City Minimum Wages

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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 nationwide minimum wage policies. This paper studies the effect of changes in the minimum wage on spatial equilibriums 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 3 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 equilibriums with a higher minimum wage for U.S. cities that are considering an increase, highlighting the role of commuting and migration responses. About two-thirds of the cities considering increases would receive fewer low-wage commuters. These commuting losses are driven by employment relocations and are similar to those suggested by the reduced form analysis.

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 increased its minimum wage to an unprecedented $15 an hour. Political movements are pushing for rises in several other cities.

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 the effects of state- or countrywide policy 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 the features of each local labor market. With the model, I build counterfactual scenarios of equilibriums for U.S. cities that are 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 crossborder 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 3 percent to 4 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.

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 to 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 distinctive feature of the model 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 analyse 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. This 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 my 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, which are larger than past increases.

In the last part of the paper, I fit the model to commuting data for 32 U.S. cities that are 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. For five cities on state borders, I estimate the parameters using the variation derived from crossborder differences in the minimum wage. For the remaining cities, I estimate 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. Two-thirds of the cities considered would experience commuting losses because of employment relocations, which is consistent with the reduced form results. One-third of the cities would experience commuting increases because employment effects are small compared with the increase in expected wages. The heterogeneity in the response across cities is driven

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by differences in the response of search and employment probabilities. Most cities experience increases in job-seeking and reductions in employment probabilities, which translate 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 provides estimates of the elasticities of commuting and migration to minimum wages at the local level, and relates them to employment effects of the minimum wage. 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 negative effect on employment. 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 the effects of the minimum wage 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 (2016) builds a spatial equilibrium model with the minimum wage and shows how traditional state panel designs may understate the employment effects of a minimum wage 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. Unlike McKinnish (2017), this paper examines commuting flows explicitly, and models the reaction of other groups of workers beyond low wage workers.

The second contribution of this paper is to the provide evidence of the effects of local minimum wages beyond a single city, 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. Jardim et al. (2017) find large employment losses associated with Seattle's recent minimum wage increase. 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.

The last contribution of this paper is to introduce unemployment into quantitative urban models. The paper is closely related to Monte et al. (2016) and Ahlfeldt et al. (2015). Monte et al. (2016) show how employment elasticities to productivity shocks may vary across locations depending on how commuting and migration respond. They also show

how traditional designs to estimate the impact of productivity that ignore this heterogeneity may be biased. These papers, however, 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 distributional effects of local minimum wage hikes. This paper focuses on the effects for cities that are in the process of increasing their minimum wage.

This paper is divided into seven sections. Section 2 outlines the reduced form analysis to estimate the effect of a minimum wage 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 context of the model. Section 5 shows how this model can be fit to data on commuting and employment. Section 6 calculates counterfactuals for cities considering minimum wage increases. Section 7 concludes. Four 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

The main data source is the Longitudinal Employer-Household Dynamics Program's Local Origin and Destination Employment Statistics (LODES) version 7.1 (2002-13).[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

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

as origin-destination pairs. The data are compiled 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 a comparison of 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 2017, 32 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 gives a large number of locations and minimum wage changes.

I use the variation in the minimum wage in adjacent areas on either side of the borders to estimate the effects of the change. The use of state borders minimizes the impact that 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) studies 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 quite local in extent so that job attractiveness diminishes substantially 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 length of the average commute in the United States is about 22 kilometers (Kneebone and Holmes 2015). However, for robustness, I also use larger bandwidths in some of the analysis. I them sum the flows in county pairs. This mitigates the imputation of workers residential locations in census blocks in the LODES data and allows the use of county covariates in the regression analysis.

There are many low-wage cross border commuters every year. From 2002 to 2013, around 200,000 people commuted across state borders on trips shorter than 22 kilometers. By 2013, crossborder commuting accounted for around 10 percent of total commuting by

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[2]Arizona, Arkansas, the District of Columbia, Kansas, Massachusetts, and New Hampshire are excluded because of incomplete data.

low-wage workers in these areas every year[3].

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 excludes borders with low population and borders across which workers do not commute (for example, the Nevada-Utah border). Using k-means cluster analysis, county pairs are divided into five clusters according to total crossborder commuting. Then, I exclude the cluster with the lowest commuting from the sample. This amounts to excluding county pairs that have fewer than 150 commuters a year.

Figure 1 shows the counties included in the sample. (All figures and tables follow the main text.) Most of these counties are located in crossborder metropolitan statistical areas or in densely populated borders. Figures E.3 and E.4 on appendix E show the amount of crossborder commuters these counties send and receive.

I focus on private sector workers who commute for their primary jobs. The LODES 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, in some states for the later years, the minimum wage is sufficiently high that they could fall in the middle category. [4]

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

For minimum wages, I use the average monthly state minimum wage from data compiled by Neumark et al. (2013).[5]

Figure 2 shows differences in the minimum wage between neighboring states. If these differences were nonexistent because neighbor states always kept the minimum wage equal, then it would be hard to attribute commuting changes to minimum wage policy. This turns out not to be the case. Although the median difference is 0 for most of the time

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[3]Figure E.1 in appendix E shows how commuting varies over time at different distances from state borders.

[4]Table E.1 of appendix E 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 the exclusion of these observations or to a redefinition of minimum wage workers to include the second category in these states and years.

[5]For robustness, I also use the data of Allegretto et al. (2013). The main results of section 2.3 are robust to this change.

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.[6]

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 counts, corporate taxes, tax credits, and gas prices. Details on the sources are provided 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 crossborder flows into areas with a higher minimum wage are lower. This 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.

The first step is the estimation of the effects on commuting. The unit of analysis is the county pair. n indexes residence counties, and i indexes workplace counties. C_{nit} denotes 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, and 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 I calculate coefficients for alternative bandwidths.

I examine how crossborder commuting flows change if the minimum wage changes on either side. I compare these flows with different counterfactuals using a differences in differences strategy. Figure 3a shows the first design, labeled the panel design. I compare flows between areas A and B with flows between areas C and D before and after a

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[6]Figure E.2 of appendix E 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.

minimum wage change occurs in area B. This is analogous to the state-panel design traditionally used in the minimum wage and employment literature (Neumark et al. 2013).

For this panel design, I estimate the following regression:

$$C_{nit} = \beta_0 + \beta_n ln(minwage_{nt}) + \beta_i ln(minwage_{it}) + \gamma_{ni} + \delta_t + \Phi_r X_{nt} + \Phi_w X_{it} + \epsilon_{nit} \quad (1)$$

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.

β_n and β_i are identified from changes in the minimum wage at residence and workplace locations. Using the data on both directions of commuting allows the identification of β_n and β_i separately.[7]

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.[8] Identification in this case requires that there be multiple county pairs per state border and per state border within a census division.

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

$$E\left(\epsilon_{nit} \times ln(minwage_{nt})\right) = E\left(\epsilon_{nit} \times ln(minwage_{it})\right) = 0, \quad (2)$$

that is, if minimum wage differences are uncorrelated with residual commuting. This requires that any unobservable differences in commuting across pairs are evolving in parallel over time. By including state trends or census division-year effects, this approach allows unobservables to exhibit different linear trends across states or vary systematically across census divisions. 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 neighbouring counties are similar in terms

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[7]An alternative would be to use net commuting flows, but these would not allow the identification of β_n and β_i, only their difference.

[8]Dube 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.

of levels and trends of covariates. Dube et al. (2010) estimates the effects of minimum wages on employment using differences in neighbouring counties across state borders. Hagedorn et al. (2016) highlights some limitations of using border designs in the context of evaluation of 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, crossborder differences in minimum wages can be as high as 35 percent of the federal minimum wage. These differences may not persist if states set minimum wages in response to their neighbor's policy. This may bias the estimates toward 0.

Dieterle et al. (2016) 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 the effects on commuting vary as I consider larger distances from the border.

The second design, shown in figure 3c, is a within design. It involves the comparison of crossborder 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 that originate in the same county. The regression specifications is as follows:

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

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 coming from residences with a different minimum wage. This is accomplished by including workplace-time fixed effects, γ_{nt}, as follows:

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

These specifications no longer identify the effect of the minimum wage at the origin or the destination separately, but identify the elasticity of low-wage commuting, β_d, to the difference in the minimum wage.

The last design, depicted in figure 3b, is a corner design, where I compare crossborder 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 crossborder 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 the sample is restricted to residence counties that have commuting flows to more than one state.

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 area is the one that receives the most commuters, and then calculate the difference in these shares across county pairs. Each county pair only enters the sample once every year. These differences are used as dependent variables in specifications (1), (3) and (4). This is analogous to a difference in differences design wherein the control counties are the neighboring counties, as in Dube et al. (2010).

To conduct inference, I use multiway 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.[9]

2.3 Main Results

2.3.1 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. The elasticity to the minimum wage in the workplace, however, is significantly negative and stable across specifications, ranging from -0.30 to -0.38.

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. 2013; Belman and 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

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[9]An alternative to correct for 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 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 -0.38 after controlling for state trends. 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.

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

If only the difference in wages determined commuting, then these coefficients would be equal in absolute value, but have opposite signs. 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 coefficient in the corner design, which would be expected if the residence wage effect were negligible. A second assumption is that the minimum wage effect does not depend on the direction on the commuting flow. An increase in the minimum wage in county B changes commuting from A to B in the same amount as a change in county A would affect commuting from B to A.

Table E.2 in appendix E also estimates this elasticity using only variation within workplace counties and using only counties in state corners, after comparting crossborder flows originating in the same county. The within-workplace estimates are small and un-

precise. If the minimum wage reduces employment among employees commuting from within and across the state similarly, these estimates should be small. The corner estimates are still negative and significant, although imprecise because of the small sample used.

2.3.2   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 three percentage points, relative to the adjacent county in the neighboring state. This reinforces the view that lower employment plays a significant part in the decrease in commuting because of the higher minimum wage. The effect dissipates as one looks away from the borders, suggesting that the effects are local (Manning and Petrongolo 2017).

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. In this case, however, all the estimates are imprecise and do not allow any inferences to be made on the effects on migration. This contrasts with Cadena (2014), who finds that workers migrate away from minimum wage increases in states. However, the incentive to migrate instead of commuting in response to the wage change is much smaller in this sample because commuting costs are much lower.

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, that they are not driven by a shift of employment to other categories, that they are present for both primary and secondary jobs, and that they are local, disappearing if one looks farther away from the border.

To test for preexisting trends and lagged effects, I estimate versions of equation (1) that include leads of up to three years of the minimum wage variables and a one year lag. This is tested on the specification with pair-specific trends.

The results are shown on figure 4 . These indicate that the elasticity of commuting only becomes negative and significant for the contemporaneous effect of the minimum wage. 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 coefficient on the lag is not significant, suggesting that the effects dissipate quickly. However, in the sample, minimum wage differences quickly reduce after a state increases the minimum wage, because neighbor states tend to follow suit. This would attenuate any lagged effects[10].

It is possible that workers are keeping their jobs, but switching to a higher wage category because of the increase in their wage. I test this by estimating the same regressions for mid-wage and high-wage commuters. The results are shown in table 5 . This indicates that the results are not simply caused by a change in categories.

Figure 5 shows commuting elasticities at different distances from the state border. The effect decays as one looks farther away from the state boundary, suggesting that the changes in commuting patterns occur at a local level. The elasticity is almost zero 66 kilometers away from the border, but exhibits large standard errors.

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 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 than the cities considering minimum wage increases, the effects on cities 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 Commuting

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 me to produce counterfactual changes in employment, commuting, and migration.

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[10]In the sample, about 15 percent of crossborder differences in minimum wages are eliminated after 1 year, and about 60 percent of the differences are reduced after 1 year. When the differences are reduced, the remaining differences are about 30 percent of the original differences

I build a quantitative urban model in the spirit of Ahlfeldt et al. (2015) and Monte et al. (2016). 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 measures of workers are given exogenously. Each worker decides on a location to live and to search for work.

3.1 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-Douglas[11]:

$$u_{ni\omega} = \frac{z^s_{ni\omega} \tilde{w}^s_{ni}}{(1 + \rho_i \kappa_{ni}) Q_n^{1-\beta}} \tag{5}$$

$\tilde{w}^s_{ni}$ 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, ρ_i, plus a residence-based unemployment benefit, R^s_n, in case of unemployment:

$$\tilde{w}^s_{ni} = \rho^s_i w^s_i + (1 - \rho_i) R^s_n \tag{6}$$

Q_n is the price of housing in n. ρ^s_i is the probability of finding a job at location i for each type of worker. $z_{ni\omega}$ is a preference heterogeneity parameter that reflects the taste for living and working in particular locations[12]. 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:

$$G^s_{ni}(z) = e^{-T^s_n X^s_i z^{-\epsilon}} \qquad T_n > 0, X_i > 0, \epsilon > 1 \tag{7}$$

T^s_n and X^s_i are scale parameters that reflect the average taste that each type of worker has for living in n and working in i, respectively. ϵ is a dispersion parameter common

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[11]This 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.

[12]Since these parameters multiply the wage, they are associated with an alternative interpretation as worker-specific productivity measures for every residence workplace pair.

to all locations. Larger ϵ implies less dispersion of preferences and lower gains from commuting.

