m, h \quad (\text{F.9})$$

Given values of σ , $\tau^s(\theta_i^s)$ and observed values of L_{Mi}^s , this system can be solved for unique values of A_i^s . To obtain $\tau^s(\theta_i^s)$, I require values of the parameters in the matching process. Given values of separation rates ξ^s and employment and unemployment by workplace, job finding probabilities can be obtained from (25) as

$$f_i^s = \frac{\xi^s L_{Mi}^s}{U_{Mi}^s} \quad (\text{F.10})$$

Given values of Ω^s and η , market tightness and vacancy filling probabilities can be obtained as

$$\begin{aligned}\theta_i^s &= \left(\frac{f_i^s}{\Omega^s} \right)^{\frac{1}{1-\eta}} \\ q(\theta_i^s) &= \Omega^s (\theta_i^s)^{-\eta}\end{aligned}\tag{F.11}$$

and given values of recruitment producer ratios r_s , $\tau(\theta_i^s)$ can be obtained from (14).

G Additional figures and tables

Table G.1: State-years where minimum wage workers are in the mid-wage category

State	Since year	Average monthly wage since year
Alaska	2015	1400
Arizona	2014	1264
Arkansas	2016	1280
California	2008	1280
Colorado	2014	1298
Connecticut	2009	1345
Delaware	2015	1287
Florida	2014	1278
Hawaii	2016	1360
Illinois	2009	1308
Maryland	2015	1303
Massachusetts	2008	1280
Michigan	2015	1304
Minnesota	2015	1347
Montana	2014	1276
Nebraska	2015	1280
Nevada	2010	1310
New Jersey	2014	1330
New York	2014	1340
Ohio	2013	1274
Oregon	2008	1387
Rhode Island	2014	1360
South Dakota	2015	1360
Vermont	2009	1353
Washington	2007	1389
West Virginia	2015	1280

Source: Author's calculations from minimum wage data on [Neumark et al. \(2014\)](#) and [Clemens et al. \(2018\)](#). Calculations are made assuming 40 hours worked per week. The results in section 2 are robust to exclusion of these observations or to a redefinition of minimum wage workers to include the second category in these states. The estimation sample in section 2 excludes: 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage.

Table G.2: Effect of minimum wages on low wage commuting: Within design, same workplace.

	Same Workplace		
	(1)	(2)	(3)
Log MW - Workplace - Log MW Residence	-0.34 (1.16)	-0.03 (0.15)	-0.02 (0.15)
Adj R sq.	0.000	0.249	0.248
Within R sq.	0.000	0.000	0.000
N	12,290	11,672	11,672
Work counties	293	260	260
Res counties	377	345	345
Res effects x Year effects		Yes	Yes
Work effects x Year effects			
Res Effects			
Work effects		Yes	Yes
Controls			Yes
Mean dep. var.	3349.5	3009.5	3009.5

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

The sample excludes 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work, and county of residence level. Column 2 includes workplace-year effects and residence effects. Column 3 also includes controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates.

Table G.3: Effect of minimum wages on low wage commuting: Corner design.

	Log Low Wage Commuters - 11 Km to Border					
	Same Residence			Same Workplace		
	(1)	(2)	(3)	(4)	(5)	(6)
Log MW Workplace -	0.32	0.20	0.01	-1.39	-0.30	-0.20
Log MW Residence	(0.80)	(0.27)	(0.40)	(1.27)	(0.18)	(0.29)
Adj R sq.	-0.001	0.536	0.531	0.004	0.694	0.692
Within R sq.	0.000	0.000	0.002	0.004	0.000	0.007
N	1,242	1,241	1,241	1,325	1,324	1,324
Work counties	43	43	43	23	23	23
Res counties	23	23	23	60	59	59
Res effects x Year effects		Yes	Yes			
Work effects x Year effects					Yes	Yes
Res Effects					Yes	Yes
Work effects		Yes	Yes			
Controls			Yes			Yes
Mean dep. var.	387.4	387.2	387.2	358.5	358.7	358.7

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

The sample excludes 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work, and county of residence level. Columns 1 to 3 implement a within residence design. They exclude residence counties that send commuters to fewer than 2 workplace states different from the residence state. Columns 2 includes residence-year effects and workplace fixed effects. Column 3 includes controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates Columns 4 to 6 implement a within workplace design. They exclude workplace counties that receive commuter from fewer than 2 residence states. Column 5 includes workplace-year effects and residence fixed effects. Column 6 includes the same controls as column 2.

