Distributional Effects of Local Minimum Wages: A Spatial Job Search Approach*

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Abstract

This paper develops and estimates a spatial general equilibrium job search model to study the effects of local and universal (federal) minimum wage policies on employment, wages, job postings, vacancies, migration/commuting, and welfare. In the model, workers, who differ in terms of location and education levels, search for jobs locally and in a neighboring area. If they receive remote offers, they decide whether to migrate or commute. Firms post vacancies in multiple locations and make offers subject to minimum wage constraints. The model is estimated using multiple databases, including the American Community Survey (ACS) and Quarterly Workforce Indicators (QWI), and exploiting minimum wage variation across state borders as well as time series variation (2005-2015). Results show that local minimum wage increases lead firms to post fewer wage offers in both local and neighboring areas and lead lower education workers to reduce interstate commuting. An out-of-sample validation finds that model forecasts of commuting responses to city minimum wage hikes are similar to patterns in the data. A welfare analysis shows how minimum wage effects vary by worker type and with the minimum wage level. Low skill workers benefit from local wage increases up to \$10.75/hour and high skill workers up to \$12.25/hour. The greatest per capital welfare gain (including both workers and firms) is achieved by a universal minimum wage increase of \$12.75/hour.

Keywords: spatial equilibrium, minimum wage, labor relocation, commuting
JEL Code: J61, J63, J64, J68; R12, R13.

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1 Introduction

Over 40 cities passed their own minimum wage ordinances since 2010. In 22 of these cities, the minimum wage is set at $15 per hour or higher, which is above the range of historical data.[1] These city-level minimum wages may have different impacts from the federal and state minimum wages that are the focus of the extensive minimum wage literature. First, the coverage rate of the working population greatly expands when the minimum wage is raised to $15 per hour. According to the 2017-2019 American Community Survey (ACS), about 50% of non-college workers and 25% of college workers earn less than $15 per hour.[2] Second, with local minimum wage ordinances, there may be incentives for workers to move across areas to arbitrage geographic wage differences. Some recent studies show that increases in local minimum wages induce substantial changes in the cross-border labor mobility. (e.g. Monras (2019); McKinnish (2017); Pérez (2022)) In addition, firms may respond to higher minimum wages by adjusting their hiring strategies to stay profitable, which may benefit some workers but adversely affect others (Horton, 2017).

As emphasized in the work of Robert Moffitt, public policies, such as tax policies, welfare programs, and minimum wage laws, often alter workers' labor supply incentives. Moffit used structural frameworks to investigate the heterogeneous effects of both existing and hypothetical programs on welfare and inequality.[3] This paper studies the distributional and welfare effects of local and universal (federal) minimum wage policies accounting for worker heterogeneity, mobility, firms' demand for workers, and considering minimum wages of varying magnitudes. To do so, we develop and estimate a spatial general equilibrium job search model that builds on a model of Flinn (2006), extending it to a spatial context. The economy consists of two adjacent regions, similar to the cross-border contiguous county pairs considered in Dube et al. (2016). Workers are differentiated by their skill levels (college educated or non-college educated) and locations. They receive job offers from local firms and neighboring county firms. Workers accept a local offer if its value exceeds the value of unemployment. When considering neighboring offers, they require extra compensation to offset migration/commuting costs.

Our job search model follows the Diamond-Mortensen-Pissarides framework (Pissarides, 2000; Mortensen, 2005), also extending it to a spatial general equilibrium setting. Firms choose both the number of vacancies and where to post the vacancies, either locally or in the neighboring area. Firms post vacancies until the

[1] These cities include San Francisco, Seattle, Los Angeles, and Washington, DC. A full list can be found http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/.

[2] Non-college workers are defined as workers who have a high school degree or below. College workers are defined as workers with some years of college or above.

[3] See, e.g., Keane and Moffitt (1998), Björklund and Moffitt (1987), Moffitt (2002), Fraker and Moffitt (1988).

marginal benefit in terms of expected profits equals the marginal cost. When a minimum wage is imposed, it affects both the probability of finding a worker and the expected profit from the match, resulting in changes to the number of vacancies. Firms also decide where to make job offers by setting contact rates that are specific to each region. We assume random search, which implies that heterogeneous workers within a location are contacted by firms at identical rates. An individual's productivity when meeting a firm is determined by his/her skill level (high or low) and an idiosyncratic random matching quality. The bargained wage is determined by a surplus division rule, subject to any minimum wage constraints (as in Flinn (2006)).

The spatial framework that we develop is motivated by reduced-from evidence, presented in this paper and from the literature, showing that an increase in the relative minimum wage between neighboring counties tends to decrease worker commuting. Because city minimum wage ordinances have only been effect for a short while and in a limited number of cities, our analysis focuses on minimum wage variation across state border and examines its association with worker commuting and migration. We find that relative minimum wage increases (the local state minimum wage divided by the neighboring state minimum wage) have a statistically significant negative impact on commuting, with magnitudes varying by travel distance and wage category of the worker. When considering a commuting band that stretches 11 kilometers on either side of a state border, a 1% relative minimum wage increase reduces the number of commuters by 1.25%, 0.83%, and 0.41% for low, middle, and high wage workers. If the width of the commuting band is doubled, the commuting elasticities remain negative and statistically significant but decrease in magnitude.

Our spatial job search model incorporates four channels through which local minimum wage changes of varying magnitudes affect low and high skill workers as well as firms. From the worker side, there are counterveiling employment and wage effects. On the one hand, a minimum wage increase dissolves marginally acceptable firm-worker matches (the *"disemployment effect"*). On the other hand, it leads some workers in sustainable job matches to get a larger share of the match surplus (the "*wage enhancement effect*"). These two effects affect local workers as well as job searchers from neighboring areas. We expect fewer mobile workers if the disemployment effect on the future present discounted value of utility outweighs the wage enhancement effect. From the firm side, a minimum wage increase reduces the incentive for local firms to post job vacancies, because they receive a smaller share of surplus from the same matches (the "*share reduction effect*"). Even workers whose wages are not directly affected when the minimum wage is imposed may be indirectly impacted via this channel. For example, fewer high skill commuters would work in the local firms if they receive fewer job offers from such firms. Finally, labor mobility alters the skill composition of workers. The random search assumption implies that firms are not able to distinguish workers' types when posting vacancies. As a result, the proportion of low skill workers among job seekers is negatively related to the expected profit per vacancy (a "*worker relocation effect*"). This last mechanism affects not only the revenues of local firms, but also the revenues of neighboring area firms. To summarize, an increase in the local minimum wage has potential spillover effects on the neighboring area as a result of both spatial job search behavior and induced changes in posted vacancies.

We estimate our spatial job search model using a method of moments estimator that combines county-level data moments from multiple sources over an eleven-year time period (2005-2015). The migration and commuting flows are obtained from the American Community Survey (ACS). Local labor market conditions (hiring rates, separation rates and employment rates) are obtained from Quarterly Workforce Indicators (QWI) survey. The payroll share of firms' expenditures, and the ratio of job postings to workers come from the Economics Wide Key Statistics (EWKS) and the Conference Board Help Wanted Online (HWOL). We evaluate the model fit using both within-sample fit criteria and through an out-of-sample validation.

Our analysis yields three main findings. First, our out-of-sample validation uses the estimated model to predict commuting responses to city wage changes, which were not used in estimating the model. Using the Longitudinal Employer-Household Dynamics Program's Local Origin and Destination Employment Statistics (LODES) data up to year 2019, we estimate commuting elasticities for workers living within 22 kilometers of a city that increased its minimum wage. We also use our estimated model to simulate the effects of minimum wage changes of the same magnitudes. The distribution of predicted commuting elasticities generated from the model (across county pairs) is then compared to the distribution of city-level elasticities calculated from the data. The model provides reasonable forecasts of how commuting responds to city-level minimum wage increases, despite city minimum wage levels being significantly higher than the state-level minimum wages used in estimation.

Second, we use the estimated model to analyze the per capita welfare implications of both local and universal minimum wage policies. Our model reveals disparate impacts on low and high education workers and for different minimum wage levels. When the local minimum wage increases from $7.25 (the current federal level) to $20.00, the welfare functions show hump shapes for both types of workers with peaks at different levels. Low skill workers achieve the greatest welfare at a wage equal to $10.75, because the *wage enhancement effect* exceeds the *disemployment effect* up until this level. In contrast, the welfare peak for high skill workers is at a higher level, $12.25, because the same minimum wage generates less disemployment for more productive workers. Some minimum wage studies argue that the costs of local minimum wages are partly passed on to consumers through higher prices for goods and services. When we adjust our welfare calculations for potential pass-through effects (using estimated price elasticities drawn from Renkin et al. (2022)), we find that they do not significantly alter the welfare conclusions. Lastly, following Hosios (1990), we also construct a Benthamite social welfare function that includes all labor market participants (workers and firms) in the local area. Under this social welfare function, the optimal universal minimum wage is $12.25.

Third, we use the estimated model to compare the effects of a local minimum wage policy to a universal one. As of July 6, 2017, 25 states have passed laws preempting local minimum wages.[4] In our simulation, we consider the welfare effects of a universal minimum wage hike in both counties for a range of minimum wage values (from $7.25 to $20.00). The social welfare function also has a hump shape, peaking at a minimum wage of $12.75. At this wage level, the per capita welfare level under the universal minimum wage policy is higher than under a local policy. This is because the universal minimum wage removes the incentive to arbitrage the difference in regional minimum wages, which saves on moving costs. For example, at the current proposed federal minimum wage of $15/hour, per capita welfare under the universal minimum wage policy is higher than under a local policy in both counties.[5] However, at an even higher minimum wage of $18/hour, per capita welfare under the universal policy is lower than under a local policy, due to greater disemployment effects that outweigh the moving cost savings.

Related Literature. This paper builds on a body of literature that examines the effect of minimum wages through the lens of different equilibrium job search models. An early paper is Eckstein and Wolpin (1990), which extends the model of Albrecht and Axell (1984) to incorporate endogenous job offer probabilities and measurement error in wages. They use the estimated model to explore the welfare effects of minimum wages. Van den Berg and Ridder (1998) also derive an endogenous wage distribution within an alternative job search framework that allows for heterogeneous workers, on-the-job search, and firing decisions, extending a framework developed by Burdett and Mortensen (1998). Our model builds most closely on Flinn (2006), which estimates a general equilibrium search-matching model with endogenous contact rates. His model incorporates match-specific capital and worker firm bargaining over match-specific rents, with minimum wages introduced as a constraint on the division of match surplus. He shows that the imposition of a minimum wage within his model could, in principle, enhance welfare on both the supply and demand sides of the market and an increase in the minimum wage does not necessarily lead to greater

[4] The minimum wage preemption laws prohibit cities from enacting their own minimum wage laws. See http://www.nelp.org/publication/fighting-preemption-local-minimum-wage-laws/for a more comprehensive policy review.

[5] On February 27, 2021, the Democratic-controlled House passed the American Rescue Plan pandemic relief package, which included a gradual minimum wage increase to $15 per hour. The measure was ultimately removed from the Senate version of the bill.

unemployment.[6]

All of these previous studies assume a single labor market and a universal minimum wage and rely on time series minimum wage variation for identification. By considering job search in geographically distinct sub-markets, our study additionally exploits cross-sectional minimum wage variation. We also use the model to explain features of the data that were not considered in previous works, such as how migration and commuting respond to regional wage disparities. Additionally, our spatial equilibrium framework allows comparisons of local and universal minimum wage policies and their effects on labor mobility, employment, migration/commuting, wages and welfare.[7] As previously noted, local minimum wages are an increasingly important (and controversial) feature of the U.S. labor market.

This paper also contributes to a body of literature that uses spatial search frameworks to analyze labor mobility. Coen-Pirani (2010) develops a dynamic general equilibrium model of worker migration with homogeneous workers to analyze gross and net worker flows across US states. Baum-Snow and Pavan (2012) develops an on-the-job search model with heterogeneous workers with different latent abilities, search frictions, firm-worker match quality, human capital accumulation and endogenous migration between large, medium and small cities to explain the positive relationship between worker wages and city size. Kennan and Walker (2011) develop and estimate a partial equilibrium model of optimal sequences of migration decisions with heterogeneous workers to explain interstate migration patterns in the US, whereby workers tend to migrate repeatedly to multiple locations or return to locations that they previously left. They find that income prospects are the primary determinants of migration decisions. Monte et al. (2018) develops a quantitative general equilibrium model that takes into account both commuting and migration. They conclude the elasticity of local employment to a labor demand shock is heterogeneous depending on the commuting openness of the local labor market. The framework closest to ours is probably Schmutz and Sidibé (2019). They develop and estimate a partial equilibrium model in which homogeneous workers face spatial frictions that make it harder to compete for distant jobs.[8]

Third, a recent literature documents how migration/commuting responds to local minimum wage changes. Cadena (2014) shows low-skilled foreign immigrants avoid moving to regions with higher minimum wages. McKinnish (2017) shows that workers are more likely to commute out of state when the local minimum wage increases. Monras (2019) builds a spatial equilibrium model of location choice and

[6] Eckstein et al., 2011; Ahn et al., 2011; Blömer et al., 2018; Flinn and Mullins, 2015; Hurst et al., 2021; Flinn and Mullins, 2021 are other examples of recent papers analyzing minimum wages within a job search framework.