3.2 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):[13]

$$Y_i = \left[A_i^\ell \left(L_{Mi}^\ell \right)^\sigma + A_i^m \left(L_{Mi}^m \right)^\sigma + A_i^h \left(L_{Mi}^h \right)^\sigma \right]^{\frac{1}{\sigma}}, \tag{8}$$

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:

$$L_{Mi}^s \equiv \sum_{n=1}^{N} L_{ni}^s \tag{9}$$

Similarly, employment by residence is the sum of employees across workplace locations:

$$L_{Rn}^s \equiv \sum_{i=1}^{N} L_{ni}^s \tag{10}$$

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. (The upper limits of the summations are dropped for the remainder of the text for convenience.)

3.3 Labor market and labor demand

This subsection describes labor demand in every area. 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 that search for a job in each area because of 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.

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

16

In equilibrium, there is unemployment in every area. This 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 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 (8), 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 $w_i(1 + \tau_i^s)$.

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

$$U_{Mi}^s = O_{Mi}^s - L_{Mi}^s. \tag{11}$$

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

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

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

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

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

$$\tau^s(\theta_i^s) = \frac{r^s}{q^s(\theta_s^i)} \tag{14}$$

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

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

where I allow matching efficiency, Ω^s, to vary by skill, but not by location. 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.

There is a binding minimum wage, w_i, in each location. 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. At the same time, the minimum wage alters the number of people who search for a job in the region, changing O_{Mi}. 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.

3.4 Labor mobility

Workers choose where to live and search for work to maximize their utility in (5). The distribution of utility for a worker of type s that lives in n and searches in i is

$$
\begin{aligned}
G_{ni}^s(u) &= \Pr(u_{ni\omega}^s \leq u) \\
&= \Pr\left(\frac{z_{ni\omega}^s \tilde{w}_{ni}^s}{(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}} \leq u \right) \\
&= \Pr\left(z_{ni\omega}^s \leq \frac{u (1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}}{\tilde{w}_{ni}^s} \right) \\
&= e^{-\psi_{ni}^s u^{-\epsilon}}
\end{aligned}
\tag{16}
$$

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

$$\psi_{ni}^s \equiv T_n^s X_i^s \left[(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta} \right]^{-\epsilon} (\tilde{w}_{ni}^s)^\epsilon \tag{17}$$

From the properties of the Fréchet distribution (Monte et al. 2016)), one may obtain the joint probabilities of living in n and searching in i, as follows:

$$o_{ni}^s = \frac{\psi_{ni}^s}{\psi^s}$$

$$\psi^s = \sum_n \sum_{i1} \psi_{ni} \tag{18}$$

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

$$o_{Rn}^s = \sum_i o_{ni}^s$$

$$o_{Mi}^s = \sum_n o_{ni}^s \tag{19}$$

These probabilities, multiplied by the exogenous measures of workers of each type, give the number of residents, O_{Rn}, and searchers, O_{Mi}, in each location. The probability of searching in i conditional on living in n is

$$o_{ni|n}^s \equiv \frac{o_{ni}^s}{\sum_b o_{nb}^s} \tag{20}$$

3.5 Employment and commuting

Job-seekers by workplace, O_{Mi}^s, are determined by choice probabilities (see above). Given these job-seekers, 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 rations of employment to job-seekers at each location:

$$\rho_i^s = \frac{L_{Mi}^s}{O_{Mi}^s} = f^s(\theta_i^s) \tag{21}$$

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

$$L_{ni}^s = O_{ni}^s \rho_i^s \tag{22}$$

Define global commuting probabilities as $l_{ni}^s \equiv \frac{L_{ni}^s}{L^s}$. Equation (22) implies that

$$l_{ni}^s = o_{ni}^s \rho_i^s = o_{ni}^s \frac{L_{Mi}^s}{O_{Mi}^s} \tag{23}$$

The probability of living in n while employed is then given by

$$l_{Rn}^s = \sum_i l_{ni}^s, \tag{24}$$

and the probability of being employed in i is

$$l_{Mi}^s = \sum_n l_{ni}^s \tag{25}$$

From these probabilities, employment and resident shares by skill may be defined as

$$
\begin{aligned}
\lambda_{Mi}^s &= \frac{l_{Mi}^s}{l_{Mi}^\ell + l_{Mi}^m + l_{Mi}^m} \\
\lambda_{Rn}^s &= \frac{l_{Rn}^s}{l_{Rn}^\ell + l_{Rn}^m + l_{Rn}^m}
\end{aligned}
\tag{26}
$$

3.6 Housing market

Land supply is inelastic and given by D_n. Because of the Cobb-Douglas specification in (5), workers spend a fraction, $1 - \beta$, of their income on housing. This 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:

$$Q_n = \frac{(1 - \beta)v_n O_{Rn}}{D_n}, \tag{27}$$

where v_n is the average expected income in each location

$$v_n = \sum_s \left(\frac{O_{Rn}^s}{\sum_t O_{Rn}^t} \sum_b o_{nb|n}^s \tilde{w}_{nb}^s \right) \tag{28}$$

3.7 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:

- Residence-search probabilities satisfy (18)

- (12) and (13) are satisfied so the labor market is in equilibrium

- Employment probabilities are consistent with ratios of search to employment and satisfy (21)

- (27) is satisfied so the housing market clears.

3.8 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

$$\xi^s L_{Mi}^s = f(\theta_i^s)(O_{Mi}^s - L_{Mi}^s) \tag{29}$$

and equation (21) becomes

$$\rho_i^s = \frac{L_{Mi}^s}{O_{Mi}^s} = \frac{f^s(\theta_i^s)}{\xi^s + f^s(\theta_i^s)} \tag{30}$$

Appendix B.1 describes an algorithm to compute equilibriums in the model allowing 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 changes in housing prices. I relate the effects found in the model to the elasticities estimated in the reduced form analysis.

4.1 A simple illustration of the effects

I illustrate the effects of the minimum wage in a model of two regions and a single labor type. Figure 6 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 (29) determine labor supply curves, L_{M1} and L_{M2}. Firms in each location exhibit 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: larger wages make location 1 more attractive to job-seekers.

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 are lower.

The overall change in employment in these locations depends on the relative strength of these effects. Figure 7a 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 unemployment are now greater in location 1 and lower in location 2, although labor demand has decreased in location 1.

Figure 7b 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. This 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 increases (or decreases) in the search 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, while others may decide to migrate to location 1, increasing the search, but decreasing commuting from 2 to 1.

4.2 Commuting and migration elasticities to minimum wages

Consider the probability of commuting from n to i among low-wage workers from equation (23)

$$l_{ni}^\ell = o_{ni}^\ell \rho_i^\ell \tag{31}$$

The change in this probability depends on how search probabilities and employment probabilities change. Consider two types of elasticities, following Monte et al. (2016). The general equilibrium elasticity, ε_x^y, considers the change in endogenous variable, y, given a change in x from an initial to a final equilibrium of the model whereby all endogenous variables change in all locations. The partial equilibrium elasticity, η_x^y, considers the change in y keeping endogenous variables constant in locations that are not analyzed, that is, in commutes from a to b, commuting across other residence-workplace pairs are kept fixed. From (23), the elasticities of commuting if the minimum wage, w_i^ℓ, changes are as follows:

$$\begin{aligned} \varepsilon_{w_i^\ell}^{l_{ni}^\ell} &= \varepsilon_{w_i^\ell}^{\rho_i^\ell} + \varepsilon_{w_i^\ell}^{o_{ni}^\ell} \\ \eta_{w_i^\ell}^{l_{ni}^\ell} &= \eta_{w_i^\ell}^{\rho_i^\ell} + \eta_{w_i^\ell}^{o_{ni}^\ell} \end{aligned} \tag{32}$$

Consider the partial equilibrium elasticity $\eta_{w_i^\ell}^{l_{ni}^\ell}$. 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.

Appendix C derives partial and general equilibrium elasticities of search probabilities to changes in the minimum wage. Here, I focus on the partial equilibrium elasticity, which is given as follows:

$$\eta_{w_i^\ell}^{o_{ni}^\ell} = \underbrace{\left(\epsilon - \epsilon o_{ni}^\ell \right) \left[\theta_{ni}^\ell - \left(1 - \theta_{ni}^\ell \right) - \frac{1}{\tilde{w}_{ni}^\ell} - \boldsymbol{\kappa}_{ab}^s \right] \eta_{w_i^\ell}^{\rho_i^\ell}}_{\text{Employment effect}} + \underbrace{\left(\epsilon - \epsilon o_{ni}^\ell \right) \theta_{ni}^\ell}_{\text{Wage effect}} - \underbrace{\left(\epsilon - \epsilon o_{ni}^\ell \right) \left(1 - \beta \right) \eta_{w_i^\ell}^{Q_n}}_{\text{Housing prices effect}} \tag{33}$$

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

The wage effect is positive and increases with the share of wages in expected income. The housing prices 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 key role in determining the value of this elasticity. As ϵ grows larger, wage effects are larger. Larger ϵ implies lower gains from commuting and lower initial commuting in equilibrium. If initial commuting is lower, then the commuting is more sensible to higher expected wages. Larger ϵ also increases the magnitude of the other effects.

Based on equation (34), the commuting elasticity becomes

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

(34)

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.

Section 2 above shows a negative average effect of minimum wages on commuting and employment relocation toward the side that did not increase the minimum wage. This implies that employment effects are negative and larger in absolute value than the sum of wage and housing price effects.

I now examine the effects on migration. Define the share of low-skill residents as

$$
\Lambda_{Rn}^\ell = \frac{l_{Rn}^\ell}{l_{Rn}^\ell + l_{Rn}^m + l_{Rn}^h}
$$

(35)

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

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

(36)

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:

$$
\varepsilon_{w_n^\ell}^{l_{Rn}^s} = \sum_b \varepsilon_{w_n^\ell}^{l_{nb}^s}
$$

(37)

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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.

4.3   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 be able 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 components of the elasticity in equation (34). 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 would be limited. The decomposition of equation (34) is only valid for a partial equilibrium elasticity, and a reduced form estimate of the effect on housing prices would require detailed rental price data.

I focus instead on the general equilibrium effects of the policy, which is calculated 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

In this section I show how to implement the model on commuting data and calculate counterfactual equilibria when exogenous variables such as the minimum wage change. First, I describe how to obtain location-specific parameters of the model from data and values associated with the other parameters. Then, I show how to calibrate non-location specific parameters in the model. Last, I outline a strategy for estimating ϵ, which governs the strength of commuting responses.

5.1   Computing unobserved parameters

Table 6 shows the parameters of the model grouped in three categories. The first group of parameters are location-specific, but may be observed in the data. I fit the model at the county level.

The wage among the low-skill group is the minimum wage used in section 2. Wages for the other skill groups are taken as 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 Bureau of Labor Statistics data. Land areas are observed from the census. Details on these variables are shown in appendix A.1

Wages for the low skill group are minimum wages used in section 2. I take wages for the other skill groups as exogenous, and I calculate them from average wages in the ACS by location and industry. 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.

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

$$log(avgcommutingcost_{ni}) = -0.394log(distance_{ni}) + log(1.352) + e_{ni} \qquad (38)$$

where $avgcommutingcost$ 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, as follows:

$$\kappa_{ni} = \frac{hours}{hours - (2 \times avgcommutingcost_{ni} \times distance_{ni})/60} \qquad (39)$$

The second group of parameters 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 D.1 describes how to obtain employment probabilities using data on unemployment 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 an equilibrium in the model, and recover the values of the parameters 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. 2016). Appendix sections D.2, D.3 and D.4 show how to calculate these parameters given values of the parameters that are constant across locations and the observed data on commuting and location-

specific parameters. Here, I describe broadly 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 D.2.

Given these workplace amenities, places that have more residents must have higher residential amenities or lower housing prices. This allows the identification of residential amenities, T_n^s, adjusted by housing prices. Details are in appendix D.3.

Given the wages, unemployment, and labor market tightness, the first-order conditions of the firm imply values of productivity by type, A_i^s. Equilibrium market tightness can be obtained from data on job finding probabilities that are related to the spatial distribution of employment through equation (30). Details are in appendix D.4.

5.2 Computing counterfactuals

With the values of the global 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 the changes in commuting and employment in general equilibrium after the minimum wage changes.

Appendix B.2 describes an algorithm to compute counterfactual equilibriums based on Monte et al. (2016). 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, o_{ni}^s, can be obtained.

5.3 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 for the US as a whole. Table 7 summarizes the calibrated parameters.

I set β as the housing share of expenditure from the Consumer Expenditure Survey following Monte et al. (2016). Davis and Ortalo-Magne (2011) estimate the parameter at around 0.24 for renters in the United States. Combes et al. (2016) estimate this share at 0.2 to 0.4 from a sample of cities in France.

σ is set at 2, in the lower end of estimates from Ottaviano and Peri (2012). Using a CES production function analogous to (8), they estimate this parameter using U.S. census data on employees by educational attainment and place of birth, among other variables. Here,

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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 kinds of labor. If σ is higher than this estimate, employment losses in the counterfactuals should be seen as a lower bound.

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. (forthcoming). There is relatively little evidence on the extent of recruiting costs or how these costs vary across types of jobs. Landais et al. (forthcoming) estimate the costs based on the size of the recruiting industry. Their vacancy filling rate is estimated from data of the Job Openings and Labor Turnover Survey.

The elasticity of the matching function 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.

5.4 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.