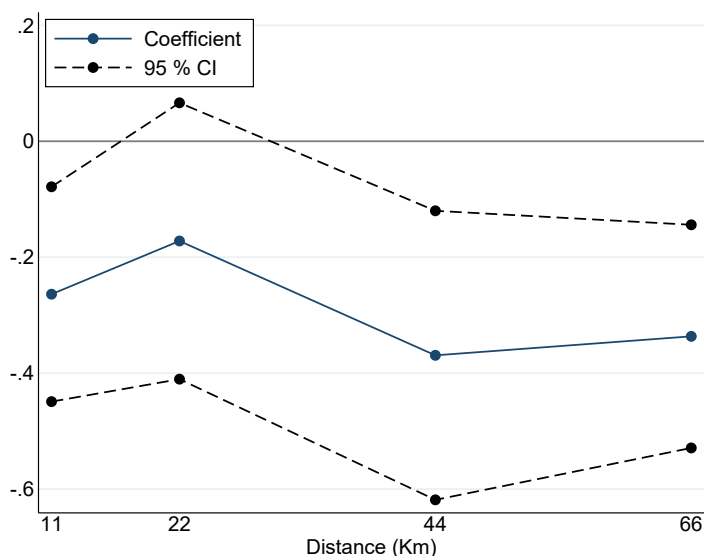
Table G.4: Effect of minimum wages on commuting: other wage categories.

Log Low Wage Commuters - 11 Km to Border						
	(1)	(2)	(3)	(4)	(5)	(6)
	Low wage Panel	Mid wage Panel	High wage Panel	Low wage Within	Mid wage Within	High wage Within
Log MW Residence	-0.00 (0.12)	-0.11 (0.10)	-0.24** (0.10)			
Log MW Workplace	-0.25** (0.10)	-0.08 (0.12)	-0.05 (0.11)			
Log MW Difference				-0.26*** (0.09)	-0.08 (0.11)	-0.02 (0.10)
Adj R sq.	0.976	0.982	0.986	0.303	0.216	0.334
N	7,603	7,555	7,537	12,136	12,172	12,118
Work counties	259	255	254	344	345	341
Res counties	290	288	285	288	291	288
Work effects				Yes	Yes	Yes
Work, res effects	Yes	Yes	Yes			
Res effects x Year effects				Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes			
Work, res trends	Yes	Yes	Yes			
Mean dep. var.	395.5	693.9	1030.3	2273.6	3858.5	3916.4

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

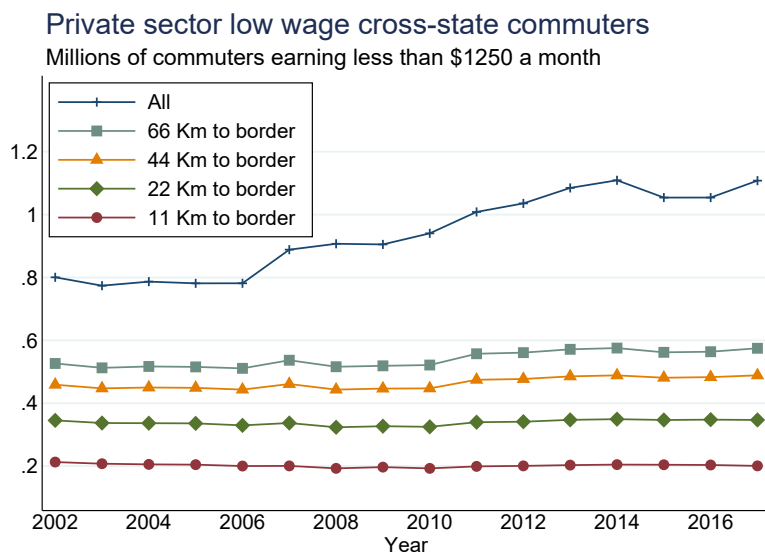
The sample excludes 1. residence-workplace pairs with average low-wage commuting below 150 a year; 2. Counties from AK, AZ, AR, DC, MA, MS, NH, or WY because of missing commuting data; 3. Counties where the local minimum wage is higher than the state's minimum wage. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work, and county of residence level. Columns 1 to 3 implement a panel design. They include fixed effects at the workplace-residence county pair level, residence and pair-specific linear time trends. Columns 3 to 6 implement a within residence design. They include residence-year effects and workplace effects. All columns include controls for county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates.