[7] The search framework we develop is somewhat similar in structure to that of Meghir et al. (2015), who develop an equilibrium wage-posting model with two labor submarkets that correspond to the formal and informal sectors.

[8] One of their policy experiments also considers local and universal minimum wages. However, their findings differ significantly from ours because they assume homogeneous workers and do not incorporate general equilibrium effects. Also, they estimate their model on French data.

shows fewer low-skilled workers move toward states that increase minimum wages. The finding in the literature that workers avoid moving to areas with higher minimum wage is relatively consistent. We show in this paper how the estimated commuting elasticities depend on distance to the border. Our results are consistent with Manning and Petrongolo (2017) who show that the attractiveness of a job decreases significantly with travel distance. Using UK data, they find that the probability of a random distant (at least 5km away) job being preferred over a random local (less than 5km away) job is only 19%. Pérez (2022) develops a spatial equilibrium of location choice to study how commuting and residence locations change in response to local minimum wage changes. His model, however, does not allow for the ripple effect of the minimum wages over the wage structure.[9]

Fourth, this paper is related to the recent literature on the potential externalities of place-based policies. For example, Serrato and Zidar (2016) studies the incidence of state corporate taxes on the welfare of workers, landowners and firm owners. In their model, a state tax cut reduces the tax liability and the cost of capital, attracting establishments into an area. Cohen et al. (2011) studies the effects of marginal tax rates on migration decisions in the U.S., while Young and Varner (2011) and Moretti and Wilson (2017) focus on the geographic locations of top earners. Bilal (2021) proposes a spatial equilibrium model to account for spatial unemployment differentials and to justify commonly used place-based policies. Although the idea that local policy may create spillover externalities has received considerable attention in the tax literature, this is the first paper to investigate its significance in the minimum wage context.[10]

Lastly, this paper also builds on a literature surveyed in Neumark and Shirley (2021) that adopts a treatment effects paradigm to evaluate minimum wage impacts. Starting with Card and Krueger (1994), cross-border comparisons became a popular approach for studying the employment effects associated with minimum wage changes. More recently, Dube et al. (2007, 2010, 2016) generalize this strategy to all contiguous county pairs and find small disemployment effects, consistent with Card and Krueger (1994). Although the cross-border design is intuitively compelling, geographic proximity between the treated and control areas raises concerns about spillover effects, particularly in cases where the minimum wage discrepancy between the areas is large. Kuehn (2016) shows that commuting spillovers may bias the effects of minimum wages in cross-border minimum wage studies. Monras (2019) demonstrates how ignoring migration decisions in response to minimum wage changes can lead to an understatement of the employment impacts. We estimate a statistically significant negative commuting elasticity, which gets larger as the commuting

[9] Cengiz et al. (2019) conclude that 40% of the total wage effects stems from the ripple effect of the minimum wage.

[10] See Glaeser et al. (2008) and Enrico (2011) for reviews. Other recent papers include Kline (2010); Busso et al. (2013); Kline and Moretti (2013)

band around state borders narrows, supporting the existence of spillover effects in our data.[11]

The paper develops as follows. The next section presents a spatial job search equilibrium model. Section 3 describes the multiple data sources we will use to estimate the model. Section 4 discusses the identification and estimation strategy. Section 5 present the empirical results. Section 6 discusses the counterfactual experiments. Section 7 concludes.

2 Model

We develop a dynamic spatial search model where individuals live and work in one of two paired counties (j, j'). Our model extends the canonical Diamond-Mortensen-Pissarides model to two regions and allows region-specific minimum wages. A job seeker in one county receives an offer either from a local firm or a firm in a neighboring county. When a worker meets a firm in county j, they bargain over the wage subject to the county's minimum wage policy. Minimum wage changes in one county can potentially affect labor market conditions in the neighboring county due to worker mobility, as described in detail below.

2.1 Framework

The search model is continuous time with infinitely-lived, risk neutral workers maximizing their expected utility (income) with a discount rate ρ. The economy has a fixed number of potential workers of different skill types. $N(a, j)$ represents the number of workers of type a in county j. Type is discrete, taking values $a \in A = \{a_1, ..., a_n\}$.[12] Individuals' working and residential status are determined by the endogenous job search process. $U(a, j)$, $E(a, j)$, $C(a, j)$ and $M(a, j)$ represent the number of type a unemployed workers, employed workers, commuters and migrants in county j. We will examine steady state job search and labor mobility behavior.

2.2 The worker's problem

A job seeker who resides in county j may receive wage offers from county j or j'. Upon meeting a firm, the match productivity is $y = a\theta$ where θ is the matching quality, assumed to be an i.i.d. draw from the cdf $G(\theta)$.[13]

[11] Dube et al. (2010) finds no significant county spillover effects. However, Dube et al. (2010) infers spillover effects by comparing employment changes in border and interior counties, and we directly examine how worker commuting changes following minimum wage increases across state borders.

[12] For computational tractability, we consider two types in the empirical analysis: some college (a_h) and non-college (a_l).

[13] The linear productivity function is a common assumption in the search literature, but the interpretation of θ varies in different contexts. For example, Postel-Vinay and Robin (2002) and Cahuc et al. (2006) use a similar functional form for the flow productivity

We assume local firms make job offers with rate λ and neighboring firms make job offers with rate λ'. Frictions reduce the efficiency of job offers received by workers: for job offers posted by firms in county j, local workers receive such offers with "effective" rate $s_j\lambda_j \leq \lambda_j$ while the neighbouring workers receive such offers with "effective" rate $(1-s_j)\lambda_j \leq \lambda_j$.[14] The value of unemployment for type a individuals living in county j can be written as:

$$
\begin{aligned}
\rho V_u(a,j) \quad = \quad & \underbrace{ab_j}_{\text{(1) flow value}} + s_j\lambda_j \underbrace{\int_{m_j}^{\infty} \{V_e(w,a,j) - V_u(a,j)\}^+ dF(w|a,j)}_{\text{(2) option value of accepting a local offer}} \\
& + \quad (1-s_j)\,\lambda_{j'} \underbrace{\int_{m_{j'}}^{\infty} \{V_e(w,a,j') - c(a,j) - V_u(a,j)\}^+ dF(w|a,j')}_{\text{(3) option value of accepting a neighboring offer}}
\end{aligned} \tag{1}
$$

The notation $\{x\}^+ \equiv \max\{x, 0\}$. ab_j represents the flow utility of remaining unemployed. m_j and $m_{j'}$ represent the minimum wage level in county j and county j'. If an individual receives an offer in location j, he/she draws a match-specific quality θ and receives a wage offer w according to the wage bargaining process specified in the next section. The job acceptance decision is based on comparing the value of unemployment $V_u(a,j)$ to the value of accepting the wage offer.

As seen in equation 1, the option values of a local offer and of a neighboring offer differ in two ways: (1) If $s_j > 0.5$, workers may have a "home bias" when looking for jobs. This could be because they spend more time searching for a local job than a remote job, or because information about local job availability reaches workers more efficiently; (2) When accepting a remote job offer, workers incurs an additional moving cost $c(a,j) > 0$.[15] If $c(a,j) = 0$ and $s_j = 0.5$, then workers in county j and county j' have exactly the same working opportunities, which means paired counties are essentially one labor market. If $c(a,j) = +\infty$ or $s_j = 1$, then the paired counties are totally isolated markets. As pointed out by Schwartz (1973) and Greenwood (1975), this moving cost combines both the psychic costs of losing local social connections with family and friends and physical transportation costs, which usually depends on distance. The parametric specification of the moving and commuting costs will be discussed in section 4.1.

The model assumes no on-the-job search. Therefore, the worker who accepts a job with wage w will not voluntarily quit the current job. Existing matches are assumed to dissolve at a constant exogenous rate

$y = a\theta$, where a and θ denote the worker's and firm's productivity type, receptively.

[14] Therefore, $s_j/(1-s_j)$ is the relative job search efficiency between local workers and neighboring workers.(Schmutz and Sidibé, 2019)

[15] Following similar assumptions in Baum-Snow and Pavan (2012) and Schmutz and Sidibé (2019). Given our utility function is linear and no borrow constraint, the lump cost is equivalent to a flow cost of $(\rho + \eta_j)c(a,j)$.

η_j. The value of employment, $V_e(w, a, j)$, has the the following form:[16]

$$V_e(w, a, j) = \frac{w + \eta_j V_u(a, j)}{\rho + \eta_j} \tag{2}$$

2.3 Bargaining with a minimum wage constraint

We next specify how the wage between the worker and the firm is determined, first considering the case without a minimum wage. If a type a worker meets a firm in location j and draws a matching quality θ, then the wage is assumed to be derived from Nash bargaining. The wage $\hat{w}(a, j, \theta)$ maximizes the weighted product of the worker's and firm's net return from the match. Upon matching, the worker gives up the value of unemployment $V_u(a, j)$, and the firm gives up the unfilled vacancy, which has zero value.[17]

$$\hat{w}(a, j, \theta) = \arg\max_{w} \left(V_e(w, a, j) - V_u(a, j)\right)^{\alpha_j} V_f(w, a, \theta, j)^{1-\alpha_j}$$

The bargaining weight α_j, which is allowed to vary by location, represents the relative strength of labor and is strictly between 0 and 1.[18] V_f is the present value of the filled vacancy for the firm. As derived in Appendix A.2, the bargained wage offer function is:

$$\hat{w}(a, j, \theta) = \rho V_u(a, j) + \alpha_j (a\theta - \rho V_u(a, j)) \tag{3}$$

The wage equation has an intuitive interpretation. Workers receive their reservation wage $\rho V_u(a, j)$ and a share α_j of the net surplus of the current match, which is the total productivity $a\theta$ minus what workers give up $\rho V_u(a, j)$.

We define the reservation match quality $\theta^*(a, j)$ as the lowest matching quality that a worker of type a will accept from a local firm (in region j). That is, the worker is indifferent between accepting a local job with match quality $\theta^*(a, j)$ and staying unemployed.

$$V_e(\hat{w}(a, j, \theta^*(a, j)), a, j) = V_u(a, j)$$

[16] The derivations of equations 1 and 2 are described in Appendix A.1. The value of being employed at a neighbouring firm $V_e(w, a, j)$ may vary depending on whether workers choose to commute or migrate. We will come back to this point in the next subsection 2.4.

[17] See discussion below in subsection 2.6

[18] We do not model different outside options for local workers and mobile workers for two reasons. First, it is unclear whether moving costs are a credible "threat point" for mobile workers because they have to pay the moving cost before they can work in the other county. Second, we assume that it is not economical for firms to make wage offers contingent on mobility status.

$$\Rightarrow a\theta^*(a,j) = \hat{w}(a,j,\theta^*(a,j)) = \rho V_u(a,j)$$
$$\Rightarrow \theta^*(a,j) = \tfrac{\rho V_u(a,j)}{a}$$

As in Flinn (2006), we introduce a minimum wage in area j as a constraint to the bargaining problem that applies to all potential job matches:

$$w(a,j,\theta) = \arg\max_{w \geq m_j} \left(V_e(w,a,j) - V_u(a,j)\right)^{\alpha_j} V_f(w,a,\theta,j)^{1-\alpha_j}$$

The effect of minimum wage depends on whether its value is larger or smaller than the reservation productivity $a\theta^*(a,j)$. If $a\theta^*(a,j) \geq m_j$, then the minimum wage has no effect on the bargained wage for type a workers, because the reservation value is high enough that all matches acceptable to workers give wages equal or larger than the minimum wage m_j. If $a\theta^*(a,j) < m_j$, then the minimum wage constraint is potentially binding. The bargained wage is then:

$$w(a,j,\theta) = \max\{m_j, \alpha_j a\theta + (1-\alpha_j)\rho V_u(a,j)\} \tag{4}$$

To characterize the wage distribution, it is useful to solve for the match quality value corresponding to the case when the worker receives exactly the minimum wage based on Equation 3, which we denote $\hat{\theta}(a,j)$

$$\hat{\theta}(a,j) = \frac{m_j - (1-\alpha_j)\rho V_u(a,j)}{a\alpha_j}. \tag{5}$$

We can obtain an affine mapping between the pdf of the matching quality, $g(\theta)$, and the probability wage distribution $f(w|a,j)$:

$$f(w|a,j) = \begin{cases} \frac{(a\alpha_j)^{-1} g(\tilde{\theta}(w,a,j))}{\tilde{G}(\frac{m_j}{a})} & w > m_j \\ \frac{\tilde{G}(\hat{\theta}(a,j)) - \tilde{G}(\frac{m_j}{a})}{\tilde{G}(\frac{m_j}{a})} & w = m_j \\ 0 & w < m_j \end{cases} \tag{6}$$

where $f(w|a,j)$ is the probability density function (pdf) of $F(w|a,j)$, $g(\theta)$ is the PDF of $G(\theta)$, and $\tilde{G}(\theta) = 1 - G(\theta)$ is the complementary function of the cumulative distribution function $G(\theta)$. $\tilde{\theta}(w,a,j) = \frac{w-(1-\alpha_j)\rho V_u(a,j)}{a\alpha_j}$ denotes the matching quality whose bargained wage is equal to w. The observed wage distribution consists of a point m_j with mass $\frac{G(\hat{\theta}(a,j)) - \tilde{G}(\frac{m_j}{a})}{\tilde{G}(\frac{m_j}{a})}$ and a continuous function (assuming $G(\theta)$ is continuous) when $\theta > \hat{\theta}$.