5.4.1 Gravity equation estimation

From equations (18) and (23), the probability of commuting from n to i among workers of type s equals

$$
\begin{aligned}
l_{ni}^s &= \rho_i^s o_{ni}^s \\
&= \rho_i^s \frac{\psi_{ni}^s}{\psi^s} \\
&= \rho_i^s \frac{T_n^s X_i^s \left[(1 + \rho_i^s \kappa_{ni}) Q_n^{1-\beta}\right]^{-\epsilon} (\tilde{w}_{ni}^s)^\epsilon}{\sum_{ab} T_a^s X_b^s \left[(1 + \rho_b^s \kappa_{ab}) Q_a^{1-\beta}\right]^{-\epsilon} (\tilde{w}_{ab}^s)^\epsilon}
\end{aligned}
\tag{40}
$$

Taking logs on both sides, commuting probabilities can be decomposed into workplace fixed effects, residence fixed effects and effects of employment probabilities, wages

and commuting costs.

$$
\begin{aligned}
log(l_{ni}^s) \;=\; & \underbrace{-ln\left(\psi^s\right)}_{\text{Constant}} + \underbrace{+ln(X_i^s)}_{\text{Workplace F.E.}} \\
& \underbrace{+ln(T_n^s) - \epsilon(1-\beta)ln(Q_n)}_{\text{Residence F.E.}} + ln(\rho_i^s) \\
& -\epsilon ln(1 + \rho_i^s \kappa_{ni}) + \epsilon ln\left(\tilde{w}_{ni}^s\right)
\end{aligned}
\tag{41}
$$

I estimate this equation using the commuting data in section 2 for each city. All labor types and years in a single regression and estimate, as follows:

$$
\begin{aligned}
log(l_{nit}^s) \;=\; & \beta_0 + \gamma^s + \gamma_{it}^s + \gamma_{nt}^s + \gamma_t \\
& +log(\rho_i^s) - \epsilon log(1 + \rho_i^s \kappa_{ni}) + \epsilon log\left(\rho_i^s w_i^s + (1-\rho_i^s)R_n\right) + \tilde{e}_{nit}^s
\end{aligned}
\tag{42}
$$

where the error term, $\tilde{e}_{nit}^s$, arises from the error in measuring commuting costs from equation (38). The time and skill fixed effects, γ^s and γ^t, capture the changes in the constant $-log(\psi^s)$ 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 estimate this using constrained least squares estimation and setting the coefficient on $log(\rho_i^s)$ at 1 and the coefficients on $log(1 + \rho_i^s \kappa_{ni})$ and $log\left(\rho_i^s w_i^s + (1-\rho_i^s)R_n\right)$ equal in absolute value, but with opposite signs. The identifying assumption is that the error term is not correlated with wages or commuting costs.

5.4.2 Structural estimation

An alternative estimation procedure involves using the variation in the minimum wage across borders that was used to estimate the results in section 2. This can only be done in the case of border cities in which the minimum wage varies by location and only based on low-wage commuting data. 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:

$$
\Delta X_{it}^\ell \Delta w_{it}^\ell = 0
\tag{43}
$$

$$
\Delta T_{nt}^\ell \Delta w_{nt}^\ell = 0
\tag{44}
$$

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 D.2 and D.3, for every city and year in my sample. I then obtain sample analogs of equations (43) and (44) and estimate ϵ through the generalized method of moments. The estimated ϵ solves the following minimization problem:

$$\hat{\epsilon} = argmin \frac{1}{NT} \sum_{i,t} \begin{bmatrix} \Delta X_{it}^{\ell} \Delta w_{it} & \Delta T_{nt}^{\ell} \Delta w_{nt}^{\ell} \end{bmatrix} W \begin{bmatrix} \Delta X_{it}^{\ell} \Delta w_{it} \\ \Delta T_{nt}^{\ell} \Delta w_{nt}^{\ell} \end{bmatrix}, \tag{45}$$

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.

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 comparting counterfactuals with changes in the minimum wage against the initial equilibriums. I show that the effects are heterogeneous across cities. Two-thirds of the cities that are considering minimum wage increases would experience reductions in low-wage commuting. The average commuting elasticity among these cities is similar to the elasticity estimated in the reduced form, and there is a nonlinear effect of the minimum wage on low-wage commuting.

6.1 City level minimum wage policies

Figure 8 shows counties with cities that are considering minimum wage increases. There are 31 cities in 29 counties considering increases, which range from $8.75 to more than $15.00 an hour. Five of these cities are in commuting zones that span borders: Flagstaff, AZ, Louisville, KY, Los Angeles, Sacramento, and St. Louis.

Figure 9 shows the relationship between commuting and the minimum wage in the associated counties in 2012, the latest year in the sample. It illustrates that places with a

higher minimum wage tend to receive more commuters, as expected if they are attracted by the higher wages. This occurs even though places with a higher minimum wage tend to have lower shares of low-wage employment, as shown in figure E.6 of appendix E .

Figure 10 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 10 percent to 60 percent. Employment probabilities range from 70 percent to 90 percent. Low-wage commuting, as a share of low-wage employment, tends to be higher in places with high employment probabilities. Larger shares of low-wage employment are not necessarily associated with larger employment probabilities, since the latter depend on the number of job-seekers. In figure E.5 of appendix E , I show that in fact, counties with higher low-wage employment tend to have fewer low-wage commuters as share of employees. This shows the relevance of considering differences in search when examining commuting.

6.2   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. Counterfactual commuting and migration data are obtained for each commuting zone. I do this to obtain an operational definition of the closed city in the model. This disregards commuting and migration responses that may occur across commuting zones. There are 22 commuting zones in which one or more counties are considering increases in the minimum wage.[14]

Based on the gravity equation in section 5.4.1, I calculate estimates of epsilon for each of the commuting zones using the commuting data described in section 2. Unemployment data from the ACS are available only since 2005, so the sample runs from 2005 to 2012. One of the commuting zones, Washington, DC, includes the equivalent of only one county, so the estimates cannot be derived. Figure 11 shows the distribution of estimates across the remaining 21 commuting zones. These estimates range from 2.5 to 12.0. The lowest estimates correspond to the Kansas City commuting zone, while the largest estimate is associated with Lexington, KY. The estimate of Monte et al. (2016) is around 3.5 based on commuting data for all workers and the entire 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. Here, the gravity equation estimates for U.S. cities are in range of the latter estimates.

---

[14]Figure E.7 of appendix E shows these commuting zones, the counties they include, and the target minimum wage.

I also estimate ϵ through GMM for five of the commuting zones that span state borders and in which the minimum wage varies. Figure 12 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 types of labor, 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 of for the analysis across all the cities. Higher values imply larger wage effects.

6.3 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 San Francisco minimum wage proposal, corresponds to an increase of 15 percent. I report elasticities of employment, commuting, and migration to these minimum wage increases.

6.3.1 Search and employment

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 13 shows the elasticity of low-wage job searchers, O_{Mi}^{ℓ}, to the minimum wage increase. About half the cities experience increases in job searches; one city–Davis, CA–experienced large increases. The rest of the cities experience modest decreases in the number of job searchers, with elasticities below 1. 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.

Appendix figure E.8 shows that the places in which employment losses are largest experience the largest reductions in job searches, as expected in the model. All counties experience reductions in employment probability. Davis, CA, and Lexington, KY, experience large increases in job searches and large drops in employment probability. For most of the cities, the elasticity of the low-wage employment probability to the minimum wage is about -1.5. Figure E.9 of appendix E shows how employment probabilities change for

other types of labor. Because of substitution away from low-wage employment, these probabilities increase slightly.

6.3.2 Commuting and migration

After establishing that half the cities would experience higher job search rates, while the others would experience decreases in job search, and that this depends on the size of the employment effects, I focus on commuting and migration. The 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 14a shows estimated elasticities of low-wage commuting, which is calculated as total low-wage employment, minus low-wage employment among nonresidents. About two-thirds of counties would experience decreases in commuting, with an average elasticity of around -0.3. This is close to the elasticity estimated in the reduced form analysis. Twelve cities would experience commuting increases.

Figure 14b shows that low-wage workers would migrate away from most of the relevant counties. The average elasticity is similar to the commuting elasticity. This shows that more of the commuting losses are caused by low-wage workers moving to areas with an increased minimum wage. Migration does not explain the commuting losses, which arise instead because of employment losses and employment relocation.

The differences in the magnitude of the wage effects explain a great deal of the heterogeneity in commuting and migration responses. This is shown on figure 15 , 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 are larger, areas tend to experience increases in commuting. The relationship between ϵ and the migration elasticity is less clear, although areas with higher values of ϵ tend to exhibit positive migration elasticities.

6.3.3 Elasticities and the size of minimum wage increases

One of the concerns about upcoming minimum wage policies is that the proposed increases are larger than historical increases of the federal or state minimum wage. Jardim et al. (2017) argue that employment responses in Seattle 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 larger. Figure 16 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 23), commuting probabilities are a non-linear 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 12 imply smaller wage effects. This suggests that commuting elasticities would be more negative if these estimates for this subset of cities were used. 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.

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 the commuting responses can be explained by employment relocation.

To clarify the drivers behind these results and to 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. The counterfactual elasticity of commuting is similar to the elasticity estimated in the reduced form analysis. Several other channels (not analyzed here) may change this elasticity. Two important 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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Table 1: Effect on minimum wages on low wage commuting: Panel design.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Low Wage Commuters - 11 Km to Border					
Log MW Residence	0.77	-0.09	0.01	0.12	0.04	0.01
	(0.85)	(0.15)	(0.12)	(0.11)	(0.13)	(0.14)
Log MW Workplace	-1.43	-0.38***	-0.38***	-0.30***	-0.36***	-0.37***
	(0.87)	(0.12)	(0.09)	(0.10)	(0.12)	(0.14)
Adj R sq.	0.007	0.968	0.970	0.971	0.972	0.998
Within R sq.	0.008	0.007	0.053	0.109	0.135	0.055
N	6,775	6,768	6,205	6,205	6,205	6,205
Work counties	278	277	276	276	276	276
Res counties	313	310	310	310	310	310
Work, res effects		Yes	Yes	Yes	Yes	Yes
Year effects		Yes	Yes	Yes		
Controls			Yes	Yes	Yes	Yes
State trends				Yes	Yes	Yes
Census div x year effects					Yes	Yes
Work, res trends						Yes
Mean dep. var.	355.4	355.7	355.2	355.2	355.2	355.2

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

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Sample excludes residence-workplace pairs with average low wage commuting below 150 a year. Excludes AZ, AR, DC, KS, MA, NH. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work, county of residence and county pair level. Columns 2 to 6 include year effects and fixed effects at the workplace-residence county pair level. Columns 3 to 6 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. Columns 4 to 6 include linear time trends interacted with state of residence and state of workplace dummies. Column 5 and 6 includes census division dummies interacted with year dummies. Column 6 includes pair-specific linear time trends.

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

Log Low Wage Commuters - 11 Km to Border				
		Same Residence		
	(1)	(2)	(3)	(4)
Log MW - Workplace - Log MW Residence	-0.96	-0.56*	-0.58**	-0.32**
	(1.74)	(0.33)	(0.26)	(0.13)
Adj R sq.	0.001	0.154	0.147	0.897
Within R sq.	0.001	0.000	0.001	0.001
N	10,764	10,379	9,514	9,514
Work counties	391	369	369	369
Res counties	334	311	311	311
Res effects x Year effects		Yes	Yes	Yes
Work effects x Year effects				
Res Effects				
Work effects		Yes	Yes	Yes
Controls			Yes	Yes
State trends				Yes
Mean dep. var.		2927.3	2927.9	2950.8	2950.8

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

Sample excludes residence-workplace pairs with average low wage commuting below 150 a year. Excludes AZ, AR, DC, KS, MA, NH. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work and county of residence level. Columns 2 to 4 include residence-year effects and workplace effects. Columns 3 to 4 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. Column 4 includes linear time trends interacted with state of residence and state of workplace dummies.

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

Difference in low wage employment shares				
	(1)	(2)	(3)	(4)
	11 Km	11 Km	11 Km	66 Km
Log MW Residence	0.01	0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.01)
Log MW Workplace	-0.04*	-0.05***	-0.03**	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)
Adj R sq.	0.851	0.874	0.884	0.941
Within R sq.	0.031	0.134	0.218	0.225
N	4,070	3,382	3,382	3,805
Work counties	171	170	170	185
Res counties	191	185	185	194
Work, res effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes
State trends			Yes	Yes
Mean dep. var.	-0.01	-0.01	-0.01	-0.01

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

Back to main text.

Sample excludes residence-workplace pairs with average low wage commuting below 150 a year. Excludes AZ, AR, DC, KS, MA, NH. 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 include year effects and fixed effects at the workplace-residence county pair level. Columns 2 to 3 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. Column 3 includes linear time trends interacted with state of residence and state of workplace dummies.

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

Dependent variable: Difference in low wage resident shares

	(1)	(2)	(3)
	11 Km	11 Km	11 Km
Log MW Residence	0.00	0.02	0.08
	(0.13)	(0.09)	(0.08)
Log MW Workplace	-0.12	-0.06	-0.05
	(0.09)	(0.05)	(0.04)
Adj R sq.	0.761	0.808	0.900
Within R sq.	0.013	0.100	0.542
N	4,110	3,382	3,382
Work counties	171	170	170
Res counties	192	185	185
Work, res effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Controls		Yes	Yes
State trends			Yes
Mean dep. var.	0.01	0.01	0.01

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

Sample excludes residence-workplace pairs with average low wage commuting below 150 a year. Excludes AZ, AR, DC, KS, MA, NH. 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 include year effects and fixed effects at the workplace-residence county pair level. Columns 2 to 3 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. Column 3 includes linear time trends interacted with state of residence and state of workplace dummies.

Table 5: Effect on minimum wages on commuting: other wage categories.