Figure G.1: Elasticities at different distances from the border



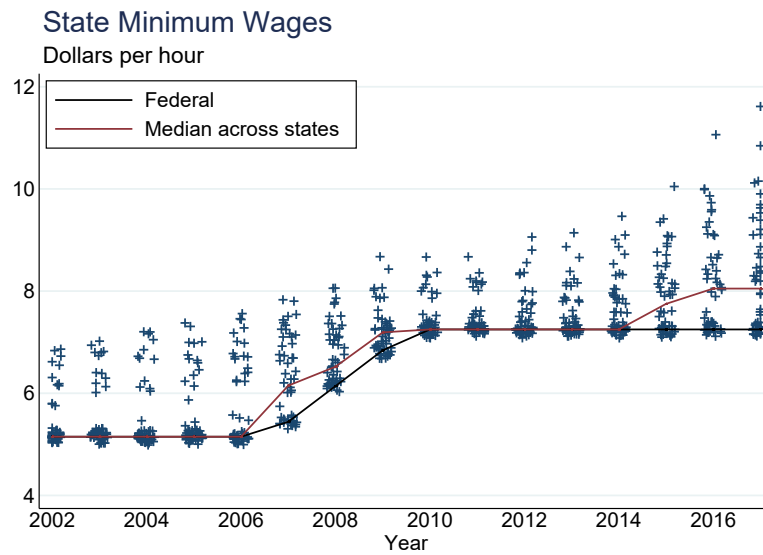
Source: Author's calculations. This graph depicts coefficients on the log minimum wage at the workplace variable from the within design of equation (3). The regressions are analogous to that of column 3 of table 2, and include controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs and average corporate tax rates.

Figure G.2



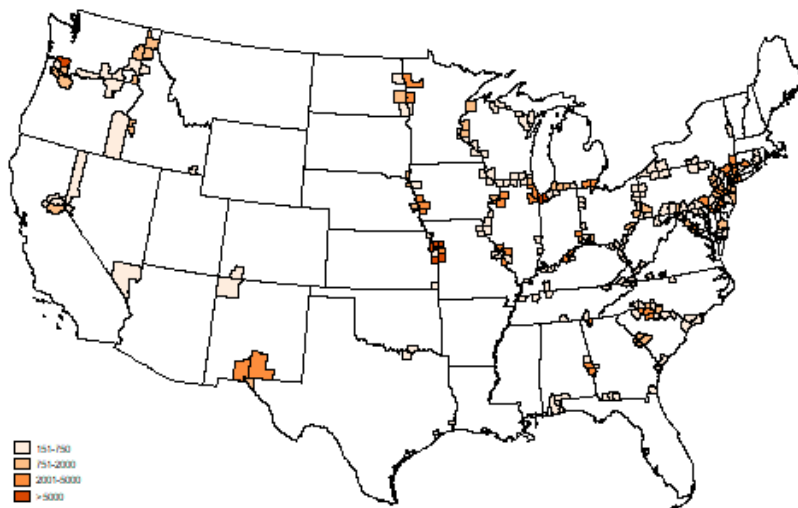
Source: LODS 7.1. Cross state commuters are those who live in one state and work in another state.