It is worth noting that a binding minimum wage affects all workers' wages, but through different channels. For the workers with matching quality $\theta \in [\frac{m_j}{a}, \hat{\theta}(a,j))$, the minimum wage directly benefits them by boosting their wage to m_j. For workers with a higher matching quality $\theta \in [\hat{\theta}(a,j), \infty)$, the minimum wage changes their value of unemployment $\rho V_u(a,j)$.[19] To summarize, introducing the minimum wage as a constraint on Nash-bargained wages converts a continuous underlying productivity distribution into a mixed continuous-discrete accepted wage distribution, with a mass point at the minimum wage.

2.4 Search strategies and migration/commuting trade-offs

Next, we characterize workers' spatial job search strategies. The timing is as follows: (1) an offer from neighboring area j' arrives at "effective" rate $(1 - s_j)\,\lambda_{j'}$. (2) After the matching quality θ is realized, the worker decides to accept/reject the offer based on the trade-off between the wage offer $w(a, j', \theta)$ net of the expected moving cost $c(a, j)$ and the value of unemployment, $V_u(a, j)$. (3) If the worker accepts the offer from the neighboring county, then the worker chooses whether to commute or migrate, as described in detail below.

The expected moving cost $c(a, j)$, is a function of the worker's type and location-specific characteristics. Following Schmutz and Sidibé (2019), we introduce a *mobility compatible indifferent matching quality* $\theta^{**}(a, j)$, that satisfies the following:

$$V_u(a,j) + c(a,j) = V_e(\theta^{**}(a,j), a, j') \tag{7}$$

where j represents the worker's place of residence and j' the place of work. The worker will accept the neighboring offer if and only if the matching quality exceeds the mobility compatible threshold $\theta \geq \theta^{**}(a, j)$. This match will also be sustainable for firms as long as $\theta \geq \frac{m_{j'}}{a}$. To summarize, the worker whose residence is in county j will accept a neighboring offer if and only if $\theta \geq \max\{\frac{m_{j'}}{a}, \theta^{**}(a,j)\}$.

To capture the different types of mobility observed in the data, we distinguish between migrating and commuting. After accepting an offer from the neighboring county, workers have two alternatives. They can either pay a lump-sum cost $cc_1(a, j)$ to migrate ($h = 1$) and become a native worker in county j' or pay a commuting cost $cc_0(a, j)$ and be a commuter ($h = 0$. The commuting cost is recurring, but we use $cc_h(a, j)$ to represent its lump-sum equivalent.

We assume the choice-specific mobility cost $cc_h(a, j)$ depends on the worker's type, the physical distance between counties, and the difference in rental prices between the paired counties. We also assume

[19] However, the sign of this change is ambiguous, depending on the trade-off between the increase in expected income and the reduction of expected working opportunities.

that the mobility cost depends on the employment values in the two counties. In particular, the employed value for commuters is

$$V_e(w, a, j'|h = 0) = \frac{w + \eta_{j'} V_u(a, j)}{\rho + \eta_{j'}} \tag{8}$$

while the employed value for migrants is

$$V_e(w, a, j'|h = 1) = \frac{w + \eta_{j'} V_u(a, j')}{\rho + \eta_{j'}} \tag{9}$$

The differences in the values are incorporated in the choice-specific moving cost functions. Its exact parametric form will be discussed in equation 18 in Section 4.1.

In addition to the costs, a workers' decision to commute or migrate also depends on an unobserved preference shock ε_{ah}. Workers choose their lowest mobility cost option, $h(a, j)$:

$$h(a,j) = \begin{cases} 0 & \text{if } \varepsilon_{a0} - cc_0(a,j) > \varepsilon_{a1} - cc_1(a,j) \\ 1 & \text{if } \varepsilon_{a0} - cc_0(a,j) \leq \varepsilon_{a1} - cc_1(a,j) \end{cases}$$

Assuming ε_{ah} follows an i.i.d. type I extreme value distribution with a location parameter 0 and a common scale parameter σ_a^c, the expected cost associated with a non-local job offer has the following form (Rust 1987):

$$\begin{aligned} c(a,j) &= E_\varepsilon \max\{\varepsilon_{a0} - cc_0(a,j), \varepsilon_{a1} - cc_1(a,j)\} \\ &= \sigma_a^c \log(\textstyle\sum_{h=0}^{1} \exp(-cc_h(a,j))/\sigma_a^c) + \sigma_a^c \gamma \end{aligned}$$

The probability of choosing option h, $h \in \{0, 1\}$, is:

$$Q_h(a,j) = \frac{exp(-cc_h(a,j)/\sigma_a^c)}{exp(-cc_0(a,j)/\sigma_a^c) + exp(-cc_1(a,j)/\sigma_a^c)} \tag{10}$$

2.5 Workers' optimal strategies

An unemployed worker residing in county j receives job offers from either a local firm or a firm in a neighboring county. Upon receiving an offer, the worker decides whether to accept the offer taking into account expected mobility costs. If the offer comes from a firm in the neighboring county, the worker receives a preference shock and makes a decision about whether to commute or relocate there.

Proposition 1. *OPTIMAL STRATEGIES*

For unemployed workers of type a in county j, the optimal strategy is:

- *accept any local job offer with matching quality higher than* $\max\{\theta^*(a,j), \frac{m_j}{a}\}$
- *accept any neighboring job offer with matching quality higher than* $\max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}$
  - *Commute with probability* $Q_0(a,j)$
  - *Migrate with probability* $Q_1(a,j)$

Below, we describe the fixed point equation system that is used to solve for $\theta^*(a,j)$ and $\theta^{**}(a,j)$. By substituting both the reservation matching quality $\theta^*(a,j)$ and mobility compatible matching quality $\theta^{**}(a,j)$ to Equation 1, we get the following system of equations:[20]

$$
\begin{aligned}
a\theta^*(a,j) \quad &= \quad \underbrace{ab_j}_{\text{(1) Flow utility}} + \tfrac{s_j\lambda_j}{\rho+\eta_j}[\underbrace{\boldsymbol{I}\left(\theta^*(a,j) < \frac{m_j}{a}\right)(m_j - a\theta^*(a,j))\left(\tilde{G}(\hat{\theta}(a,j)) - \tilde{G}(\frac{m_j}{a})\right)}_{\text{(2) Local offer with wage } m_j} \\
&+ \quad \underbrace{\int_{\max\{\hat{\theta}(a,j),\theta^*(a,j)\}} a\alpha_j(\theta - \theta^*(a,j))dG(\theta)]}_{\text{(3) Local offer with wage } w_j > m_j} \\
(11) \qquad &+ \quad \tfrac{(1-s_j)\lambda_{j'}}{\rho+\eta_{j'}}[\underbrace{\boldsymbol{I}(\theta^{**}(a,j) < \frac{m_{j'}}{a})(m_{j'} - a\theta^*(a,j'))\left(\tilde{G}(\theta^{**}(a,j)) - \tilde{G}(\frac{m_{j'}}{a})\right)}_{\text{(4) Neighbouring offer with wage } m_{j'}} \\
&+ \quad \underbrace{\int_{\max\{\hat{\theta}(a,j'),\theta^{**}(a,j)\}} a\alpha_j(\theta - \theta^*(a,j'))dG(\theta)}_{\text{(5) Neighbouring offer with wage } w_{j'} > m_{j'}} \\
&- \quad \underbrace{(\rho+\eta_{j'})\left(\frac{a(\theta^*(a,j) - \theta^*(a,j'))}{\rho} + c(a,j)\right)\tilde{G}(\max\{\hat{\theta}(a,j'),\theta^{**}(a,j)\})]}_{\text{(6) The unemployed value difference between staying/moving}}
\end{aligned}
$$

with

$$
\begin{aligned}
\hat{\theta}(a,j) &= \tfrac{m_j - (1-\alpha_j)a\theta^*(a,j)}{a\alpha_j} \\
\hat{\theta}(a,j') &= \tfrac{m_{j'} - (1-\alpha_{j'})a\theta^*(a,j')}{a\alpha_{j'}} \\
\theta^{**} \text{ solves } & V_u(a,j) + c(a,j) = V_e(\theta^{**}(a,j), a, j')
\end{aligned}
$$

In equation 11, the value of the matching quality $a\theta^*(a,j)$ consists of six components: (1) the flow utility ab when unemployed; (2) the expected value associated with a local offer with binding minimum wage m_j; (3) the expected value associated with a local offer with wage $w_j > m_j$; (4) the expected value associated with an acceptable neighboring offer with binding minimum wage $m_{j'}$; (5) the expected value associated with an acceptable neighboring offer with wage $w_{j'} > m_{j'}$; (6) the unemployed utility difference between staying and moving, which includes both the moving cost $c(a,j)$ and the change of the option value of

[20] The derivation of equation 11 can be found in Appendix A.3

being unemployed $a\theta^*(a,j) - a\theta^*(a,j')$.

The intuition underlying equation 11 is straightforward. The value difference between accepting the lowest acceptable job and remaining unemployed $a\theta^*(a,j) - ab_j$ reflects an opportunity cost, which is the expected value of finding a better job in the future. This job could be either a local one or a one from a neighboring area, where accepting a neighboring job incurs an expected moving cost $c(a,j)$.

2.6 The endogenous contact rate

We next consider how the contact rates $\lambda_j, j = 1, 2$, are determined in equilibrium. We assume that firms in county j randomly encounter workers searching for jobs in county j with equal probability, including local and mobile workers. Workers applying for the same position may have different productivities but are substitutable with each other. We adapt the Mortensen and Pissarides (1994) framework and allow firms to post vacancies K_j in county j with constant cost ψ_j. The matching technology is assumed to be constant returns to scale.

Because workers divide their job search time between local jobs and neighboring jobs, the number of unemployed workers seeking jobs in county j ia:

$$N_j = \sum_{a \in A} (s_j U(a,j) + (1 - s_{j'})U(a,j'))$$

where $s_j U(a,j)$ denotes the number of workers of type a in county j searching locally, while $(1 - s_{j'})U(a,j')$ the unemployed workers of type a in county j searching for jobs in the neighboring county. If the firms in county j create K_j vacancies, then the total number of potential matches created in county j, M_j, is given by

$$M_j = N_j^{\omega_j} K_j^{1-\omega_j}$$

where ω_j is the matching elasticity parameter in market j. We use a Cobb-Douglas matching function with constant return to scale and total factor productivity equal to 1. The parameter ω_j characterizes heterogeneity in the matching functions across labor markets j.

The contact rate per job in county j, $q_j(k_j)$, can be represented as:

$$q_j(k_j) = \frac{M_j}{K_j} = (\frac{N_j}{K_j})^{\omega_j} = k_j^{\omega_j}$$

where $k_j = \frac{N_j}{K_j}$ is a measure of market "tightness." The correlation between market tightness and job arrival probability λ_j is

$$\lambda_j = k_j(K_j, N_j)^{\omega_j - 1} \tag{12}$$

It is critical to emphasize that job seekers in different counties may accept jobs at different rates for two reasons: (1) The search efficiency varies by location. Local workers receive job offer information with a probability of s_j, whereas neighboring workers receive the same information with a probability of $1 - s_{j'}$; (2) When encountering the same job opportunity, neighboring workers are pickier about their jobs because the job value must compensate for the additional moving cost. The total number of matches created by the firms in county j is:

$$\text{Total Hires} = \frac{M_j}{N_j} \sum_{a \in A} \left(\underbrace{s_j U(a,j) G\left(\max\{\theta^*(a,j), \frac{m_j}{a}\}\right)}_{\text{Local Hires}} + \underbrace{(1 - s_{j'}) U(a,j') G\left(\max\{\theta^{**}(a,j'), \frac{m_j}{a}\}\right)}_{\text{Neighboring Hires}} \right)$$

The firm's match value can be represented as:

$$V_f(\theta, a, j) = \frac{a\theta - w(a,\theta,j)}{\rho + \eta_j} \tag{13}$$

The expected value of a vacancy for firms V_v in county j is:

$$\begin{aligned} V_v = -\psi_j + \frac{k_j(K_j, N_j)^{\omega_i}}{N_j} \sum_{a \in A} [& \underbrace{s_j U(a,j) \int_{\max\{\theta^*(a,j), \frac{m_j}{a}\}} V_f(\theta,a,j) dG(\theta) +}_{\text{Profit from local workers}} \\ & \underbrace{(1 - s_{j'}) U(a,j') \int_{\max\{\theta^{**}(a,j'), \frac{m_j}{a}\}} V_f(\theta,a,j) dG(\theta)]}_{\text{Profit from neighboring workers}} \end{aligned} \tag{14}$$

where ψ_j is the vacancy cost at county j.