	Log 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	0.01	-0.02	-0.18			
	(0.14)	(0.14)	(0.13)			
Log MW Workplace	-0.37***	-0.03	-0.11			
	(0.14)	(0.13)	(0.11)			
Log MW Difference				-0.32**	-0.38*	-0.21
				(0.13)	(0.22)	(0.29)
Adj R sq.	0.998	0.998	0.998	0.897	0.910	0.918
Within R sq.	0.055	0.074	0.107	0.001	0.001	0.001
N	6,205	6,142	6,109	9,514	9,552	9,475
Work counties	276	272	269	369	368	367
Res counties	310	305	303	311	311	310
Work effects				Yes	Yes	Yes
Res effects						
Work, res effects	Yes	Yes	Yes			
Year effects	Yes	Yes	Yes			
Res effects x Year effects				Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State trends	Yes	Yes	Yes	Yes	Yes	Yes
Census div x year effects	Yes	Yes	Yes			
Work, res trends	Yes	Yes	Yes			
Mean dep. var.	355.2	632.5	635.9	2950.8	2917.3	2919.1

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

Sample excludes residence-workplace pairs with average low wage commuting below 150 a year. Excludes AZ, AR, DC, KS, MA, NH. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work and county of residence level. Columns 1 to 6 include controls for total county population and population by age groups, lags of yearly state employment, gas prices, average percentage refund from state EITCs, average corporate tax rates, and linear time trends interacted with state of residence and state of workplace dummies . Columns 1 to 3 include year effects and fixed effects at the workplace-residence county pair level, census division dummies interacted with year dummies and pair-specific linear time trends. Columns 3 to 6 include residence-year effects and workplace effects.

Table 6: 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	$L^s, \epsilon, \beta, \sigma, \Omega^s, \eta, r^s, \xi^s$

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Table 7: Calibrated parameters

Parameter	Value	Source
β	0.4	Monte et al. (2016) 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 (Landais et al. forthcoming)
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 (Landais et al. forthcoming)

Figure 1: Included counties in sample
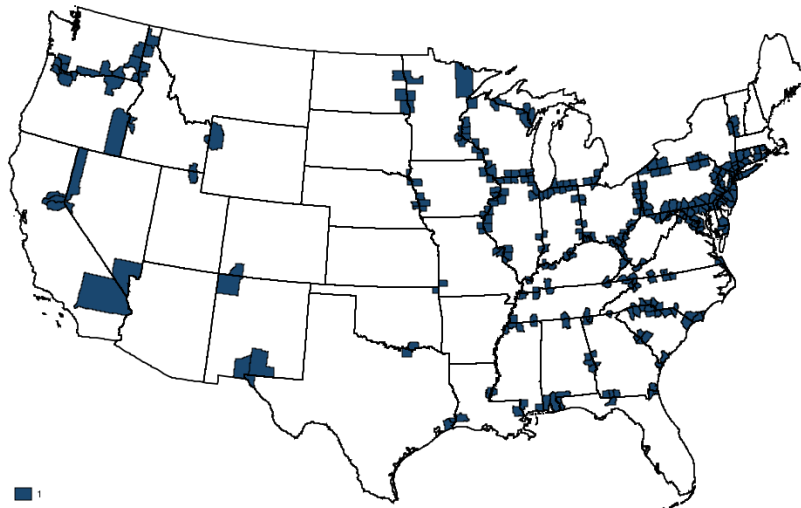
Highlighted counties are included in the reduced form analysis sample.

Figure 2: Difference in minimum wage between neighbor states
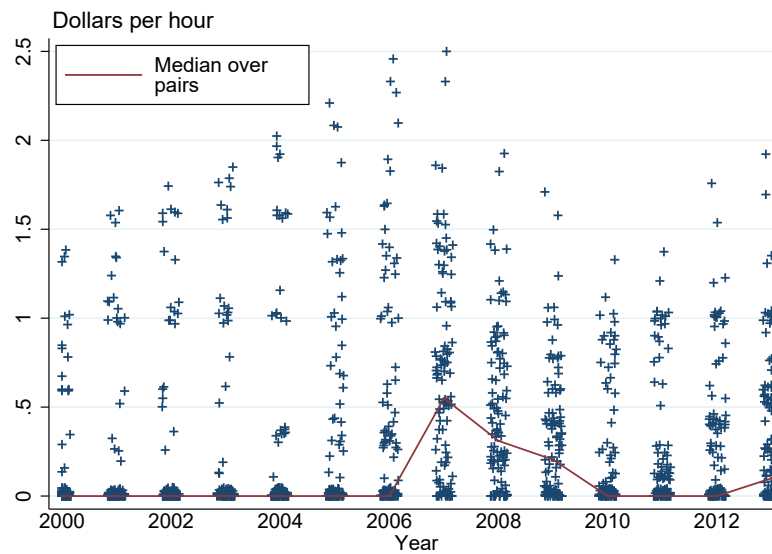
Source: Author's calculations based on data from Neumark et al. (2013). Points have been jittered to show that many state pairs have the same difference in minimum wages.

Figure 3: Empirical strategy

(a) Panel design

(b) Corner design

(c) Within design
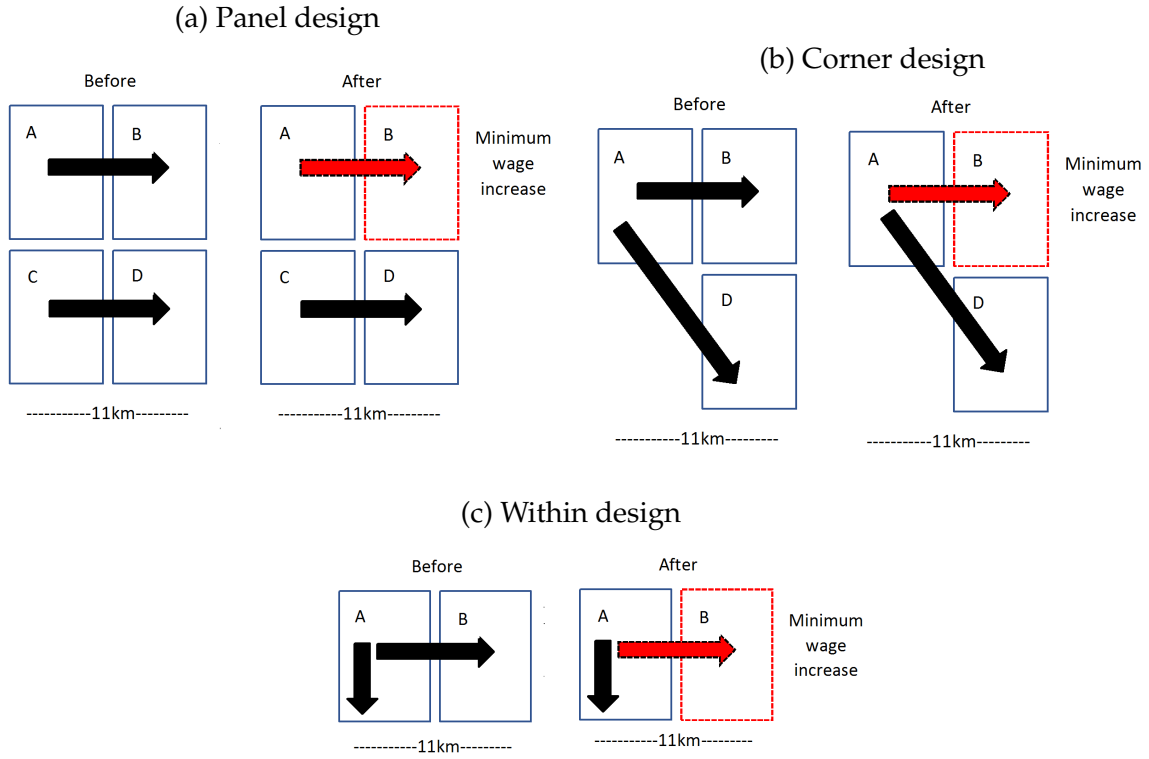
Back to main text.

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 "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.

Panel (c) 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.

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Figure 4: Preexisting trends in commuting regression
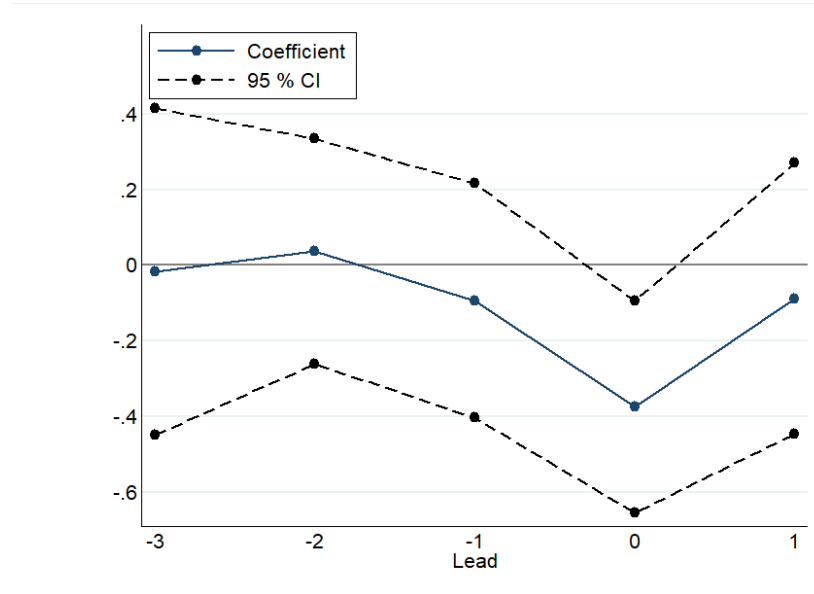
Source: Author's calculations. This graph depicts coefficients on three leads, one lag and the contemporaneous effect of the log minimum wage at the workplace variable from equation 1. The regression includes controls, state trends, census division times year effects, and pair-specific trends, as in column (6) of table 1.

Figure 5: Elasticities at different distances from the border
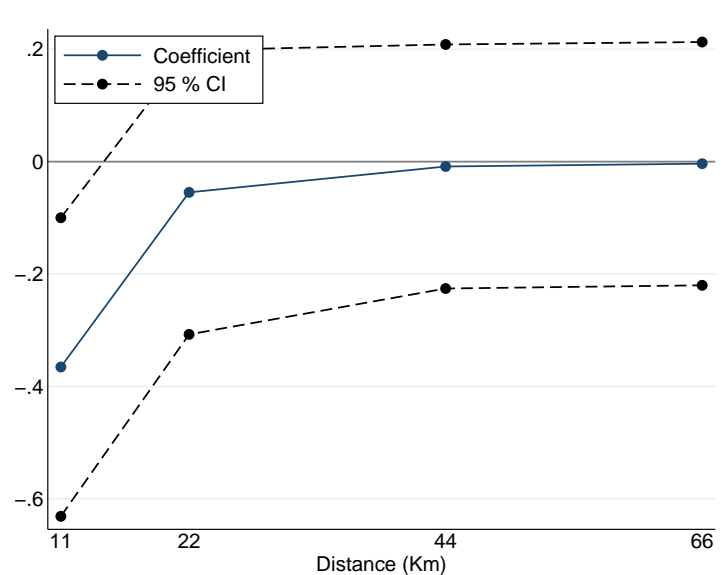
Source: Author's calculations. This graph depicts coefficients on the log minimum wage at the workplace variable from equation 1, using residence and workplace data at different distances from state borders. The regression includes controls, state trends, census division times year effects, and pair-specific trends, as in column (6) of table 1.

Figure 6: Labor market equilibrium for a model with two locations
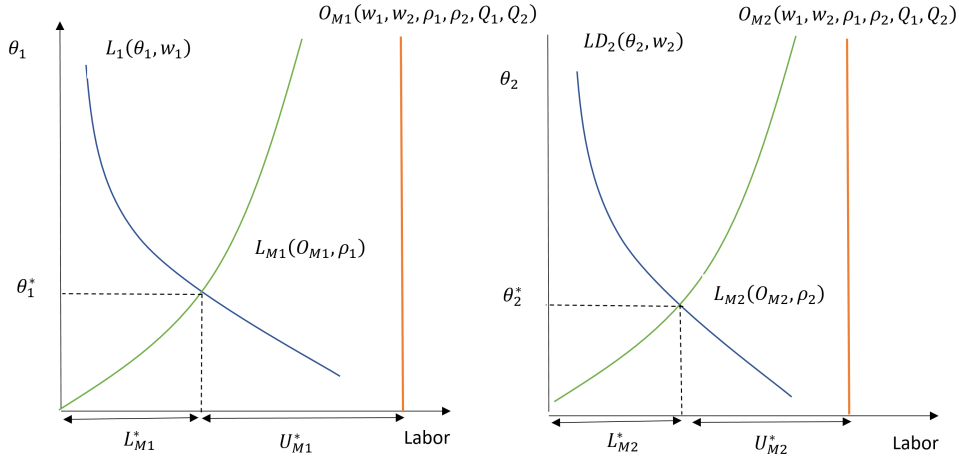
The figure depicts an equilibrium in labor markets for a model with two locations $i, n = 1, 2$ and a single labor type. O_{M1} and O_{M2} are the supply of searchers in each market, which depends on wages w_i, employment probabilities ρ_i and housing prices Q_n. L_{M1} and L_{M2} are labor supply curves that are upward sloping in market tightness θ_i since more workers are hired as tightness increases. L_1 and L_2 are labor demand functions which are decreasing in market tightness since higher tightness implies higher recruiting costs. L_{M1}^* and L_{M2}^* are equilibrium employment levels. U_{M1}^* and U_{M2}^* are equilibrium unemployment levels. θ_1^* and θ_2^* are equilibrium market tightness levels.