Figure G.3



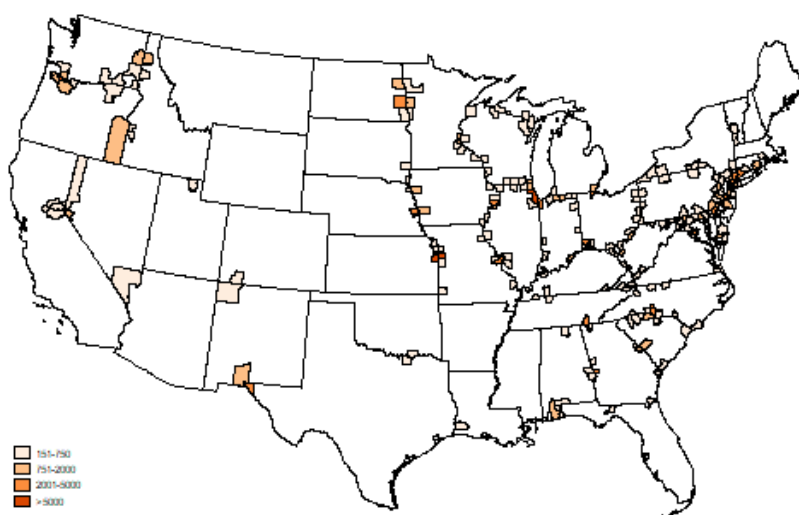
Source: Author's calculations based on data from [Neumark et al. \(2014\)](#) and [Clemens et al. \(2018\)](#). Points have been jittered to show that many states have the same minimum wage.

Figure G.4: Included counties by yearly sent cross border commuting



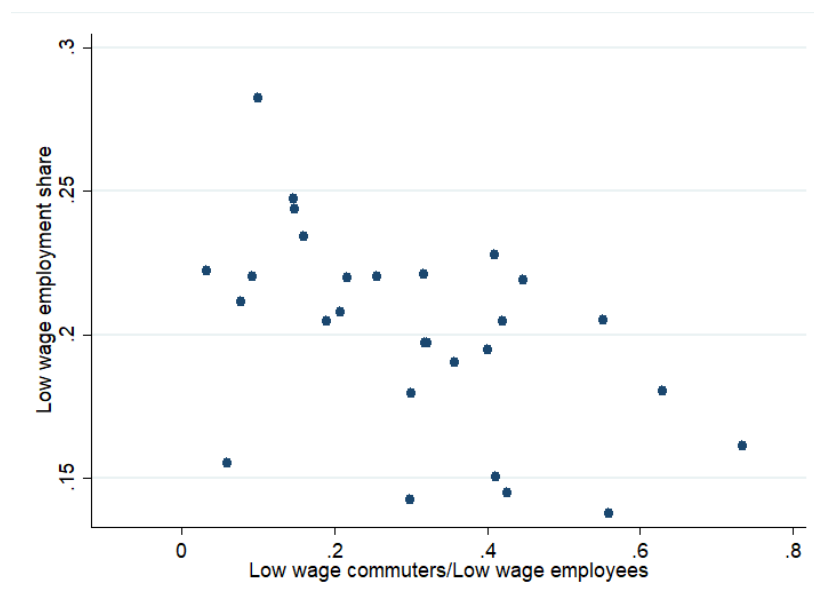
Source: Author's calculations from LODES. Highlighted counties are included in the reduced form analysis sample. Colors represent the amount of commuters they send across the border every year, i.e. the number of workers who live in the county and work in another county across the border.