Assuming each county has a population of potential firm entrants with an outside option equal to 0, firms will continue to create vacancies until the expected profit equals 0 ($V_v = 0$). Under the free entry condition (FEC), the endogenous contact rate $\lambda_j = k_j(K_j, N_j)^{\omega_j - 1}$ is determined by the following equation:

$$\psi_j = \frac{M_j}{K_j} \times E[V_f(\theta,a,j)] = \left(\frac{K_j}{N_j}\right)^{1-\omega_j} \sum_{a\in A} [\ s_j U(a,j) \int_{\max\{\theta^*(a,j),\frac{m_j}{a}\}} V_f(\theta,a,j)dG(\theta) +$$

$$(1-s_{j'})U(a,j') \int_{\max\{\theta^{**}(a,j'),\frac{m_j}{a}\}} V_f(\theta,a,j)dG(\theta)\ ] \tag{15}$$

The increase of minimum wage at county j could affect firm's incentives to post job vacancies due to two reasons: (1) it reduces firm's share in the total surplus as both $\int_{\max\{\theta^*(a,j),\frac{m_j}{a}\}} V_f(\theta,a,j)dG(\theta)$ and $\int_{\max\{\theta^*(a,j'),\frac{m_j}{a}\}} V_f(\theta,a,j)dG(\theta)$ monotonically decrease as m_j increases; (2) The composition of job seekers, $U(a,j)$ and $U(a,j')$, may also change as a result of worker relocation in response to changes in the minimum wage. This would also have an impact on the firm's expected profit, but the sign is ambiguous.

2.7 Definition of a steady-state spatial equilibrium

Let $\theta \in \boldsymbol{R_+}$, $a \in \boldsymbol{A} = \{a_l, a_h\}$, $j \in \boldsymbol{J} = \{1,2\}$, and let $\boldsymbol{S_1} = \boldsymbol{R_+} \times \boldsymbol{A} \times \boldsymbol{J}$ and $\boldsymbol{S_2} = \boldsymbol{A} \times \boldsymbol{J}$. Let $\boldsymbol{B(R_+)}$ be the Borel $\sigma-$algebra of $\boldsymbol{R_+}$ and $\boldsymbol{P(A)}$, $\boldsymbol{P(J)}$ the power sets of $\boldsymbol{A}$ and $\boldsymbol{J}$, respectively. Let $\boldsymbol{\aleph} = \boldsymbol{B(R_+)} \times \boldsymbol{P(A)} \times \boldsymbol{P(J)}$, and $\boldsymbol{M}$ be the set of all finite measures over the measurable space $(\boldsymbol{S_1}, \boldsymbol{\aleph})$

Definition 1. A steady-state spatial equilibrium is a set of individual functions for workers $V_u : \boldsymbol{S_1} \to \boldsymbol{R_+}$ and $V_e, \theta^*, \theta^{**}, Q_h : \boldsymbol{S_2} \to \boldsymbol{R_+}$, a set of the functions for firms $V_f : \boldsymbol{S_1} \to \boldsymbol{R_+}$ and $\{K_j\}_{j=1,2}$, a set of contact rates $\{\lambda_j\}_{j=1,2}$ and wage rates $w : \boldsymbol{S_1} \to \boldsymbol{R_+}$ and a set of aggregate measures of different working status $E, U, M, C : \boldsymbol{S_2} \to \boldsymbol{R_+}$, the following conditions hold:

1. Worker's problem: given the contact rate, wage and initial condition, V_u and V_e are the solutions of Eqs. 1 and 2, respectively. The optimal strategies θ^*, θ^{**} are described by Proposition 1 and $\{Q_h\}_{h=0,1}$ is characterized by Eq. 10. The functions $\{V_u, V_e, \theta^*, \theta^{**}, Q_h\}$ are measurable with respect to $\boldsymbol{\aleph}$.

2. The firm's problem: given the contact rate, wage and initial condition, V_f is solved by Eq. 13 and K_j is solved by Eq. 15.

3. The bargained wage: the bargained wage with a minimum wage constraint is defined by Eq. 4.

4. Endogenous contact rate (labor market clearing): the contact rate λ_j is solved by Eq. 12.

5. The aggregate measures of each group (employment workers $E(a, j)$, unemployed workers $U(a, j)$, commuters $C(a, j)$, migrants $M(a, j)$) are constant.

$$\underbrace{\lambda_j \left(s_j U(a,j)\tilde{G}(\max\{\theta^*(a,j), \frac{m_j}{a}\}) + (1-s_{j'})U(a,j')\tilde{G}(\max\{\theta^{**}(a,j'), \frac{m_j}{a}\}) \right)}_{\text{Inflow to } E(a,j)\text{(employed workers of type a in county } j)} = \underbrace{E(a,j)\eta_j}_{\text{Outflow from } E(a,j)}$$

$$\underbrace{U(a,j) \left(s_j \lambda_j \tilde{G}(\max\{\theta^*(a,j), \frac{m_j}{a}\}) + (1-s_j)\lambda_{j'}\tilde{G}(\max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}) \right)}_{\text{Outflow from } U(a,j) \text{ (unemployed residences of types a in county } j)} = \underbrace{\left(E(a,j) - M(a,j') \right)\eta_j}_{\text{Inflow into } U(a,j)}$$

$$\underbrace{(1-s_j)\lambda_{j'}U(a,j)P_1(a,j)\tilde{G}(max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}))}_{\text{migrants from j to j'}} = M(a,j)$$

$$\underbrace{(1-s_j)\lambda_{j'}U(a,j)P_0(a,j)\tilde{G}(max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}))}_{\text{commuters from j to j'}} = C(a,j)$$

The market clearing (#5) is imposed in the model's estimation (see below).

3 Data and descriptive statistics

City-level minimum wage ordinances are a fairly recent phenomenon. As of 2020, 42 municipalities instituted local minimum wage laws, with more than half of these laws enacted after 2013. Cities are often of interest because of their high population densities, but the number of cities that have enacted local minimum wage laws thus far is too limited to be the basis for estimating our search model parameters. For this reason, we base the model's estimation rather on a sample of county-pairs, following a design originally proposed by Dube et al. (2010, 2016). Our model's identification/estimation exploits state-level wage differences across county borders as well as time series variation. After estimating the model parameters, though, we will use the model to predict commuting responses to city minimum wage ordinances and compare the predictions to the data as a model validation exercise.

3.1 Data and Sample Construction

We primarily use three sources of data on contiguous county pairs along state borders: the Quarterly Workforce Indicators (QWI) for local labor market information, the American Community Survey (ACS) and the Longitudinal Employer-Household Dynamics Program's Local Origin and Destination Employment Statistics (LODES) for labor mobility information.

3.2 Data sources

QWI data: The QWI contains information on the number of job stocks and flows, and average earnings by industry, worker demographics, employer age, and size for each county. QWI comes from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata.[21] It has near-universal coverage of worker-employer information, covering 96% of private-sector jobs. The QWI also provides worker demographic information including age, sex, race/ethnicity, and education, which permits analysis of the demographics of a particular local market or industry.[22] Lastly, QWI has labor flow information, including hires, separations, and turnovers, which is important because the most direct impacts of minimum wage hikes are on job turnovers rather than employment stocks.[23] We analyze data from years 2005-2015.[24]

ACS data: We use the 2005-2015 ACS data to measure commuting and migration flows between different counties. Commuters are defined as people whose place of work differs from their place of residence, whereas migrants are defined as those who changed their place of residence in the past year. The basic geographic units in the ACS are "Public Use Micro Areas" (PUMAs) which are non-overlapping partitions in each state containing between 100,000 to 300,000 residents. There were a total of 2,071 PUMAs in the 2000 census. We use the PUMA-to-County crosswalk provided by Michigan Population Studies Center to generate commuting and migration flows at the county level.[25]

LODES data: We use LODES data to analyze how cross-border commuting patterns respond to minimum wage changes. According to Manning and Petrongolo (2017), labor markets are quite local, with job attractiveness decreasing sharply with distance. As a result, minimum wage effects may not be as apparent in a county-level analysis as in an analysis that focuses on workers residing close to state borders. For each pair of census blocks (referred to as "origin-destination census block pairs"), the LODES data counts the number of workers who live in one census block and work in another. We use this information to derive a measure of cross-border commuting flows within a band that stretches a short distance on both sides of state lines.[26] We expect that workers who live within a narrower commuting band are more affected by minimum wage changes in neighboring counties than workers who live further away, which is what we find.

[21] These data are collected through a unique federal-state data sharing collaboration between the U.S. Census Bureau and state labor market agencies. Data for Massachusetts, Puerto Rico, and the US Virgin Islands are still under development.

[22] Workers are identified by their Social Security number and linked with a variety of sources, including the 2000 Census, Social Security Administrative records, and individual tax returns to get their demographic information. Although the CPS contains similar information based-on household surveys, it has smaller sample sizes when focusing on particular industries or areas.

[23] See Dube et al. (2010, 2016) for detailed discussions.

[24] The states missing from the QWI dataset prior to 2005 are not random, with smaller states being under-represented. By 2005, all states except Massachusetts joined the QWI program. Massachusetts does not join until 2010.

[25] We do this for two reasons. First, because PUMAs are population-based, they are not natural jurisdictions for local policy analysis. In urban areas, a single county may contain multiple PUMAs. For example, Los Angeles County, California is comprised of 35 PUMAs. Likewise, a PUMA will consist of several counties in less populated areas. Second, we want to match the ACS to county-based statistics from the QWI. See Appendix C.3 and http://www.psc.isr.umich.edu/dis/census/Features/puma2cnty/for details.

[26] Appendix C.2 describes the restrictions imposed in constructing the LODES analysis sample.

Table 1: Minimum wage differences across border county pairs (2005-2015)

Year	Share of pairs with a minimum wage differential	Percent difference in minimum wages
2005	27.6%	18.6%
2006	33.6%	19.1%
2007	66.0%	15.6%
2008	63.7%	11.1%
2009	52.2%	8.7%
2010	31.8%	5.8%
2011	36.2%	6.0%
2012	37.8%	7.7%
2013	44.1%	7.4%
2014	49.0%	8.6%
2015	68.5%	9.4%
Average	46.4%	10.7%

3.3 Contiguous border county pairs and their associated minimum wages

Similar to the the sample design proposed by Dube et al. (2010, 2016), we divide all U.S. counties into two sub-samples: counties that border another state (border counties), and counties that do not (interior counties). Out of 3,124 counties, 1,139 counties are border counties and we construct 1,181 unique county pairs.[27] Between 2005 and 2015, there were 332 minimum wage adjustments (see Table A.4 in appendix C for state-level minimum wage policies by year). 78 of the minimum wage changes are driven by the federal minimum wage law, the Fair Minimum Wage Act of 2007, and the other 164 events were due to state ordinances. Between 2005 and 2015, all counties (except for those in Iowa) increased their local minimum wage at least three times, which provides useful time series variation for identifying the effects of minimum wage changes in addition to the cross-border cross-sectional variation.[28] In a given year, about half of the county pairs differ in terms of minimum wages. The differences average about 10%, but there is substantial heterogeneity across years (see Table 1).

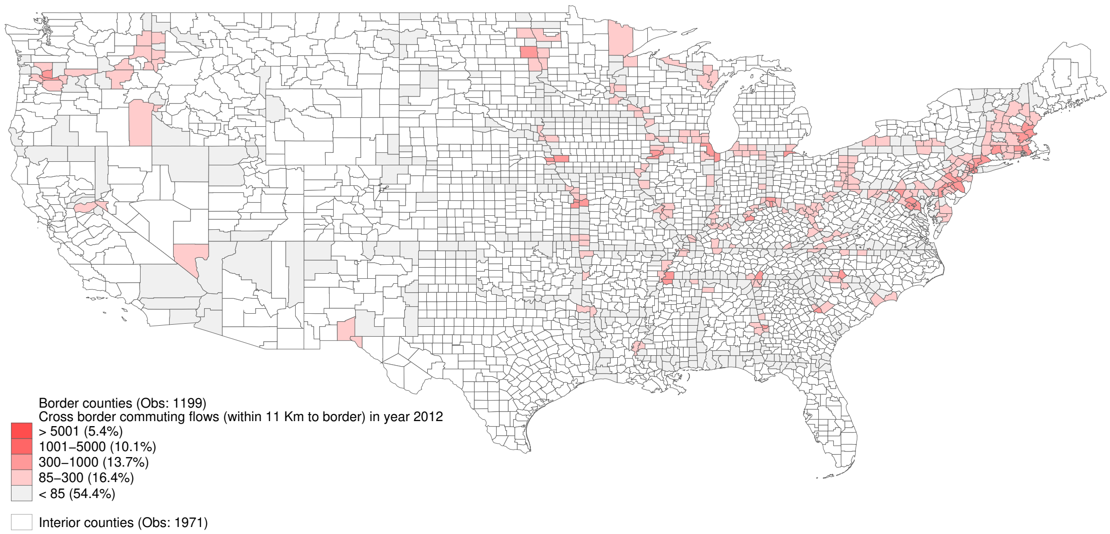
3.4 Analysis of how migration and commuting responds to minimum wage changes

We next estimate regression models to analyze how commuting and migration respond to minimum wage changes.

[27] Counties may border more than one county in the adjacent state, resulting in more pairs than border counties.

[28] The Act raised the federal minimum wage in three stages: to $5.85 60 days after enactment (2007-07-24), to $6.55 one year after that (2008-07-24), then finally to $7.25 one year after that (2009-07-24).