Figure 7: Changes in labor market equilibrium when the minimum wage increases in location 1

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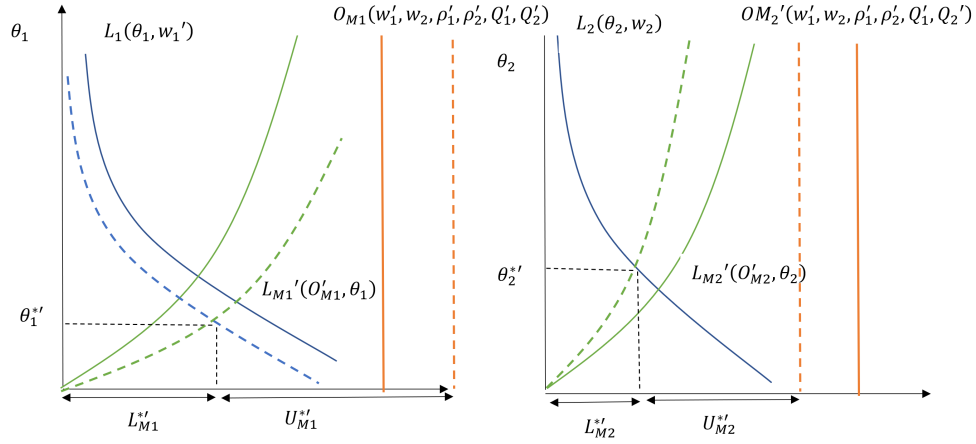
(b) Decrease in employment in location 1
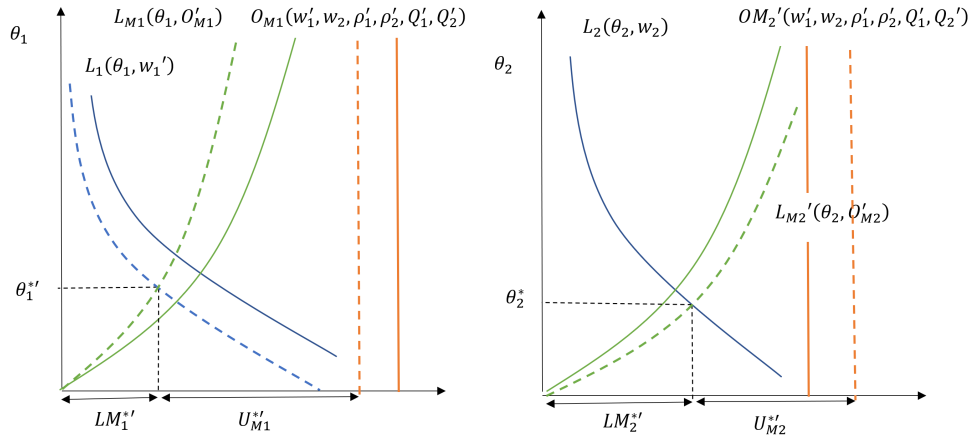
The figure depicts how equilibrium changes after a wage increase in a single market, for a model with two locations $i, n = 1, 2$ and a single labor type. Solid lines depict the initial equilibrium and dashed lines depict the new equilibrium. The wage increases in location 1 from w_1 to w_1'.

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.

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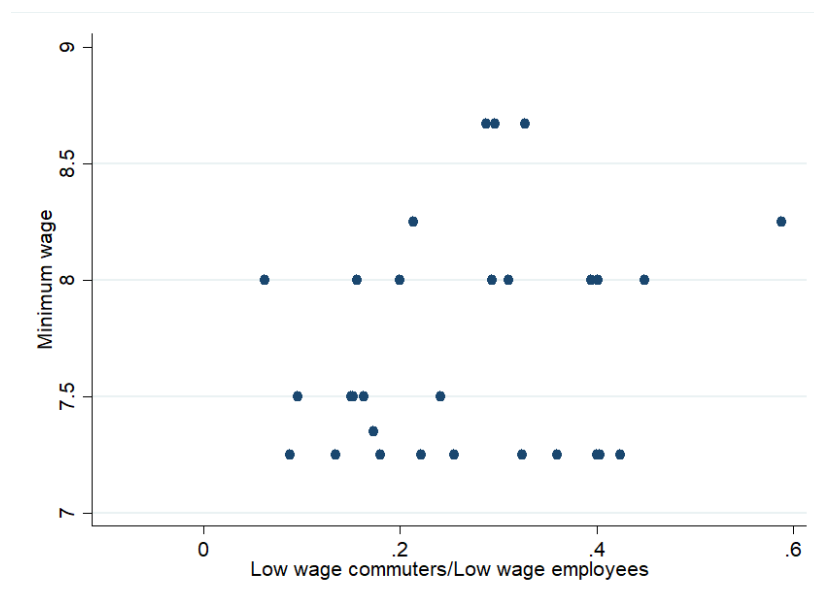
Figure 8: Counties for cities with proposed minimum wage increases
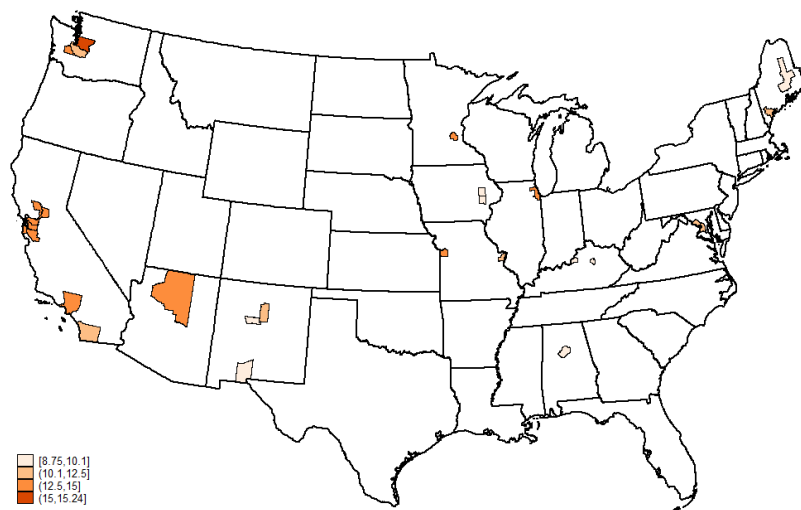
Source: Author's calculations based on National Employment Law Project (2016) The colors list the maximum minimum wage proposed. Target years for minimum wage increases differ across counties.
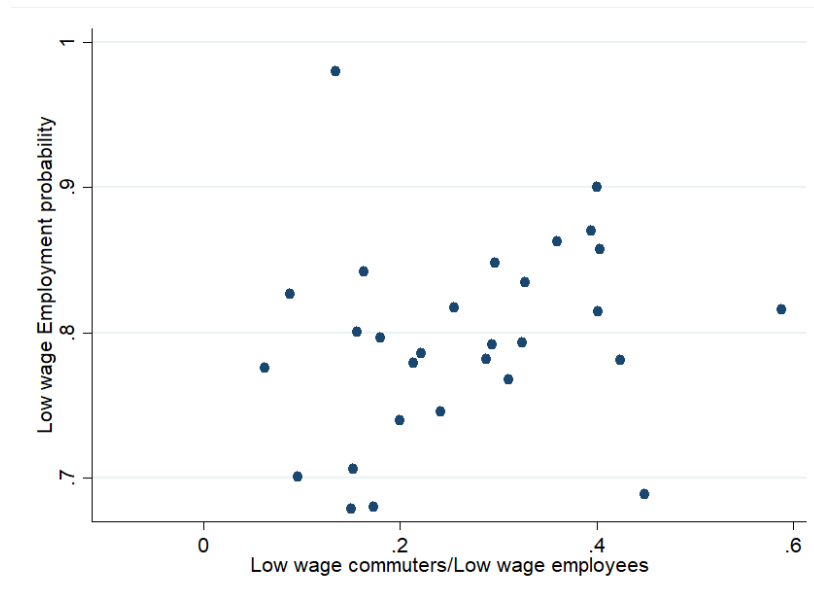
Figure 9: Low wage commuting and minimum wages. 2012.

Source: Author's calculations based on LODES. Counties that include cities with approved proposals for minimum wage increases.
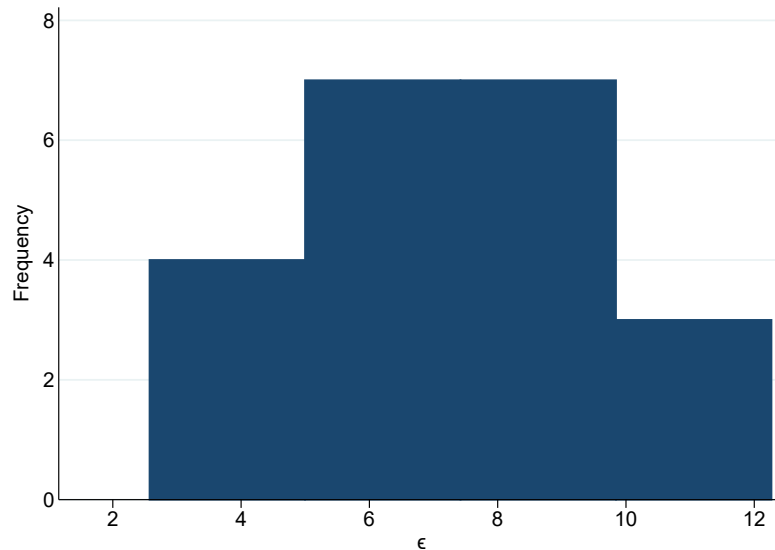
Figure 10: Low wage commuting and employment probabilities. 2012.

Source: Author's calculations based on LODES. Employment probabilities are calculated using unemployment data and the algorithm described in section D.1. Counties that include cities with approved proposals for minimum wage increases.
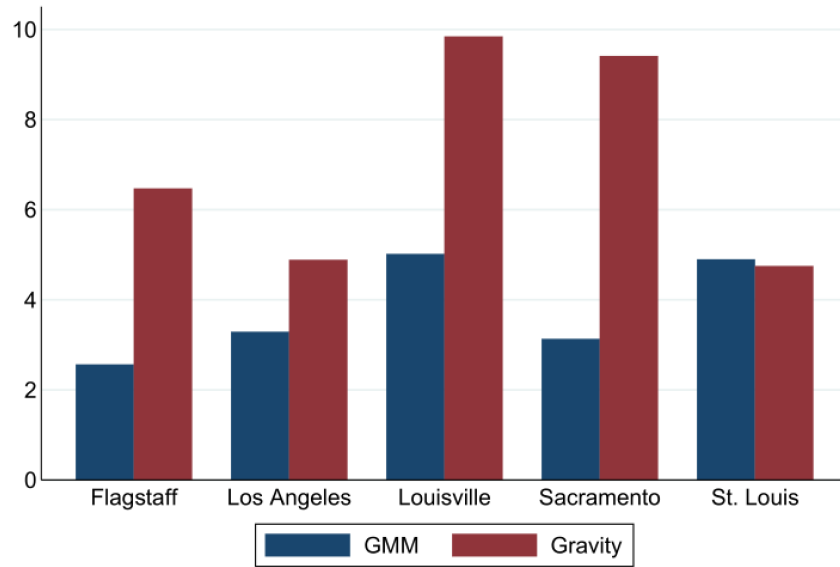
Figure 11: Distribution of estimated ϵ : Gravity equation

Source: Author's calculations. Observations are 21 commuting zones with cities considering minimum wage increases. Values of ϵ are estimates using equation (42) with commuting data from section 2. Sample goes from 2005 to 2012.

Figure 12: Estimates of ϵ for border cities.