Figure G.5: Included counties by yearly received cross border commuting



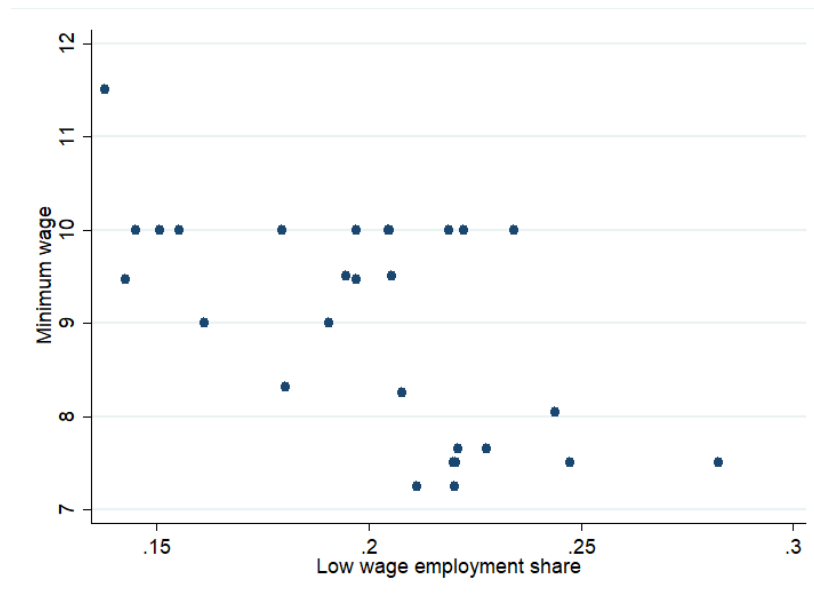
Source: Author's calculations from LODES. Highlighted counties are included in the reduced form analysis sample. Colors represent the amount of commuters they receive from across the border every year, i.e. the number of workers who work in the county and live in another county across the border.

Figure G.6: Low wage commuting and employment, 2017.



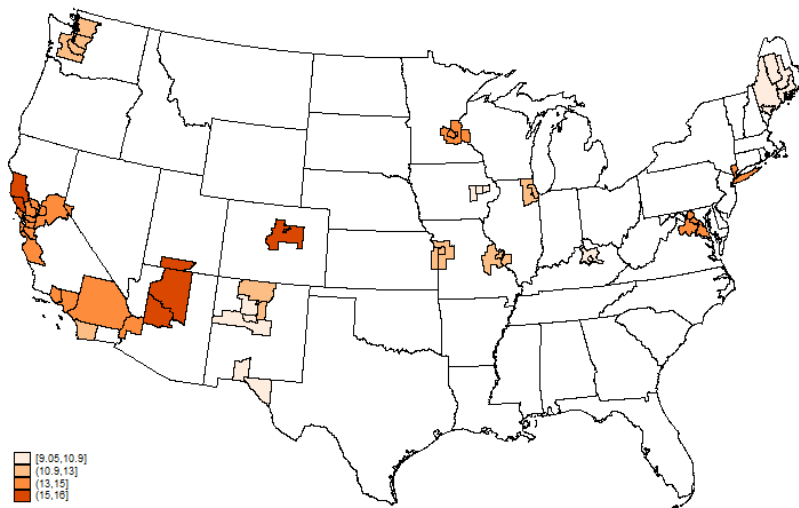
Source: Author's calculations based on LODES. Counties that include cities with approved proposals for minimum wage increases.

Figure G.7: Low wage employment and minimum wages. 2017.