Figure 1: Included counties by the number of cross-border commuters they received



Note: Author's calculations from LODES. Highlighted counties are the ones included in the analysis. Colors represent the amount of commuters they send across the border in year 2012, i.e. the number of workers who work in the county and live in another county across the border.

3.4.1 Measuring commuting flows

The LODES data contain information on individuals living close to state boundaries that can be used to analyze how commuting responds to minimum wage changes.[29] According to Kneebone and Holmes (2015), a typical commuting distance is 7 miles (11 kilometers), so we define our baseline sample as individuals who live within 11 kilometers of the state boundary. As a robustness check, we do similar calculations doubling the commuting bandwidth to 22 kilometers. We exclude from the analysis county pairs that do not have a sufficient number of cross-state commuters, which are typically borders with low population density or ones where workers have difficulty commuting (for example, the Nevada-Utah border).[30] Figure 1 shows the included counties that receive more than the threshold number of cross-border commuters and the associated number of commuters they receive from cross-border counties.[31]

[29]We exclude Alaska and Hawaii from our analysis because they are remote states with few commuters to other states.

[30]The LODES data classifies workers into three wage categories: less than $1,250 per month, between $1,250 and $3,333 per month, and more than $3,333 per month. We restrict our sample to the pairs that the low wage commuters are more than 85. More counties in eastern states are included than in western states, as eastern counties on state borders are more likely to be located in metropolitan statistical areas or along densely populated borders.

[31]Figure A.1 shows the included counties that send more than the threshold number of cross-border commuters.

3.4.2 Measuring the share of mobile workers.

We obtain the share of commuters and migrants from the American Community Survey (ACS) data. To focus on workers potentially most affected by minimum wage changes, we limit our analysis sample to individuals age 16 and 30 who live in the continental United States and are not in the military.[32] We divide this sample into two education groups: low (no college) and high (some college or more).

Our spatial search model distinguishes between migrants who move out of a county and commuters who work in neighboring counties. Descriptive statistics for commuting outflows to other states and migration inflows from other states are shown in Table 2.[33] The rate (a value between 0 and 1) represents the share of commuters in the labor force. All statistics are at the county-level and are grouped by whether they are border or interior counties. As seen in Table 2, border counties have higher migration and commuting rates. More educated workers also have higher rates of migrating and commuting.

Table 2: Summary statistics of migrants and commuters (2005-2015)

		Interior counties		Border counties	
		Count	Rate	Count	Rate
ALL workers					
Migrants	Mean	829	0.029	939	0.070
	S.D.	2659	0.083	2881	0.131
Commuters	Mean	188	0.034	849	0.081
	S.D.	581	0.094	2732	0.150
Low education (no college)					
Migrants	Mean	273	0.026	307	0.062
	S.D.	796	0.078	757	0.124
Commuters	Mean	68	0.032	288	0.077
	S.D.	210	0.093	859	0.149
High education (some college)					
Migrants	Mean	556	0.031	632	0.076
	S.D.	1957	0.089	2265	0.140
Commuters	Mean	120	0.035	561	0.084
	S.D.	407	0.097	1999	0.154
Observations		28,042		15,932	

Note: Data sources is the ACS. All statistics are reported at the county level. Migrants refers to individuals whose place of residence last year differs from the place this year. The rate (a value between 0 and 1) is the proportion of migrants in the local population. Commuters refers to workers whose state of work differs from the state of current residence. The rate (a value between 0 and 1) represents the proportion of commuters in the labor force.

Local labor market outcomes. We use the QWI data to obtain four key quarterly variables that

[32]Young people and less-educated people are more likely to be minimum wage workers (Deere et al. (1995); Burkhauser et al. (2000); Neumark (2001)).

[33]The other two potential labor mobility measures are commuting inflows and migrating outflows. They can, in principle, be calculated by summarizing all workers who migrate from/commute into the targeted PUMA in the sample. However, this calculation suffers from serious measurement error because the migrants from the particular PUMA and the commuters working in the particular PUMA are a small minority in other PUMAs and thus unlikely to be sampled.

describe local labor market characteristics: average monthly earnings, employment, hiring rates, and job separation rates. To make the QWI sample more comparable to the ACS sample, we restrict workers' ages to be between 19-34.[34] As seen in Table 3, average earnings, number employed, job separation rates, hiring rates, and labor force participation rates are similar for interior and border counties. (Labor force participation information is derived from the ACS.)

Table 3: County-level labor market summary statistics (2005-2015)

	Interior counties		Border counties	
	Mean	SD	Mean	SD
Monthly earnings	1,932	739	1,930	739
Employment	14,883	54,878	13,045	45,968
Separation rates	0.299	0.111	0.301	0.103
Hire rates	0.326	0.171	0.326	0.128
Labor force participation rate				
All	0.813	0.102	0.818	0.098
High educated	0.638	0.152	0.643	0.151
Low educated	0.714	0.126	0.720	0.123

Note: All statistics are quarterly and from QWI except labor force participation, which is from the ACS. Monthly earnings are in nominal dollars.

3.4.3 Estimated elasticities in response to minimum wage changes

We next perform a panel data analysis of how migrating/commuting responds to minimum wage changes. The following regression that relates changes in the flows of migrants and commuters to relative minimum wage changes:

$$\log y_{wht} = \beta_0 + \beta_1 \log \frac{MW_{s(w),t}}{MW_{s(h),t}} + \tau_{c(w,h)} + \delta_t + \epsilon_{wht}. \tag{16}$$

Here, y_{wht} is the log of migrants or commuters from county h to county w, at time t for different skill groups (high or low). The minimum wage ratio $\frac{MW_{s(w)t}}{MW_{s(h)t}}$ is the ratio of the minimum wage in state $s(w)$ that county w belongs to and the neighboring state $s(h)$ of county h. Dube et al. (2010, 2016) show that neighboring counties tend to be similar in their covariates' levels and trends. Nevertheless, we control for potential unobservables by including county-pair fixed effects $\tau_{c(w,h)}$ as well as time effects δ_t. The coefficient β_1, the primary parameter of interest, gives the elasticity of labor flows y_{wht} with respect to a change in the relative minimum wage ratio.

We estimated various versions of specification 16 using both the LODES and ACS data. For the sake of

[34] The division of age groups in QWI are 19-21, 22-24, 25-34, 35-44, 45-54, 55-64, and 65-99. To roughly match with the selected ACS sample whose ages are between 16-30, we combine the first four age spans 14-18, 19-21, 22-24, and 25-34.

Table 4: Commuting flows in response to minimum wage ratio changes: LODES data

	Distance to border	
Worker wage category	(1) Within 11 km	(2) Within 22 km
Low wage (< 1250)	-1.287***	-0.451***
	(0.445)	(0.147)
	[3,495]	[3,959]
Middle wage ($[1250, 3333]$)	-0.920*	-0.299**
	(0.547)	(0.145)
	[3,547]	[3,809]
High wage (> 3333)	-0.423**	-0.319**
	(0.212)	(0.142)
	[3,564]	[3,959]
incl. time effects	Y	Y
incl county pair specific fixed effects	Y	Y

Note: See Appendix C.2 for a description of the LODES sample. The table reports coefficients associated with the log of relative minimum wage ratio (log $\frac{MW_{st}}{MW_{\bar{st}}}$). Robust standard errors, in parentheses, are clustered at the the paired-county levels. * for 10%. ** for 5%, and *** for 1%. Sample sizes are reported in brackets below the standard error for each regression.

brevity, results for LODES are shown here and results for ACS are shown in Appendix B.1. LODES divides workers into three groups based on monthly earnings: below \$1,250 per month (low wages), between \$1,250 and \$3,333 per month (middle wages), and above \$3,333 per month (high wages). Most minimum wage workers fall in the lowest wage category (equivalent to hourly rate \$7.82 for a full time worker (160h/month)), which we expect to be more responsive to minimum wage changes compared to the other groups.

The estimates show that less-educated workers on net commute/migrate away after a local increase in the minimum wage relative to the neighboring county. As seen in column (1) of table 4, relative minimum wage increases have a statistically significant negative effect on commuters coming into the area for workers in all categories, but particularly for low wage workers. When there is a 1% relative minimum wage increase, the commuter flows decrease by 1.248%, 0.827% and 0.407% in the low, middle, and high categories. These patterns are consistent with McKinnish (2017), who finds a higher minimum wage is associated with lower commuting inflows into a PUMA. However, our estimates are greater in magnitude than hers, likely because the observed commuting response is greater for individuals residing close to state borders. To explore whether and to what extent distance to the border matters, in column (2) we expand the commuting distance band from 11 km to 22 km. The commuting inflow elasticity estimates decrease in magnitude, but are still statistically significant at conventional levels.

3.4.4 Analysis of Pre-trends.

A concern that is sometimes raised in the minimum wage literature is that states tend to pass minimum wage increases during good economic times, which could lead favorable wage and employment changes to be falsely attributed to minimum wage increases. (Card and Krueger (1994); Neumark et al. (2007); Monras (2019)) For this reason, we next explore whether there are "pre-trends" in commuting flows that occur before the minimum wage changes. Following Freyaldenhoven et al. (2019), we modify equation 16 to incorporate leads and lags up to three years of the relative minimum wage ratio between workplace and residence:

$$\log y_{wht} = \beta_{-4+}\left(1 - \log \frac{MW_{s(w),t+3}}{MW_{s(h),t+3}}\right) + \sum_{k=-2}^{3} \beta_{-k}\Delta \log \frac{MW_{s(w),t+k}}{MW_{s(h),t+k}} + \beta_{3+} \log \log \frac{MW_{s(w),t-3}}{MW_{s(h),t-3}} + \tau_{c(w,h)} + \delta_t + \epsilon_{wht} \tag{17}$$

The coefficients $\beta_k, k = \{-4+, -3, -2, ..., 2, 3, 3+\}$ measure the lead and lag effects of the changes in the relative minimum wage ratio on these pair-wise commuting flows. β_{-4+} indicates the effects 4 years before the change while β_{3+} indicates the effects 3 years after the change. If the estimated coefficient $\beta_k, k < 0$ are not significantly different from 0, we are able to rule out the existence of pre-trends.

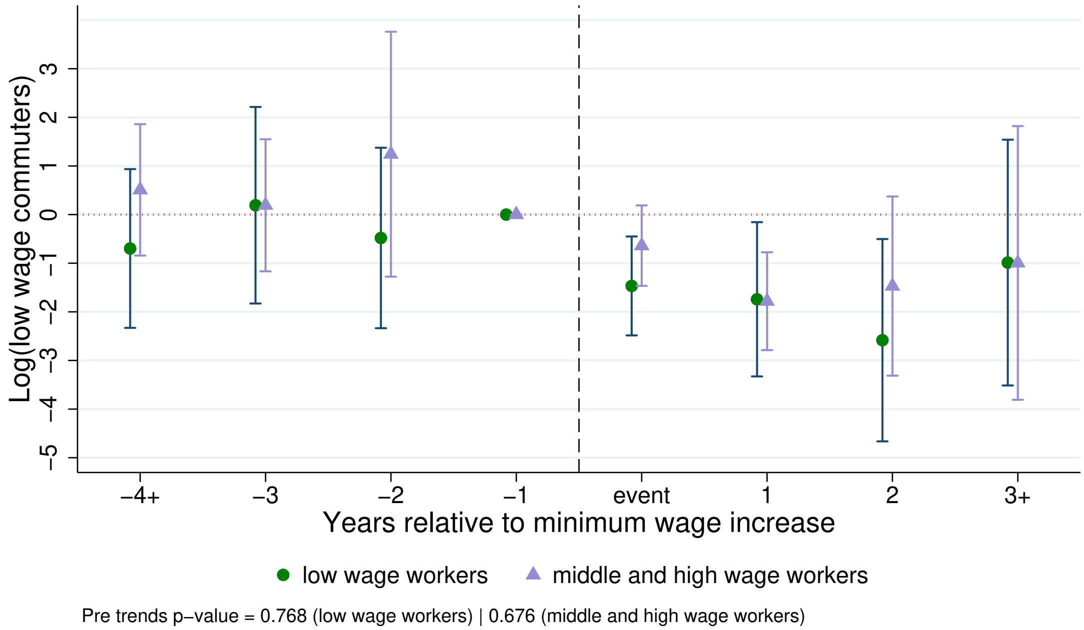
Figure 2 plots the $\hat{\beta}_k$ estimated from the equation 17. The green dots show the estimates for low wage workers and the purple triangles show the estimates for all workers. In both cases, the lead coefficients ($k < 0$) are not statistically significantly different from 0, so there is no evidence for pre-trends. However, the estimated coefficients diverge substantially from zero after the minimum wage changes. The coefficients for low wage workers increase in absolute value, with point estimates for the low-wage commuting elasticity of around -1 after two years and -2 in the third year. The estimated coefficients for all workers increase modestly but are not statistically significant, indicating that the minimum wage changes have a persistent effect mainly on low wage worker's commuting patterns.

4 Estimation strategy

4.1 Parameterization

To implement the spatial search model described in section 2, we first classify workers by education types and specify some parametric assumptions on their choice-specific moving costs. As previously noted, we assume workers are of two types, a_h and a_l, where high type workers are those with some college and low type workers are those with no college. The proportion of these two worker types are p_h and p_l.