Source: Author's calculations. Observations are 21 commuting zones with cities considering minimum wage increases. Gravity estimates of ϵ are estimated using equation (42) with commuting data from section 2. GMM estimates are estimated using the strategy in section 45. Sample goes from 2005 to 2012.
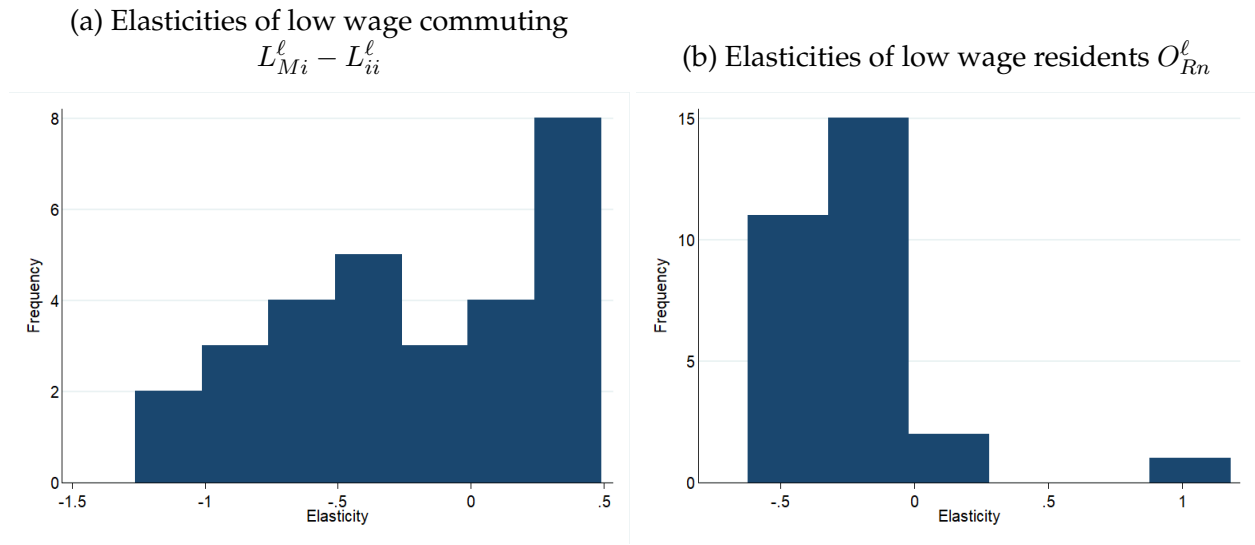
Figure 13: Elasticity of low wage searchers O^{ℓ}_{Mi}
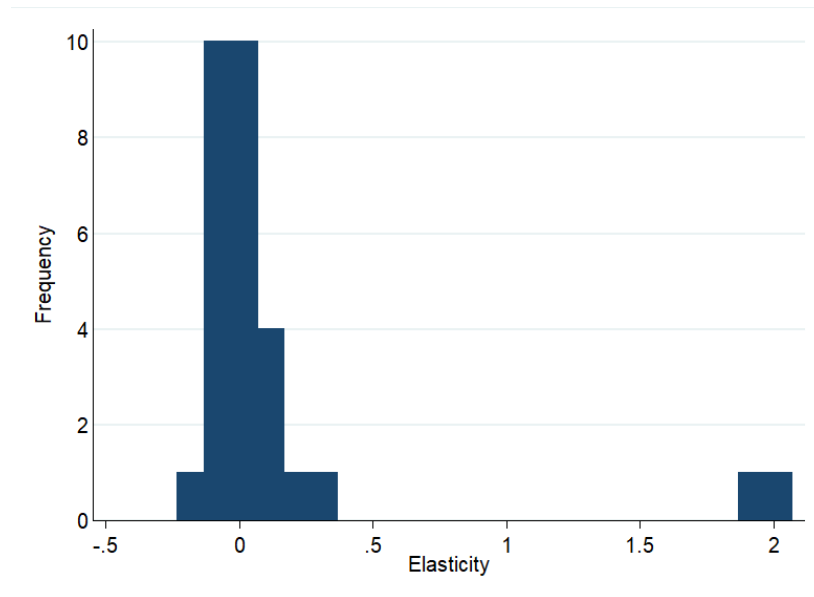
Source: Author's calculations. Observations are 29 counties considering minimum wage increases. Values are elasticities of the number of low wage searchers O^{ℓ}_{Mi} to an increase in the minimum wage, calculated from comparing an initial equilibrium to a model counterfactual with a minimum wage increase. In the counterfactuals, minimum wages were increased by 5 %.

Figure 14: Elasticities of commuting and migration to changes in the minimum wage
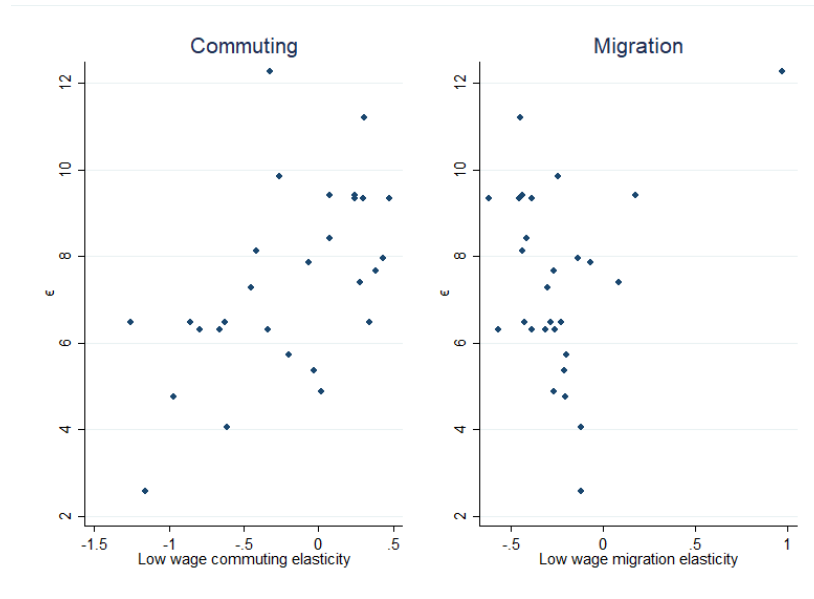
(a) Elasticities of low wage commuting
$$L^\ell_{Mi} - L^\ell_{ii}$$

(b) Elasticities of low wage residents O^ℓ_{Rn}

Source: Author's calculations. Observations are 29 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 5 %.

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

Panel (b) show elasticities of low wage residents O^ℓ_{Rn} to an increase in the minimum wage.
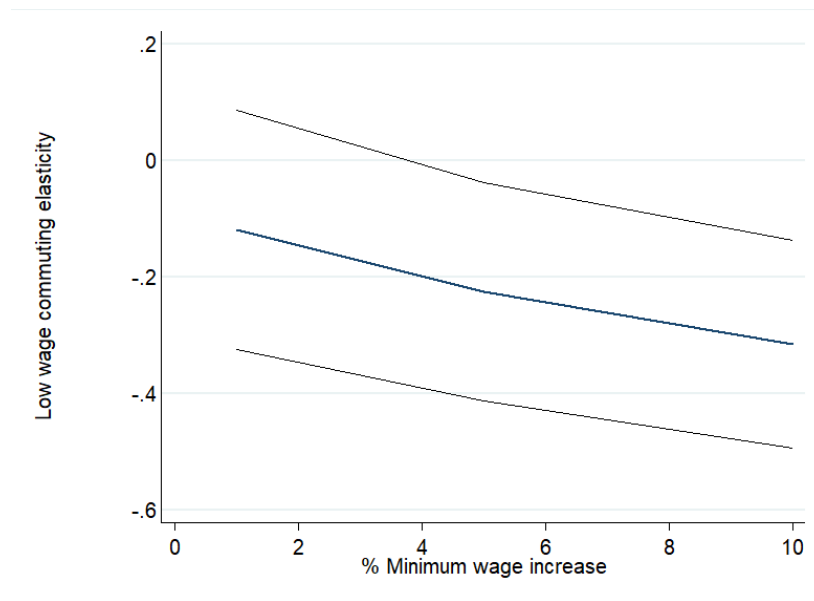
Figure 15: Low wage commuting and migration elasticities and value of ϵ

Source: Author's calculations. Observations are 29 counties considering minimum wage increases. The left panel shows values of the elasticity of low wage commuting $L^{\ell}_{Mi} - L^{\ell}_{ii}$ 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^{ℓ}_{Rn} 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 to the area that experiences the minimum wage increase. In the counterfactuals, minimum wages were increased by 5 %.

Figure 16: 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 that are considering minimum wage increases. The thick line shows the average elasticity across 29 counties. Thin lines are 95 % confidence intervals for the mean. 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 to the area that experiences the minimum wage increase.

Appendices

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 2005-2013. 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 2014. I combine information from the 2000-2010 estimates and 2010-2014 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 Algorithms for computing equilibria and counterfactuals

B.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 (18).

2. Compute searchers by residence and workplace $(O^s_{Mi})^t$ and $(O^s_{Ri})^t$ according to (19)

3. Compute equilibrium tightness and recruitment mark-ups with a fixed-point algorithm

   (a) Set the recruiting mark-up $(\tau^s(\theta^s_i))^t = 0$. Compute equilibrium values of θ^s_i using (29) and (13)

   (b) Update $(\tau^s(\theta^s_i))^t$ using (14)

   (c) Iterate until convergence in $(\tau^s(\theta^s_i))^t$. Obtain $(\theta^s_i))^t$

4. Compute equilibrium employment by workplace $(L_{Mi})^t$ using (29) and (13) given the equilibrium mark-ups.

5. Compute unemployment as $(U^s_{Mi})^t = (O^s_{Mi})^t - (L^s_{Mi})^t$

6. Compute employment by residence workplace pair $(l^s_{ni})^t$ using (23)

7. Update employment probabilities ρ^s_i using (30)

$$(\rho^s_i)^{t+1} = \frac{f^s\left((\theta^s_i)^t\right)}{\xi^s + f^s\left((\theta^s_i)^t\right)} \tag{B.1}$$

8. Calculate expected income $(v_n)^t$ using (28)

9. Update housing prices using (27)

$$(Q_n)^{t+1} = \frac{(1-\beta)\,(v_n)^t\,(L_{Rn})^t}{D_n} \tag{B.2}$$

10. Iterate until convergence in ρ^s_i and Q_n

B.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 $f(\theta^s_i))$ and the search probabilities o^s_{ni} 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^s_n, X^s_i, A^s_i and ρ^s_i using the algorithms of sections D.1, D.2, D.3 and D.4.

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

1. Find the change in employment probabilities using equation (30)

$$\left(\hat{\rho}_i^s \right)^t = \frac{\left(\hat{f}_i^s \right)^t \left(\xi^s + f_i^s \right)}{\xi^s + f_i^s \left(\hat{f}_i^s \right)^t} \tag{B.3}$$

2. Find the new number of searchers by workplace and residence using equation (19)

$$\left(o_{ni}^s \right)^t = o_{ni}^s \left(\hat{o}_{ni}^s \right)^t \tag{B.4}$$

$$\left(O_{Mi}^s \right)^t = \sum_n L^s \left(o_{ni}^s \right)^t \tag{B.5}$$

$$\left(O_{Rn}^s \right)^t = \sum_i L^s \left(o_{ni}^s \right)^t \tag{B.6}$$

3. Find counterfactual changes in expected wages using equation (6)

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

4. Find counterfactual changes in expected income using equation (28)

$$\left(\hat{v}_n^s \right)^t = \frac{1}{v_n^s} \sum_i \frac{o_{ni}^s \left(1 + \rho_i^s \kappa_{ni} \right)^\epsilon \left[1 + \rho_i^s \left(\hat{\rho}_i^s \right)^t \kappa_{ni} \right]^{-\epsilon} \hat{T}_n^s \hat{X}_i^s \left(\hat{\tilde{w}}_{ni}^s \right)^t}{\sum_b o_{ab}^s \left(1 + \rho_b^s \kappa_{nb} \right)^\epsilon \left[1 + \rho_b^s \left(\hat{\rho}_b^s \right)^t \kappa_{nb} \right]^{-\epsilon} \hat{T}_n^s \hat{X}_b^s \left(\hat{\tilde{w}}_{nb}^s \right)^t} \tilde{w}_{ni}^s \left(\hat{\tilde{w}}_{ni}^s \right)^t \tag{B.8}$$

$$\left(\hat{v}_n \right)^t = \frac{1}{v_n} \sum_s \frac{\left(O_{Rn}^s \right)^t}{O_{Rn}^s} \hat{v}_n^s \tag{B.9}$$

5. Find counterfactual changes in housing prices using equation (27)

$$\left(\hat{Q}_n \right)^t = \left(\hat{v}_n \right)^t \frac{\sum_s \left(O_{Rn}^s \right)^t}{\sum_s O_{Rn}^s} \tag{B.10}$$

6. Compute new changes in search probabilities using (18)

$$
\left(\hat{o}_{ni}^s\right)^{t'} = \frac{(1 + \rho_i^s \kappa_{ni})^\epsilon \left[1 + \rho_i^s \left(\hat{\rho}_i^s\right)^t \kappa_{ni}\right] \left[\left(\hat{Q}_n\right)^t\right]^{-\epsilon(1-\beta)} \hat{T}_n^s \hat{X}_i^s \left[\left(\hat{\tilde{w}}_{ni}^s\right)^t\right]^{-\epsilon}}{\sum_a \sum_b (1 + \rho_b^s \kappa_{ab})^\epsilon \left[1 + \rho_b^s \left(\hat{\rho}_b^s\right)^t \kappa_{ab}\right] \left[\left(\hat{Q}_a\right)^t\right]^{-\epsilon(1-\beta)} \hat{T}_a^s \hat{X}_b^s \left[\left(\hat{\tilde{w}}_{ab}^s\right)^t\right]^{-\epsilon}}
$$
(B.11)

7. Compute new searchers by workplace using (19)

$$
\left(O_{Mi}^s\right)^{t+1} = \sum_n L^s o_{ni}^s \left(\hat{o}_{ni}^s\right)^{t+1}
$$
(B.12)

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 (29) 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

$$
\left(\hat{f}_i^s\right)^{t'} = \frac{f_i^s \xi^s \left(LM_i^s\right)^t}{\left(O_{Mi}^s\right)^{t+1} - \left(LM_i^s\right)^t}
$$
(B.13)

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

$$
\begin{aligned}
\left(\hat{o}_{ni}^s\right)^{t+1} &= \zeta \left(\hat{o}_{ni}^s\right)^{t'} + (1-\zeta) \left(\hat{o}_{ni}^s\right)^t & \text{(B.14)} \\
\left(\hat{f}_i^s\right)^{t+1} &= \zeta \left(\hat{f}_i^s\right)^{t'} + (1-\zeta) \left(\hat{f}_i^s\right)^t & \text{(B.15)}
\end{aligned}
$$