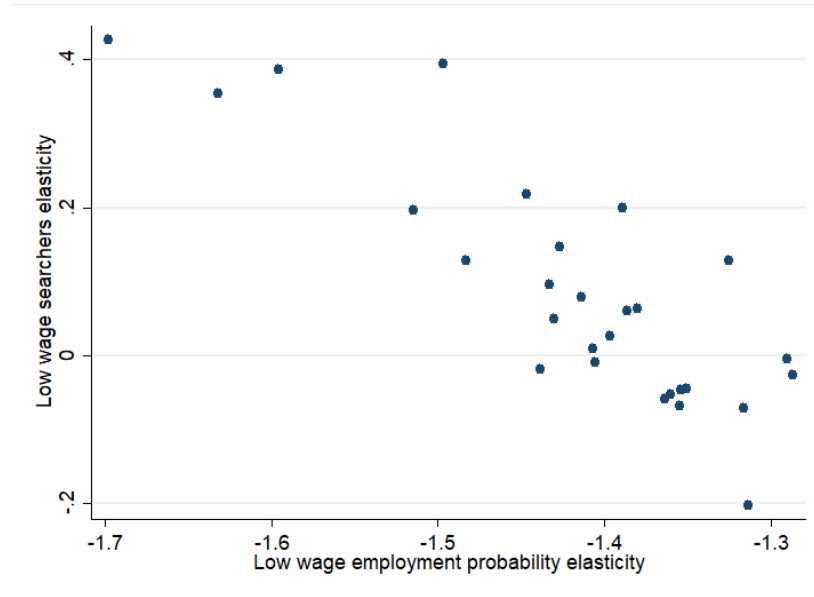
Source: Author's calculations based on LODES. Counties that include cities with approved proposals for minimum wage increases.

Figure G.8: Commuting zones for cities with proposed minimum wage increases



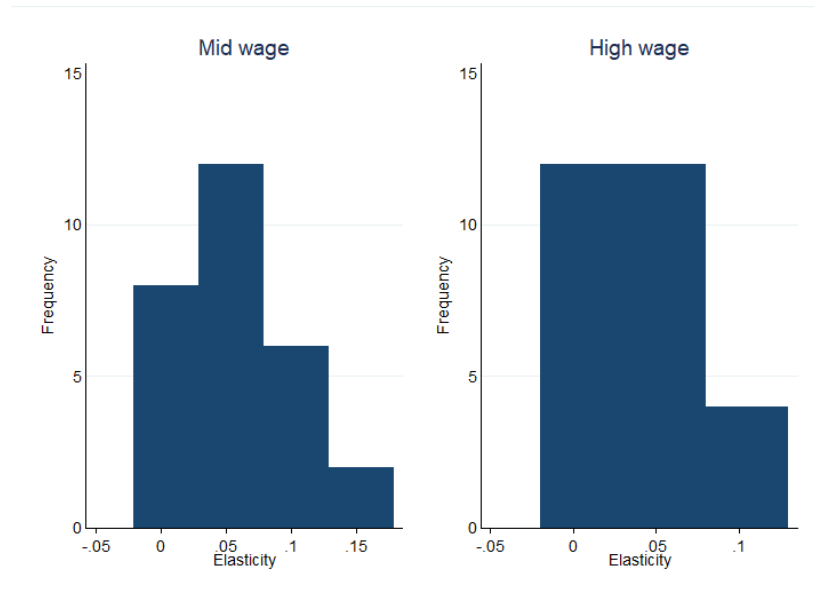
Source: Author's calculations based on [National Employment Law Project \(2016\)](#) and [Dube and Lindner \(2020\)](#). The colors list the maximum minimum wage proposed. Target years for minimum wage increases differ across commuting zones. Thick borders denote commuting zones. Thin borders denote counties.

Figure G.9: Elasticities of low wage searchers O_{Mi}^ℓ and low wage employment probability ρ_i^ℓ



Source: Author's calculations. Observations are 28 counties considering minimum wage increases. Values are elasticities of low wage employment probabilities ρ^ℓ and low wage searchers O_{Mi}^ℓ to an increase in the minimum wage, calculated from comparing an initial equilibrium to a model counterfactual with a minimum wage increase. In the counterfactuals, minimum wages were increased by 5 %.

Figure G.10: Elasticity of mid and high wage employment probabilities ρ_i^m and ρ_i^h



Source: Author's calculations. Observations are 28 counties considering minimum wage increases. Values are elasticities of mid and high wage employment probability ρ_i^m and ρ_i^h to an increase in the minimum wage, calculated from comparing an initial equilibrium to a model counterfactual with a minimum wage increase. In the counterfactuals, minimum wages were increased by 5 %.