Figure 2: Test for pre-trends in commuting flows in response to minimum wage changes



Note: The vertical bars give 95% confidence intervals, calculated based on robust standard errors, with clustering at the county pair level. The horizontal axis label at 0 shows the mean of the dependent variable at $k = -1$. Pre trends p-value comes from a test of $\beta_{-4+} = \beta_{-3} = \beta_{-2} = \beta_{-1} = 0$.

We assume that moving costs depend on the worker's type a, the physical distance $d_{jj'}$, a cost of living difference $\gamma_j - \gamma_{j'}$ between the two counties, as well as the migration/commuting choice h.

(18)

$$cc_h(a,j) = \begin{cases} \beta_{0j} + \beta_{0d} d_{jj'} + \beta_{0a} I(a = a_h) + \beta_{0\gamma}(\gamma_j - \gamma_{j'}) + \frac{\eta_{j'}}{\rho + \eta_{j'}}(V_u(a,j) - V_u(a,j')) & \text{if } h = 0 \\ \beta_{1j} + \beta_{1d} d_{jj'} + \beta_{1a} I(a = a_h) + \beta_{1\gamma}(\gamma_j - \gamma_{j'}) & \text{if } h = 1 \end{cases}$$

Equation 18 is a modified gravity equation for migration/commuting options. β_{hj} measures the relative openness of labor market j, which is county-specific and differs by the mobility choice h (commuting or migrating). The different impacts of distance on migrants and commuters are captured by β_{0d} and β_{1d}.[35] The coefficients β_{0a} and β_{1a} represent the cost difference paid by high type workers. Asymmetries in mobility and moving costs across different regions can be attributed in part to different local amenities, which we measure by differences in housing rental prices (γ_j and $\gamma_{j'}$). Lastly, the term $\frac{\eta_{j'}}{\rho + \eta_{j'}}(V_u(a,j) - V_u(a,j'))$ captures the difference in values of being employed in the two locations (obtained from equations 8 and 9) when the worker chooses commuting over migration.[36]

[35] Although the distance between centroids is only a proxy for the real commuting time between two counties, some evidence shows the correlation between these two measures is quite high. (Phibbs and Luft (1995);Boscoe et al. (2012)).

[36] Intuitively, if a mobile worker in county j lost her job, she would receive unemployment benefits b_j in county j if she were commuting, but would receive unemployment benefits b_j in county j' if she chose to migrate.

Table 5: County-level parameters derived from the data

	Interpretation	How obtained	County j Mean	County j S.D.	County j' Mean	County j' S.D.	Data source
α_j	Labor share in surplus	payroll/revenue	0.313	0.048	0.305	0.045	EWKS 07, 12
k_j	Market tightness	job ads/unemployment	2.802	1.410	2.893	1.414	HWOL 05-15
η_j	Job destruction rate	separations/employment	0.354	0.116	0.353	0.113	QWI 05-15
γ_j	Local amenity	local housing rental price	692	219	702	233	ACS 05-15
p_h	fraction of high education workers	fraction some college or above	0.512	0.095	0.514	0.103	ACS 05-15
p_l	fraction of low educated workers	fraction no college	0.488	0.095	0.486	0.103	ACS 05-15
m_j	minimum wage	minimum wage in $Q1$	7.414	0.739	7.312	0.733	Dube et al. (2016)
$d_{jj'}$	(log) distance between j and j'	(log) centroid distance	3.535	0.206	3.535	0.206	Dube et al. (2016)

Note: County j and j' are randomly assigned within county pairs.

As discussed in Flinn and Heckman (1982), it is necessary to assume a parametric distribution for the matching quality $G(\theta)$ for identification and the distribution needs to satisfy a "recoverability condition" that they specify. We assume the matching quality distribution follows a log-normal distribution, which satisfies this condition. (A similar assumption is made in Flinn (2006) and Flinn and Mullins (2015).)

Given the above assumptions, the economy is characterized by the vector S which combines a set of general parameters, common across all counties, and a set of county-specific parameters.

$$\Theta = \{\rho, \mu_G, \sigma_G, a_h, a_l, \beta_{0d}, \beta_{0a}, \beta_{0r}, \beta_{1d}, \beta_{1a}, \beta_{1\gamma}, \sigma_0, \sigma_1\} \bigcup \qquad \text{General}$$
$$\{b_j(n), s_j(n), \psi_j(n), \beta_{0j}(n), \beta_{1j}(n), m_j(n), \eta_j(n), \alpha_j(n), \omega_j(n), \gamma_j(n), d_{jj'}(n), p_h(n), p_l(n)\}_{(j,n)\in\{1,2\}\times N} \qquad \text{County}$$

To incorporate county-level heterogeneity while at the same time keeping the number of model parameters parsimonious, we impose a random coefficient structure on the county-specific parameters $\theta_j(n) \in \{b_j(n), s_j(n), \psi_j(n), \beta_{0j}(n), \beta_{1j}(n)\}$. These correspond to the unemployment benefit, the cost of posting vacancies, and the intercept terms in the commuting and moving cost functions. The other county-specific parameters $\left\{m_j(n), \eta_j(n), \alpha_j(n), \omega_j(n), \gamma_j(n), d_{jj'}(n), p_h(n), p_l(n)\right\}_{j=1,2}$ are derived directly from the data, their values and sources are shown in table 5.

Given the close geographic proximity between paired counties, we allow the parameters in the $\theta_j(n)$ and $\theta_{j'}(n)$ vectors to be correlated across within pairs by assuming that each of the components is bivariate normally distributed. Specifically, we make the following distributional assumptions:

$$
\begin{aligned}
\begin{pmatrix} b_j \\ b_{j'} \end{pmatrix} &\sim N\left(\begin{bmatrix} \mu_b \\ \mu_b \end{bmatrix}, \begin{bmatrix} \sigma_b^2 & \rho_b\sigma_b^2 \\ \rho_b\sigma_b^2 & \sigma_b^2 \end{bmatrix}\right) \\
\begin{pmatrix} \log\psi_j \\ \log\psi_{j'} \end{pmatrix} &\sim N\left(\begin{bmatrix} \mu_\psi \\ \mu_\psi \end{bmatrix}, \begin{bmatrix} \sigma_\psi^2 & \rho_\psi\sigma_\psi^2 \\ \rho_\psi\sigma_\psi^2 & \sigma_\psi^2 \end{bmatrix}\right) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{bmatrix} \mu_{\beta 0} \\ \mu_{\beta 1} \end{bmatrix}, \begin{bmatrix} \sigma_{\beta 0}^2 & \rho_\beta\sigma_{\beta 0}\sigma_{\beta 1} \\ \rho_\beta\sigma_{\beta 0}\sigma_{\beta 1} & \sigma_{\beta 1}^2 \end{bmatrix}\right) \\
\log\left(\frac{s_j}{1-s_j}\right) = \log\left(\frac{s_{j'}}{1-s_{j'}}\right) &\sim N\left(\mu_s, \sigma_s^2\right)
\end{aligned}
$$

The joint distributions of these 4 pairs of random coefficients are fully characterized by 13 parameters: 5 means, μ_θ; 5 variances, σ_θ^2; and 3 correlations, ρ_θ. We assume that the search efficiency s_j and $s_{j'}$ is the same within a county pair.[37]

4.2 The method of moments estimator

The model parameters are estimated by the method of moments (MOM), which is a natural approach for combining moments from multiple databases. The moments used in estimation are shown in Tables 6 and 7. These moments have an analytical expression derived from the model, as derived in Appendix A.4. Model simulations are only required to perform the numerical integration over the county-specific random coefficient parameters. The model is estimated using 10 time periods, corresponding to the years 2005-2015. We select the county pairs using the same criteria that we impose when conducting the regression analysis; that is, we only include county pairs that are close with each other (centroids $\leq$ 44 km) and have sufficient numbers of mobile workers (the average fraction of both migrants and commuters are more than 1.5%). The unit of observation is a county-pair observed in a particular time period, and our final sample size is n=2742 (2742 observations from 290 distinct county pairs). The minimum wage and earnings values are adjusted to 2015 US dollars. Appendix C provides more details on the sample construction.

The estimation proceeds as follows:

- We first specify an initial vector of parameters Ω that includes the parameters governing the random coefficient distributions, $(\mu_\theta, \sigma_\theta, \rho_\theta : \theta \in \{b, s, \psi, \beta_0, \beta_1\})$, in addition to the set of general (not county-specific) parameters $\{\rho, \mu_G, \sigma_G, a_h, a_l, \beta_{0d}, \beta_{0a}, \beta_{0\gamma}, \beta_{1d}, \beta_{1a}, \beta_{1\gamma}, \sigma_0, \sigma_1\}$,
- Given Ω, we draw the county-level random coefficients $\{b_j, s_j, \psi_j, \beta_{0j}, \beta_{1j}\}_{j=1,2}$ for each county pair in a particular time period n from the joint distributions previously specified.[38]

[37] This assumption eliminates workers' incentives to move in order to arbitrage differences in search efficiency.
[38] This means the same county pair in two different periods would get separated draws of the county-level random coefficients.

Table 6: County-level Moments

Empirical moments	County j		County j'		Identified
	Mean	S.D.	Mean	S.D.	Parameters
Moments from mean and S.D. in county pair $p(j, j')$					
Employment rate (high edu)	0.901	0.085	0.908	0.064	$\mu_b, \sigma_b, \mu_\psi, \sigma_\psi$
Employment rate (low edu)	0.791	0.100	0.801	0.086	$\mu_b, \sigma_b, \mu_\psi, \sigma_\psi$
Proportion of migrants (high edu)	0.102	0.104	0.107	0.119	$\mu_s, \sigma_s, \mu_{\beta 0}, \sigma_{\beta 0}, \beta_{0a}$
Proportion of migrants (low edu)	0.073	0.082	0.078	0.099	$\mu_s, \sigma_s, \mu_{\beta 0}, \sigma_{\beta 0}, \beta_{0a}$
Proportion of commuters (high edu)	0.113	0.114	0.120	0.134	$\mu_s, \sigma_s, \mu_{\beta 1}, \sigma_{\beta 1}, \beta_{1a}$
Proportion of commuters (low edu)	0.094	0.102	0.100	0.124	$\mu_s, \sigma_s, \mu_{\beta 1}, \sigma_{\beta 1}, \beta_{1a}$
Correlation between migrants and distance	-0.108	-	-0.117	-	β_{0d}
Correlation between commuters and distance	-0.106	-	-0.114	-	β_{1d}
Correlation between migrants and rent cost	0.020	-	0.044	-	$\beta_{0\gamma}$
Correlation between commuters and rent cost	0.010	-	0.031	-	$\beta_{1\gamma}$

Note: County j and j' are randomly assigned within county pairs. For details about how the moment are derived, see Appendix A.4.

- Using these parameters as well as the set of parameters derived directly from the data (see Table 5), we compute the vector of simulated moments $\tilde{M}_N(\Omega)$.

Model parameters are estimated by minimizing the weighted difference between the simulated moments $\tilde{M}_N(\Omega)$ and the actual data moments M_N, using the distance function

$$\hat{\Omega}_N = \arg\min_{\Omega} \Big((M_N - \tilde{M}_N(\Omega))' \hat{W}_N(\Omega)(M_N - \tilde{M}_N(\Omega)) \Big)$$

where M_N denotes the data moments for all county pairs (N of them), and $\tilde{M}_N(\Omega)$ represents the simulated moment evaluated at Ω. $\hat{W}_N$ is the optimal weighting matrix obtained using a two-step procedure described in Gourieroux et al. (1996). The variance-covariance matrix Q of the estimated parameters is calculated using the GMM formula:

$$\hat{Q} = [\hat{D}_N \hat{W}_N \hat{D}_N]^{-1}$$

where $\hat{D}_N$ denotes the numerical matrix of first derivatives, obtained numerically. (See Hansen (1982).)

4.3 Identification and selection of moments

Flinn (2006) estimates a search model with homogeneous workers and one labor market, that he uses to analyze the effects of minimum wages. This paper extends Flinn (2006) by incorporating two worker types and by allowing workers to search and firms to post offers in two geographically connected markets. Flinn (2006) shows that identification requires restricting the class of parametric matching distributions $G(\theta)$,

Table 7: National-level moments

Empirical moments	Value	Parameters identified by moment
Moments at the national level		
Average hourly wage: mean (high edu)	17.11	μ_b, a_h, μ_G
Average hourly wage: S.D. (high edu)	3.17	σ_b, a_h, σ_G
Wage diff between local and mobile (high edu)	1.26	$\mu_{\beta 0}, \sigma_{\beta 0}, \mu_{\beta 1}, \sigma_{\beta 1}, \rho_\beta, \beta_{1a}$
Average hourly wage: mean (low edu)	12.75	μ_b, a_l, μ_G
Average hourly wage: S.D. (low edu)	1.75	σ_b, a_l, σ_G
Wage diff between local and mobile (low edu)	1.05	$\mu_{\beta 0}, \sigma_{\beta 0}, \mu_{\beta 1}, \sigma_{\beta 1}, \rho_\beta, \beta_{0a}$
Elasticity from the regression analysis $\left(\frac{\log y_{ct}}{\log(MW_{s'(c),t}/MW_{s(c),t})}\right)$		
Commuting elasticity (low edu)	-0.304	$\mu_s, \sigma_s, \mu_{\beta 0}, \sigma_{\beta 0}, \beta_{0a}$
Commuting elasticity (high edu)	-0.455	$\mu_s, \sigma_s, \mu_{\beta 0}, \sigma_{\beta 0}, \beta_{0a}$
Migration elasticity (low edu)	-0.218	$\mu_s, \sigma_s, \mu_{\beta 1}, \sigma_{\beta 1}, \beta_{1a}$
Migration elasticity (high edu)	-0.138	$\mu_s, \sigma_s, \mu_{\beta 1}, \sigma_{\beta 1}, \beta_{1a}$

Note: For details about how the moments are derived, see Appendix A.4.

to ones that satisfy a "recoverability condition".[39] The same is required in our model. We assume, as he does, that the matching quality distribution is log-normal. Flinn (2006) shows that the model parameters are then parametrically identified except for the discount factor and unemployment utility (ρ, b), which cannot be separately identified, because they enter into the likelihood function jointly and only through the critical value θ^*. He shows that if the discount factor ρ is fixed, then the other model parameters $\{b, G(\theta), \alpha, \eta, \lambda\}$ are identified. The vacancy cost ψ is also shown to be identified when the matching technology ω is assumed to be a Cobb-Douglas.