11. Iterate until convergence

C Computing elasticities

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

I consider two types of elasticities, following Monte et al. (2016). 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 (23), the elasticity of commuting to a minimum wage change is

$$\varepsilon_{w_i^\ell}^{l_{ni}^\ell} = \varepsilon_{w_i^\ell}^{\rho_i^\ell} + \varepsilon_{w_i^\ell}^{o_{ni}^\ell} \tag{C.1}$$

The first term $\eta_{w_i^\ell}^{\rho_i^\ell}$ summarizes how the employment probability changes as the minimum wage changes. The second term summarizes how the search probability $\eta_{w_i^\ell}^{o_{ni}^\ell}$ 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 (18), the elasticity of the residence-search probability o_{ni}^s to changes in the minimum wage in area j, w_j^ℓ is

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

To solve for $\varepsilon_{w_j^\ell}^{\psi_{ni}^s}$, take logs of 17 and differentiate to get

$$\ln\left(\psi_{ni}^s\right) = \ln\left(T_n^s\right) + \ln\left(X_i^s\right) - \epsilon \ln\left(1 + \rho_i^s \kappa_{ni}\right) - \epsilon\left(1-\beta\right)\ln\left(Q_n\right) + \epsilon\ln\left(\rho_i^s w_i^\ell + \left(1-\rho_i^s\right)R_n\right)$$

$$\varepsilon_{w_j^\ell}^{\psi_{ni}^s} = -\frac{\epsilon}{1+\rho_i^s\kappa_{ni}}\left(\frac{d\rho_i^s}{d\ln\left(w_j^\ell\right)}\kappa_{ni}\right) - \epsilon\left(1-\beta\right)\varepsilon_{w_j^\ell}^{Q_n}$$

$$+\frac{\epsilon}{\rho_i^s w_i^\ell + \left(1-\rho_i^s\right)R_n}\left(\frac{d\rho_i^s}{d\ln\left(w_j^\ell\right)}w_i^s + \rho_i\frac{dw_i^s}{d\ln\left(w_j^\ell\right)} - \frac{d\rho_i^s}{d\ln\left(w_j^\ell\right)}R_n\right)$$

$$= -\frac{\epsilon}{1+\rho_i^s\kappa_{ni}}\left(\varepsilon_{w_j^\ell}^{\rho_i^s}\rho_i^s\kappa_{ni}\right) - \epsilon\left(1-\beta\right)\varepsilon_{w_j^\ell}^{Q_n}$$

$$+\frac{\epsilon}{\rho_i^s w_i^s + \left(1-\rho_i^s\right)R_n}\left(\varepsilon_{w_j^\ell}^{\rho_i^s}\rho_i^s w_i^s + \rho_i^s w_i\varepsilon_{w_j^\ell}^{w_i^s} - \rho_i^s\varepsilon_{w_j^\ell}^{\rho_i^s}R_n\right)$$

$$= \varepsilon_{w_j^\ell}^{\rho_i^s}\left[\frac{\epsilon\rho_i^s\left(w_i^s - R_n\right)}{\tilde{w}_{ni}^s} - \frac{\epsilon\rho_i^s\kappa_{ni}}{1+\rho_i^s\kappa_{ni}}\right] + \frac{\epsilon\rho_i^s w_i\varepsilon_{w_j^\ell}^{w_i^s}}{\tilde{w}_{ni}^s} - \epsilon\left(1-\beta\right)\varepsilon_{w_j^\ell}^{Q_n} \tag{C.3}$$

Define

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

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

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

Plugging in the previous expression and simplifying

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

$$-\sum_{a,b}o_{ab}^s\left\{\varepsilon_{w_j^\ell}^{\rho_b^s}\left[\theta_{ab}^s - \left(1-\theta_{ab}^s\right) - \frac{1}{\tilde{w}_{ab}^s} - \kappa_{ab}^s\right] + \theta_{ab}^s\varepsilon_{w_j^\ell}^{w_b^s} - \left(1-\beta\right)\varepsilon_{w_j^\ell}^{Q_a}\right\} \tag{C.6}$$

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 $\eta_{w_i^s}^{l_{ni}^\ell}$. The partial equilibrium elasticity of commuting to the minimum wage is an analog of the general equilibrium elasticity:

$$\eta_{w_i^\ell}^{l_{ni}^\ell} = \eta_{w_i^\ell}^{\rho_i^\ell} + \eta_{w_i^\ell}^{o_{ni}^\ell} \tag{C.7}$$

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:

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

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

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

Replacing $s = \ell$ for low skilled labor yields equation (34) 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.

D Computing unobserved location-specific parameters

D.1 Computing search and employment probabilities

We observe data on employment by workplace l^s_{Mi} and unemployment by workplace UR^s_n. Unemployment at the workplace level U^s_{Mi} 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

$$U^s_{Rn} = \sum_b \frac{L^s_{nb}}{L^s_{Mb}} U^s_{Mb} \tag{D.1}$$

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

$$O^s_{Mi} = U^s_{Mi} + L^s_{Mi} \tag{D.2}$$

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

$$O^s_{ni} = \frac{L^s_{ni} O^s_{Mi}}{L^s_{Mi}} \tag{D.3}$$

From these we can obtain residents as:

$$O^s_{Rn} = \sum_b O^s_{nb} \tag{D.4}$$

Search probabilities are then

$$o^s_{ni} = \frac{O^s_{ni}}{\sum_a \sum_b O^s_{ab}} \tag{D.5}$$

And employment probabilities are

$$\rho^s_i = \frac{O^s_{Mi}}{L^s_{Mi}} \tag{D.6}$$

D.2 Computing workplace productivities

Given data on residents per residence location O^s_{Rn}, searchers per workplace O^s_{Mi}, wages w^s_i, employment probabilities ρ^s_i , unemployment benefits R^s_n, a dispersion parameter ϵ and commuting costs κ_{ni}, there is a unique (up to a normalization) vector of search costs X^s_i consistent with the data being an equilibrium of the model. From the commuting

equilibrium

$$O^s_{Mi} = \sum_a o_{ai|a} O_{Ra}$$

$$= \sum_a \frac{X^s_i \left(1 + \rho^s_i \kappa_{ni}\right)^{-\epsilon} \tilde{w}^\epsilon_{ni}}{\sum_b X^s_b \left(1 + \rho^s_b \kappa_{nb}\right)^{-\epsilon} \tilde{w}^\epsilon_{nb}} O^s_{Rn} \tag{D.7}$$

Where $\tilde{w}^s_{ni} = \rho^s_i w_i + (1 - \rho^s_i) R^s_n$. From Lemmas S.6. and S.7 of Ahlfeldt et al. (2015), this system has a unique solution for X^s_i, up to a normalization,

D.3 Computing residential amenities

Given productivities X^s_i, data on residents per location O^s_{Rn}, wages w^s_i, employment probabilities ρ^s_i, unemployment benefits R^s_n; and a dispersion parameter ϵ, there is a unique (up to a normalization) vector of amenities T^s_n that is consistent with the data being an equilibrium of the model. From (19) and (17)

$$o^s_{Rn} = \frac{T^s_n \left(Q^{1-\beta}_n\right)^{-\epsilon} \sum_b X^s_b \tilde{w}^\epsilon_{ns} \left(1 + \rho^s_b \kappa_{ns}\right)^{-\epsilon}}{\psi}$$

$$\frac{(T^s_n)^{\frac{1}{\epsilon}} Q^{-(1-\beta)}_n}{\psi} = \frac{(o^s_{Rn})^{\frac{1}{\epsilon}}}{\left(\sum_b X^s_b \tilde{w}^\epsilon_{ns} \left(1 + \rho^s_b \kappa_{ns}\right)^{-\epsilon}\right)^{\frac{1}{\epsilon}}} \tag{D.8}$$

So T^s_n can be identified up to a normalization by psi^s and housing prices Q_n. Using (27), housing prices can be identified using data on land D_n and expected income v_n, which can be calculated using equation (28). This allows us to identify T^s_n up to a normalization.

D.4 Computing productivities

From the first order conditions of the firm

$$Y^{1/\sigma_1 - 1} \left(L^s_{Mi}\right)^{\sigma-1} = w^s_i \left(1 + \tau^s_i(\theta^s_i)\right), \quad s = \ell, m, h \tag{D.9}$$

Given values of σ, $\tau^s(\theta^s_i)$ and observed values of L^s_{Mi}, this system can be solved for unique values of A^s_i. To obtain $\tau^s(\theta^s_i)$, 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 (30) as

$$f^s_i = \frac{\xi^s L^s_{Mi}}{U^s_{Mi}} \tag{D.10}$$

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

$$\theta_i^s = \left(\frac{f_i^s}{\Omega^s} \right)^{\frac{1}{1-\eta}}$$

$$q\left(\theta_i^s\right) = \Omega^s \left(\theta_i^s\right)^{-\eta} \tag{D.11}$$

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

E   Additional figures and tables

Table E.1: States and years where minimum wage workers would fall in middle wage category of LODES data

State	Since year	Average monthly wage
California	2008	1280
Connecticut	2010	1320
Illinois	2009	1304
Nevada	2010	1306
Ohio	2013	1256
Oregon	2008	1360
Vermont	2009	1322
Washington	2007	1371

Source: Author's calculations from minimum wage data on Neumark et al. (2013). Calculations are made assuming 40 hours worked per week.

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

	Same Workplace			
	(1)	(2)	(3)	(4)
Log MW - Workplace - Log MW Residence	-0.95	-0.21	-0.20	-0.19
	(1.78)	(0.34)	(0.28)	(0.18)
Adj R sq.	0.001	0.221	0.214	0.902
Within R sq.	0.001	0.000	0.000	0.000
N	10,385	10,013	9,180	9,180
Work counties	302	278	278	278
Res counties	392	369	369	369
Res effects x Year effects		Yes	Yes	Yes
Work effects x Year effects				
Res Effects				
Work effects		Yes	Yes	Yes
Controls			Yes	Yes
State trends				Yes
Mean dep. var.	3127.5	3024.9	3050.0	3050.0

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

Sample excludes residence-workplace pairs with average low wage commuting below 150 a year. Excludes AZ, AR, DC, KS, MA, NH. Columns 2 to 5 include year effects and fixed effects at the workplace-residence county pair level. Columns 3 to 6 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. Columns 4 to 6 includes linear time trends interacted with state of residence and state of workplace dummies. Column 5 and 6 includes census division dummies interacted with year dummies. Coulmn 6 includes pair specific linear time trends. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work and county of residence level.
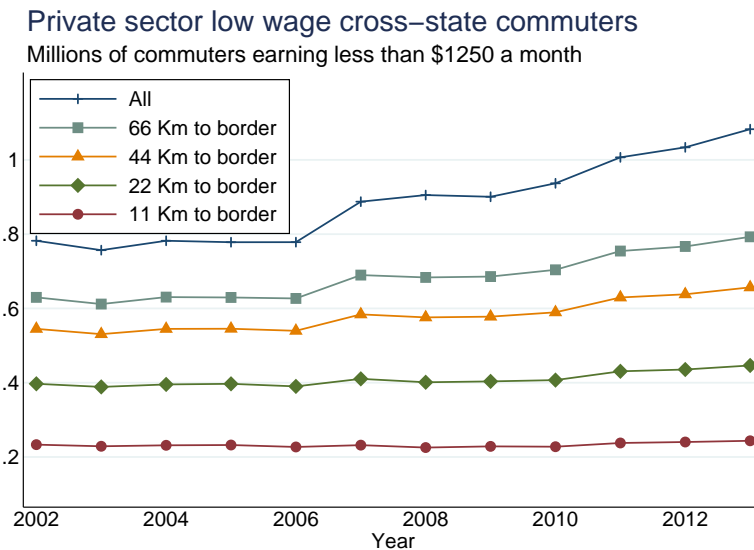
Table E.3: Effect on minimum wages on low wage commuting: Corner design.

| | Log Low Wage Commuters - 11 Km to Border | | | | | |
| | Same Residence | | | Same Workplace | | |
	(1)	(2)	(3)	(4)	(5)	(6)
Log MW Workplace -	0.16	-1.12*	-0.92**	-0.40	-0.65	-0.35
Log MW Residence	(1.41)	(0.61)	(0.34)	(1.31)	(0.53)	(0.24)
Adj R sq.	-0.001	0.845	0.842	-0.000	0.847	0.818
Within R sq.	0.000	0.001	0.004	0.000	0.001	0.003
N	1,444	1,172	1,074	1,713	1,480	958
Work counties	53	41	41	44	24	20
Res counties	42	18	18	75	64	29
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.	395.5	434.7	431.5	401.1	426.7	400.2

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

Sample excludes residence-workplace pairs with average low wage commuting below 150 a year. Excludes AZ, AR, DC, KS, MA, NH. Columns 2 to 5 include year effects and fixed effects at the workplace-residence county pair level. Columns 3 to 6 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. Columns 4 to 6 includes linear time trends interacted with state of residence and state of workplace dummies. Column 5 and 6 includes census division dummies interacted with year dummies. Coulmn 6 includes pair specific linear time trends. Robust standard errors, in parentheses, are calculated with multidimensional clustering at border segment, county of work and county of residence level.