In our model, workers split their searching time between the local labor market (s_j) and the neighboring labor market ($1 - s_j$). They have different reservation wages for local jobs and neighboring jobs; that is, they accept a local offer if $\theta \geq \theta^*(a, j)$ and accept a neighboring offer if $\theta \geq \theta^{**}(a, j)$. Below, we will discuss how to identify the model parameters in our set-up.

We begin by discussing the parameters that we obtain directly from the multiple data sources that we use, as summarized in Table 5. First, we obtain the labor share α_j as the average payroll share of firms' expenditures at the county level provided by the Economy Wide Key Statistics (EWKS), which is the U.S. government's official five-year measure of American business and the economy.[40] Second, we obtain the matching technology parameter ω_j from a measure of market tightness k_j, defined as the state-level ratio of job demand to labor supply (constructed from the Conference Board Help Wanted OnLine (HWOL)).[41]

[39] A comprehensive discussion about the "recoverability condition" can be found in Flinn and Heckman (1982).

[40] Although the bargaining power in principle can be identified without additional information. Flinn (2006) demonstrates using a Monte Carlo experiment that it is difficult to identify this parameter reliably in practice. Therefore, we follow Flinn (2006) in using the ratio of total wages paid to firm revenue to capture the labor share α_j.

[41] Beginning in 2005, HWOL provides a monthly series that covers the universe of vacancies advertised on about 16,000 online

Third, the job destruction rate η_j is obtained from the QWI data as the ratio of total separations to total number employed. Fourth, the share of high educated works p_j^h, the share of low educated workers p_j^l, and the local amenity γ_j(approximated by the local housing rental cost) are derived from the county-level ACS data, using information on educational attainment levels and rental costs. Lastly, we also directly observe the centriod distance within any county pairs $d_{jj'}$ and the local minimum wage m_j series, which is provided in Dube et al. (2016) but adjusted using the value of 2015 US dollar.

We now consider identification of the remaining model parameters that not directly observed, including the education ability values, $\{a_l, a_h\}$ and county-specific values, $\{s_j, c(a,j), \theta^*(a,j), \theta^{**}(a,j)\}_{\{a_l,a_h\}\times\{j,j'\}}$. First, we can jointly estimate the parameters $\{a, \theta^*(a,j), \theta^{**}(a,j)\}$ from the wage distributions for local workers and mobile workers. When plugging in $a\theta^*(a,j) = \rho V_u(a,j)$ into equation 3, the bargained wage has the expression:

$$\hat{w}(a,\theta,\theta^*) = a\theta^*(a,j) + \alpha_j(a\theta - a\theta^*(a,j)) = a(\alpha_j\theta + (1-\alpha_j)\theta^*(a,j))$$

The observed wage, which is constrained by the minimum wage m_j, is determined by the following equation:

$$w(a,\theta,\theta^*) = \begin{cases} m_j & \theta \in [\frac{m_j}{a}, \hat{\theta}(a,\theta^*)] \\ a(\alpha_j\theta + (1-\alpha_j)\theta^*(a,j)) & \theta > \hat{\theta}(a,\theta^*) \end{cases} \tag{19}$$

where $\hat{\theta}(a,\theta^*)$ refers to the critical matching quality when the bargained wage is set equal to m_j, based on equation 5. Recall that the bargaining value α_j and minimum wages m_j are directly derived from data. A wage offer for a worker with education level a in location j is determined by three values: the education level a, the matching quality draw θ and the reservation matching quality $\theta^*(a,j)$. We can jointly identify $\{a, \theta^*(a,j)\}$ from the mean and variance of the wage distribution of local workers, given by the following expressions:

$$E[w_{local}(a,\theta^*)] = \int_{\max\{\theta^*, \frac{m}{a}\}} w(a,\theta,\theta^*)G(\theta)$$

$$Var[w_{local}(a,\theta^*)] = \int_{\max\{\theta^*, \frac{m}{a}\}} \left(w(a,\theta,\theta^*) - E(w_{local}(a,\theta^*))\right)^2 G(\theta).$$

Similarly, we can identify $\{a, \theta^{**}(a,j)\}$ from the wage distribution of mobile workers. Notice that we

job boards and online newspaper editions. Although HWOL only collects the job openings advertised online, its pattern is quite similar with the general pattern measured by JOLTS, especially before 2013. A detailed comparison between HWOL and JOLTS can be found in Şahin et al. (2014).

assume the same wage determination protocol (equation 19) for both local workers and mobile workers. Therefore, mobile workers differ from local workers only in terms of their reservation matching quality $\theta^{**}(a,j)$. As a result, we can identify $\theta^{**}(a,j)$ from the mean and variable of the wage distribution for mobile workers:[42]

$$E[w_{mobile}(a,\theta^*,\theta^{**})] = \int_{\max\{\theta^{**},\frac{m}{a}\}} w(a,\theta,\theta^*)G(\theta)$$

$$Var(w_{mobile}(a,\theta^*,\theta^{**})) = \int_{\max\{\theta^{**},\frac{m}{a}\}} \left(w(a,\theta,\theta^*) - E(w_{mobile}(a,\theta^*))\right)^2 G(\theta)$$

Once both $\theta^{**}(a,j)$ and $\theta^*(a,j)$ are identified, the expected moving cost $c(a,j)$ can be obtained from equation 7:

$$V_e(\theta^*(a,j),a,j) + c(a,j) = V_e(\theta^{**}(a,j),a,j')$$

Given the identified $c(a,j)$ and observed migration/commuting choices $P_0(a,j)$ and $P_1(a,j)$, the choice-specific moving costs $cc_0(a,j)$ and $cc_1(a,j)$ are identified from equation 18, which was derived under the logistic assumption.

Lastly, the parameters $\{s_j, s_{j'}\}$ are identified from the observed relative sizes of local and mobile workers as follows.

$$\frac{\text{local worker in j}}{\text{mobile worker from j' to j}} = \frac{s_j\tilde{G}(\max\{\theta^*(a,j),\frac{m_j}{a}\})}{(1-s_{j'})\tilde{G}(\max\{\theta^{**}(a,j'),\frac{m_j}{a}\})}$$

$$\frac{\text{local worker in j'}}{\text{mobile worker from j to j'}} = \frac{s_{j'}\tilde{G}(\max\{\theta^*(a,j'),\frac{m_{j'}}{a}\})}{(1-s_{j'})\tilde{G}(\max\{\theta^{**}(a,j),\frac{m_{j'}}{a}\})}$$

As previously discussed, the moments we use and the associated parameters are shown in Table 6 and 7. It is worth noting that we also incorporated commuting and migration elasticities from regression 16 as extra moments. (the lower panel in table 7) These auxiliary moments are not required for identification purposes. However, one of our goals is to use the model to predict changes in commuting and migration flows in response to minimum wage changes, so the model needs to provide a good fit to these features of the data.

[42] This identification requires the condition $a\theta^{**}(a,j) > m$. Given the empirical pattern that average wages for mobile workers are higher than average wages for local workers, we verify that this condition holds for at least some county pairs.

5 Empirical results

In this section, we first present some evidence on the model's goodness of fit and then discuss the estimated model parameters.

5.1 Model fit

The estimated model reproduces many features of the data at both the county level (Table 8) and at the national level (Table 9). As reported in Table 8, simulations based on the model closely match average employment rates, although the employment rate dispersion is lower than in the data. For both low and high educated groups, the simulated migration and commuter rates are fairly close to the data. The model simulations also reproduce the negative correlation between labor mobility patterns and distance between county j and j', although the magnitudes are smaller relative to the data. Lastly, our model simulations show almost no correlation between migration/commuting and rent costs, whereas the data shows a slightly positive correlation. Model simulations also fit the pattern that high education workers have much higher wages than low education workers. They also show that mobile workers' average wages are higher than those of local workers, which occurs because mobile workers are more selective about wage offers to compensate for the extra moving costs. Lastly, our model accurately fits the minimum wage elasticities of commuters and migrants. Commuting is more sensitive to minimum wage changes than migration. The model simulations also show that low educated commuters are more responsive to the minimum wage changes than high educated commuters.

5.2 Model estimates

Table 10 shows the estimates of both the general parameters and the county-specific moving cost equation parameters (see Equation 18). The mean of the log-normal distribution of matching quality is $\mu_\theta = 0.694$, and the standard deviation is $\sigma_\theta = 0.747$. The value of unemployment, $\left(b_j, b_{j'}\right)$, is estimated to be relatively similar across paired counties, with a high within pair correlation $\rho_b = 0.881$ and a low standard deviation $\sigma_b = 0.110$. In contrast, the vacancy cost ψ varies considerably across counties. Its mean value is 214, which is equivalent to $34,240 if a filled worker works 160 hours per month. The large standard deviation and low correlation between county pairs suggest that vacancy costs are spatially diverse.

The mean value of the search efficiency parameter s_j is 0.735, which means that the number of neighboring offers a typical worker receives is roughly one-third of the number of local job offers. This mag-

Table 8: Model fit: county level statistics

Empirical moments	County j		County j'	
	Data	Sim	Data	Sim
Employment rate: mean	0.847	0.837	0.855	0.839
Employment rate: std	0.085	0.024	0.067	0.023
Proportion of migrants: mean (low edu)	0.074	0.096	0.078	0.096
Proportion of migrants: std (low edu)	0.082	0.087	0.099	0.087
Proportion of commuters: mean (low edu)	0.094	0.114	0.100	0.114
Proportion of commuters: std (low edu)	0.102	0.098	0.124	0.098
Proportion of migrants: mean (high edu)	0.102	0.100	0.107	0.100
Proportion of migrants: std (high edu)	0.103	0.092	0.119	0.092
Proportion of commuters: mean (high edu)	0.114	0.103	0.120	0.103
Proportion of commuters: std (high edu)	0.114	0.092	0.134	0.092
Correlation between migrants and distance	-0.109	-0.033	-0.117	-0.033
Correlation between commuters and distance	-0.106	-0.028	-0.114	-0.028
Correlation between migrants and rent cost	0.020	-0.013	0.031	-0.002
Correlation between migrants and rent cost	0.010	0.004	0.043	0.032

Note: County j and j' are randomly assigned within county pairs.

Table 9: Model fit: average across counties (national) statistics

Empirical moments	Data	Sim
Average wage rate: mean (high edu)	17.11	16.09
Average wage rate: std (high edu)	3.170	4.549
Wage diff between local and mobile (high edu)	1.260	1.362
Average wage rate: mean (low edu)	12.75	12.40
Average wage rate: std (low edu)	1.610	3.063
Wage diff between local and mobile (low edu)	1.050	0.817
Commuting elasticity (low edu)	-0.304	-0.275
Commuting elasticity (high edu)	-0.455	-0.484
Migration elasticity (low edu)	-0.218	-0.023
Migration elasticity (high edu)	-0.138	-0.111

nitude is consistent with Manning and Petrongolo (2017), who note that the effective labor market for job seekers is quite local. The probability of a random job 5km distant being preferred to a random local job is only 19%. Furthermore, the estimates reveal that the average productivity of workers with higher education is significantly greater than that of workers with lower education ($a_h = 10.454$ vs. $a_l = 8.233$). When comparing mobility costs, migrating is more costly ($\beta_1 = 0.684$) than commuting ($\beta_0 = 0.510$), which can explain why the fraction of commuters is on average larger than the fraction of migrants.