Figure E.1

Private sector low wage cross–state commuters
Millions of commuters earning less than $1250 a month

Legend:
- All
- 66 Km to border
- 44 Km to border
- 22 Km to border
- 11 Km to border

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

Figure E.2
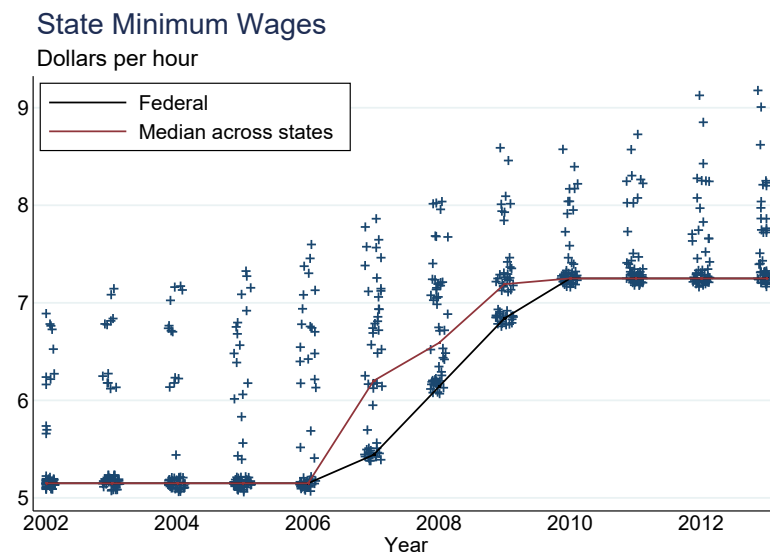
State Minimum Wages
Dollars per hour

Legend:
- Federal
- Median across states

Source: Author's calculations based on data from Neumark et al. (2013). Points have been jittered to show that many states have the same minimum wage.

Figure E.3: Included counties by yearly sent cross border commuting
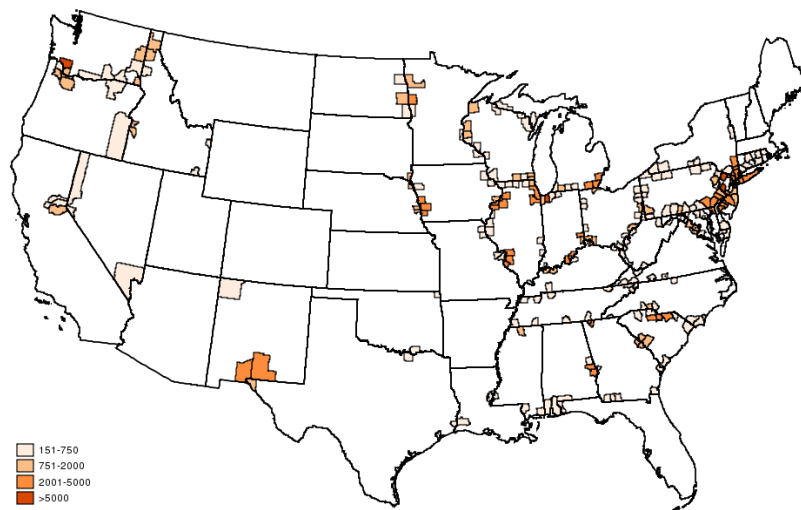

151-750
751-2000
2001-5000
>5000

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 E.4: Included counties by yearly received cross border commuting
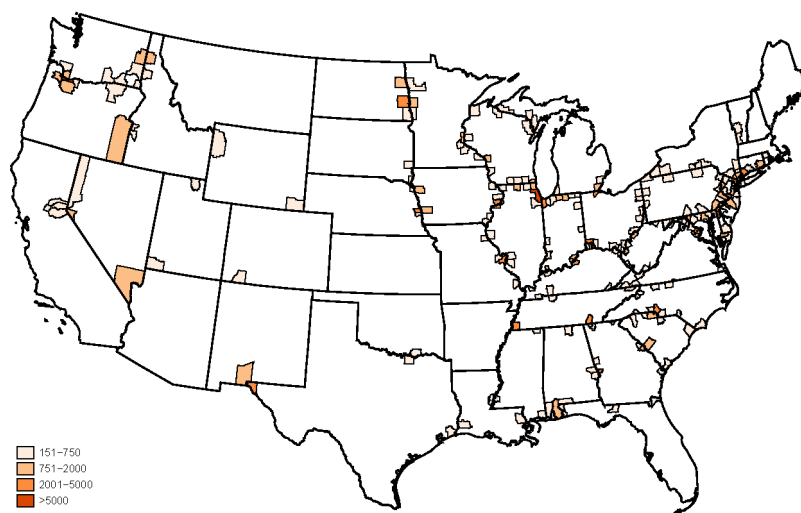
151–750
751–2000
2001–5000
>5000

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 E.5: Low wage commuting and employment, 2012.
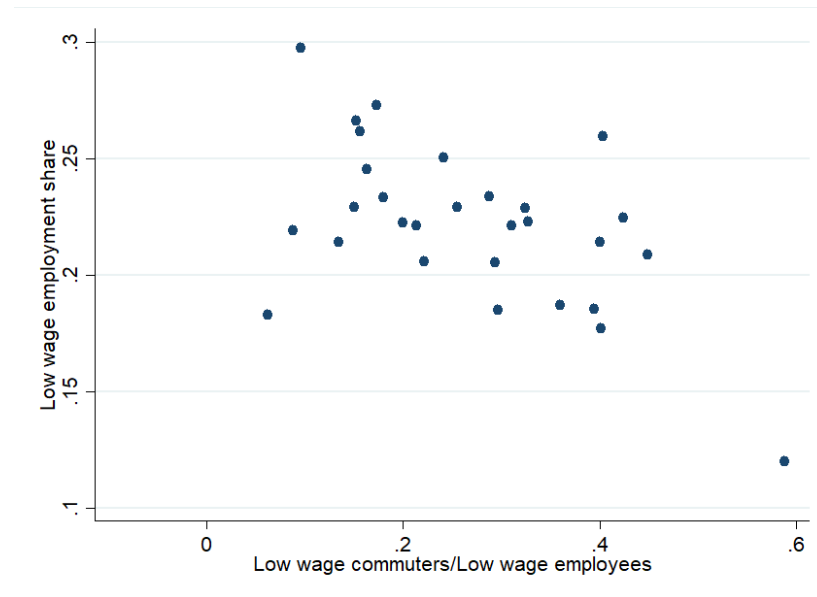
Source: Author's calculations based on LODES. Counties that include cities with approved proposals for minimum wage increases.

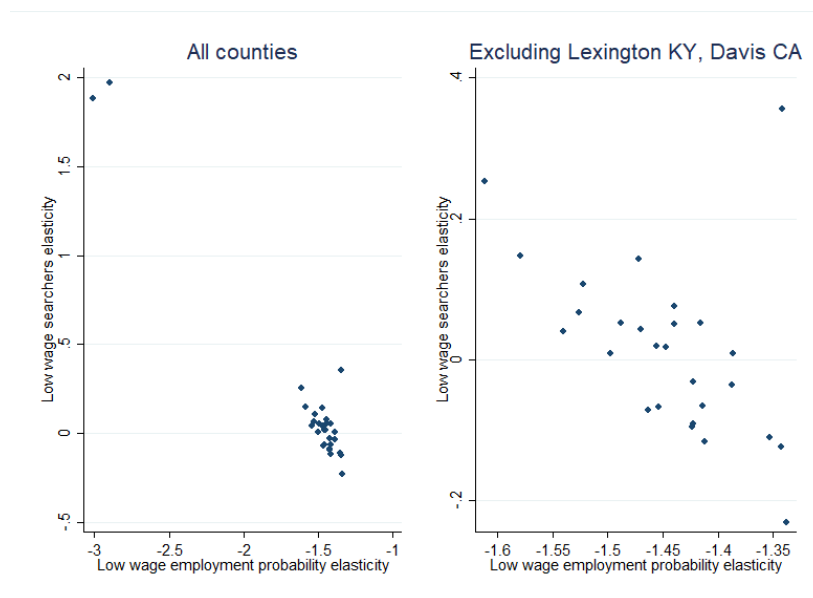Figure E.6: Low wage employment and minimum wages. 2012.
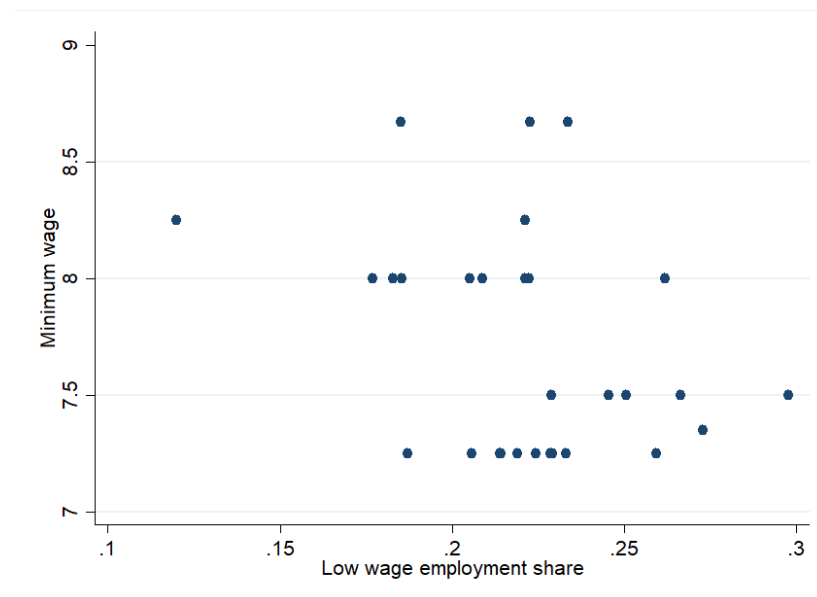
Source: Author's calculations based on LODES. Counties that include cities with approved proposals for minimum wage increases.

Figure E.7: Commuting zones for cities with proposed minimum wage increases
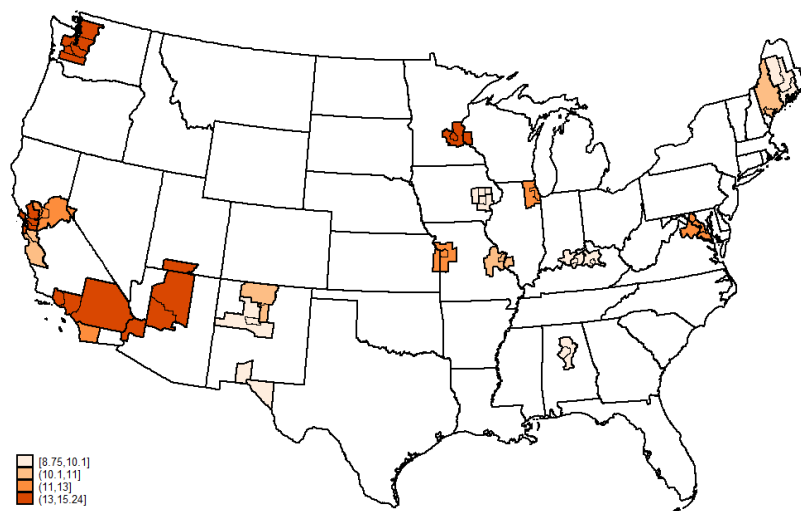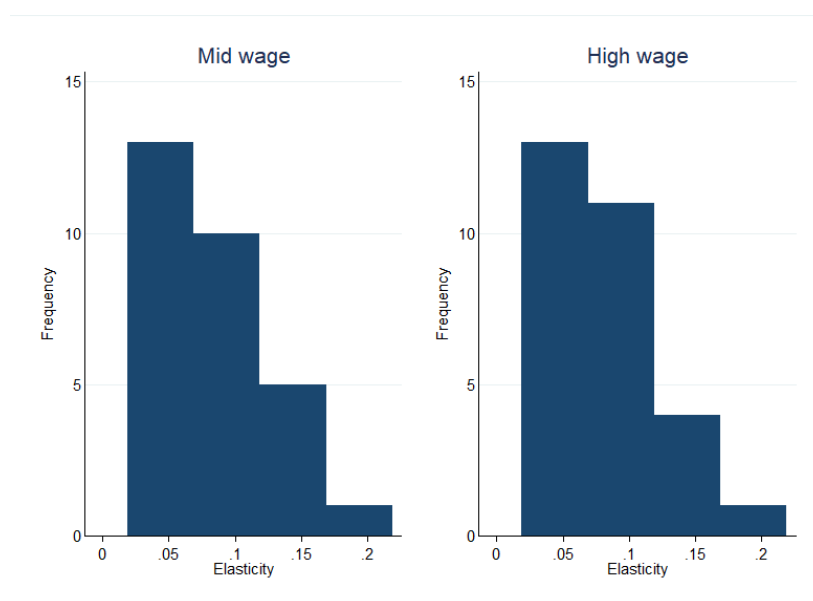

Source: Author's calculations based on National Employment Law Project (2016) The colors list the maximum minimum wage proposed. Target years for minimum wage increases differ across commuting zones. Thick borders denote commuting zones. Thin borders denote counties.

Figure E.8: Elasticities of low wage searchers O^ℓ_{Mi} and low wage employment probability ρ^ℓ_i

Source: Author's calculations. Observations are 29 counties considering minimum wage increases. Values are elasticities of low wage employment probabilities ρ^ℓ and low wage searchers O^ℓ_{Mi} to an increase in the minimum wage, calculated from comparing an initial equilibrium to a model counterfactual with a minimum wage increase. Panel on the left includes all counties. Panel on the right excludes Lexington, KY (Fayette county) and Davis, CA (Yolo county). In the counterfactuals, minimum wages were increased by 5 %.

Figure E.9: Elasticity of mid and high wage employment probabilities ρ_i^m and ρ_i^h

Source: Author's calculations. Observations are 29 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 %.