The lower panel in Table 10 reports the additional parameters in the estimated moving cost functions $cc_h(a, j)$, besides the constant terms β_0 and β_1. Both β_{0a} and β_{1a} have a positive signs, indicating that workers with higher education levels face higher costs to be mobile workers than workers with less education. The next two coefficients, $\beta_{0\gamma}$ and $\beta_{1\gamma}$ relate the moving cost to the local housing rental price, which is

Table 10: Model parameter estimates

General parameters				
Parameters	Notation	Mean μ	S.D. σ	Corr. ρ
Matching quality	θ	0.694	0.747	-
		(0.058)	(0.025)	-
Unemployed flow utility	b	-4.478	0.370	0.881
		(0.252)	(0.042)	(0.197)
Search efficiency	s	0.735	0.198	-
		(0.029)	(0.029)	-
Vacancy cost	ψ	214	272	-0.089
		(8.857)	(3.145)	(0.064)
High type productivity	a_h	10.45	-	-
		(0.366)	-	-
Low type productivity	a_l	8.233	-	-
		(0.554)	-	-
Commuting cost (constant term)	β_0	0.510	0.821	0.204
		(0.305)	(0.906)	(0.210)
Migration cost (constant term)	β_1	0.684	1.317	
		(0.907)	(0.676)	
Additional moving and migration cost equation parameters $cc_h(a, j)$				
	Commuting ($h = 0$)		Migration ($h = 1$)	
Additional cost for high education	β_{0a}	3.963	β_{1a}	2.941
		(0.263)		(0.610)
Coefficient for local amenity (rental cost)	$\beta_{0\gamma}$	0.133	$\beta_{1\gamma}$	0.125
		(0.196)		(0.066)
Coefficient for distance	β_{0d}	0.161	β_{1d}	0.114
		(0.174)		(0.304)
Scale of preference shock (low type)	σ_l^c	6.527		
		(3.589)		
Scale of preference shock (high type)	σ_h^c	6.000		
		(6.360)		

Note: Standard errors in parentheses.

used to proxy for local amenities. A positive sign of $\beta_{0\gamma}$ and $\beta_{1\gamma}$ indicates the commuting/migration costs are higher for workers coming from areas with high housing costs. The coefficients β_{0d} and β_{1d} account for distance costs associated with commuting or migrating. As expected, both commuting and migration costs increase with distance between the county pairs. However, because $\beta_{0d} > \beta_{1d}$, commuting costs are more sensitive to travel distance than are migration costs. Lastly, the scale parameters for low-education workers are similar to those for high-education workers.

Table 11 reports the distribution of moving costs. The left panel shows summary statistics of the ex-ante moving costs $c(a, j)$ for workers differentiated by education levels and locations. According to our estimates, the ex-ante moving cost is on average about $4,500 for low educated workers and $10,000 for high educated workers. These costs include the time and expense associated with commuting and the relo-

Table 11: Moving costs and neighboring county preference

	Lump-sum ex-ante moving cost (unit: $)			
	Low educated		*High educated*	
	County j	County j'	County j	County j'
10th	1,853	1,845	7,220	7,241
25th	2,543	2,501	7,914	7,877
Median	3,810	3,795	9,221	9,236
75th	5,516	5,504	11,232	11,153
90th	7,739	7,750	13,494	13,547
Mean	4,503	4,462	10,021	9,981
SD	3,085	3,076	3,226	3,218

Note: The dollar value of ex-ante moving cost $c(a, j)$ is estimated based on a representative full time worker working 160 hours/month.

cation costs associated with migration.(Schwartz (1973), Greenwood (1975)) These moving costs are much lower than some costs reported in the previous literature. For example, Kennan and Walker (2011) estimate a moving cost value of $312,000 for an average move across states in the US. Schmutz and Sidibé (2019) find the average moving cost between French cities is around €15,000. We might expect our estimated moving costs to be lower for two reasons. First, we focus on migration/commuting flows between two contiguous counties that are in close proximity. Second, we concentrate on younger workers, who are most likely to be impacted by minimum wage laws and for whom the opportunity costs of moving are typically lower.

5.3 Out of sample validation: predicting effects of city minimum wage ordinances

As previously noted, we do not exploit wage variation around cities in estimating the model, because the sample of cities that implemented minimum wage laws is modest in size. However, as an out-of-sample validation exercise, we use our estimated model to predict changes in commuting that occur after cities pass minimum wage ordinances. According to Figure 3, 37 cities from ten states have their own minimum wages in 2019, ranging from $9.2 to $16.3. We compare the commuting elasticities predicted by the model to those calculated from the LODES data (up to 2019), which were not used in estimating the model.[43] We focus on workers living within 22 kilometers of the city (in the suburbs). We use the following formula to calculate their commuting elasticity in response to relative minimum wage changes:

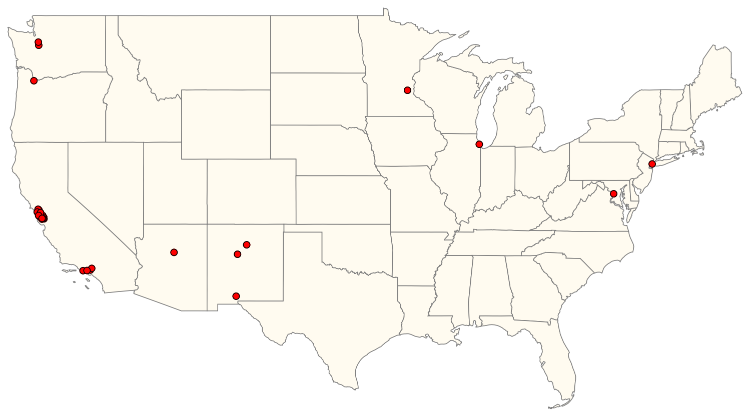
(20)
$$E_k = \frac{\log C_{k,t} - \log C_{k,t-1}}{\log \frac{MW_{k,t}}{MW_{s(k),t}} - \log \frac{MW_{k,t-1}}{MW_{s(k),t-1}}}.$$

C_{kt} is the number of workers who live in the suburb of city k but work in the city k in year t. And

[43] LODES only provides commuting flows but not migration flows, so here we analyze commuting patterns. The county-level ACS data is not localized enough to determine city-suburb mobility patterns.

$\frac{MW_{k,t}}{MW_{s(k),t}}$ captures the ratio between the city minimum wage $MW_{k,t}$ and the state minimum wage it belongs to $MW_{s(k),t}$. To obtain a meaningful elasticity, we require that the city k implement its own minimum wage for at least one year and that the value of the minimum wage ratio $\frac{MW_{k,t}}{MW_{s(k),t}}$ changes at least 2% between two years. We focus on low-wage workers (as reported in the LODES wage categories) as they are the most susceptible to minimum wage changes (see table 4).

Figure 3: Cities with minimum wage ordinances in year 2019



Note: This figure is reproduced based on Dube and Lindner (2021) and shows the cities having minimum wages above the state-level one in year 2019.

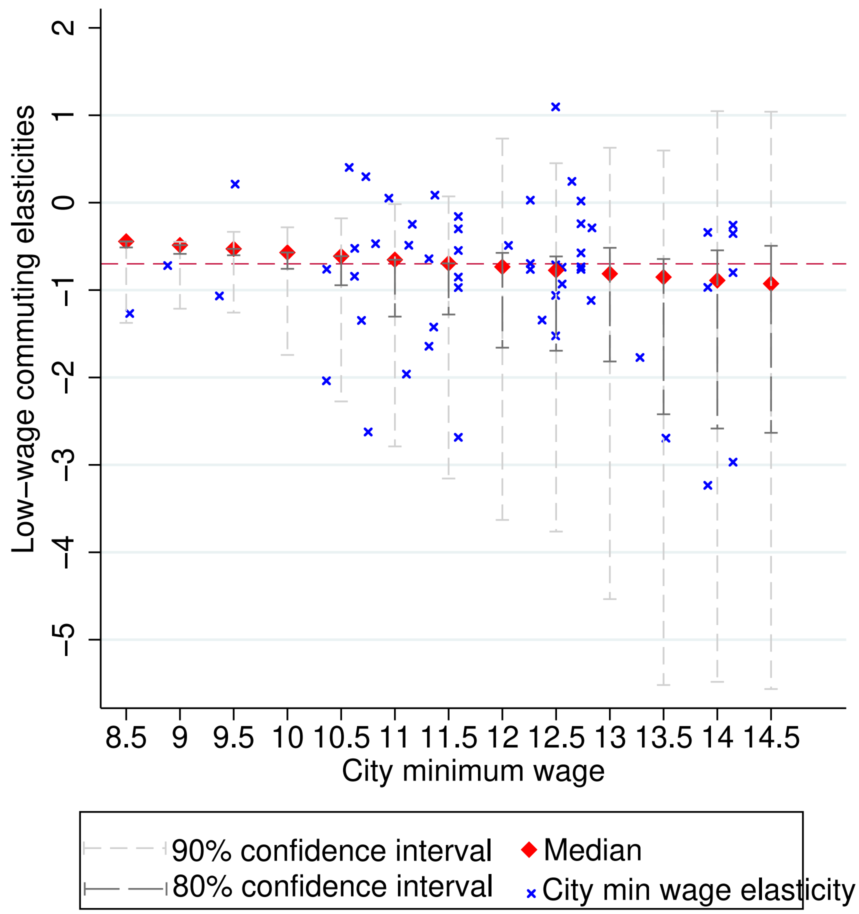
Our validation exercises uses the estimated model to simulate how the commuting elasticity responds to minimum wage increases ranging from \$8.5 to \$15. Specifically, we calculate the predicted commuting elasticity for each county pair at each proposed minimum wage level. The distribution of predicted elasticities is then compared to the city-level elasticities (calculated from the data by the method described above in equation 20).

Figure 2 shows the comparison. The blue crosses represent the city-level elasticities based on LODES data. Commuting by workers in the lowest LODES wage category decreases in 46 of 55 city-year observations, with an average elasticity of around -0.84. These patterns support our previous findings that a higher local minimum wage deters commuters from neighboring areas. We then plot the predicted elasticities for low educated commuters obtained from the model, varying the minimum wage from \$8.5 to \$14.5.[44] The red diamonds represent the median estimated elasticities obtained from the model (across county-pairs), with the dark grey long-dash vertical line representing the 80% confidence interval and the light grey dash line representing the 90% confidence interval. Although the data sources used to estimate the model and to calculate the elasticities are different, the city-level elasticities observed in the data fall within the 90% confidence interval of the predicted elasticity distribution.

[44] All real values of city minimum wages are below \$14.5 measured by 2015 US dollars.

As seen in the figure, actual elasticities (blue crosses) are not evenly distributed but are instead concentrated around the middle of the distribution. This is perhaps expected, as cities with their own minimum wages are concentrated in a few states (24 of these observations are cities in the San Francisco Bay Area). Overall, we conclude that our estimated model provides reasonable predictions of commuting patterns in response to city-level minimum wage ordinances.

Figure 4: The low wage commuting elasticities at different minimum wage levels



Source: Author's calculations. The blue crosses show the city-level elasticities of low-wage commuters based on LODES data. The red diamonds show the elasticities (median level) obtained from simulating the model at each proposed minimum wage level (from \$8.5 to \$14.5), with the dark grey long-dash vertical line representing the 80% confidence interval and the light grey dash line representing the 90% confidence interval. The reference line (the horizontal cranberry dash line), indicating the median elasticity when minimum wage equals to 11.5, is set at $y = -0.7$. Minimum wages are adjusted using 2015 US dollars.

6 Welfare and distributional effects of local and universal minimum wage policies

6.1 Effects of local minimum wage increases

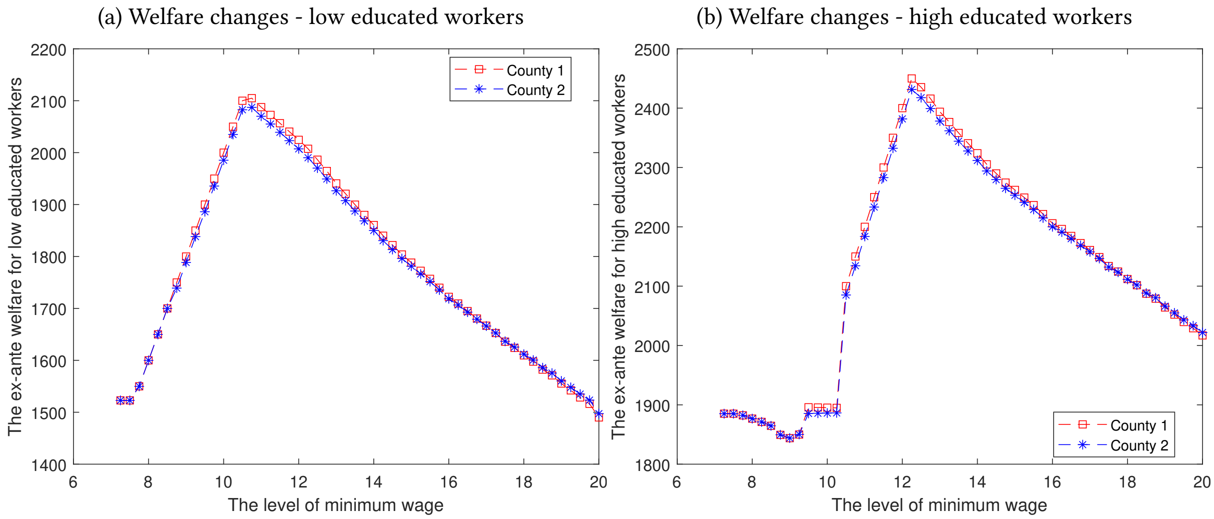
In this section, we use the estimated model to examine the welfare and distributional effects of local minimum wages. We first look at how the minimum wage affects workers differently based on their skill level a and location j, using the ex-ante value of unemployment as our welfare measure. We then investigate the impact on total welfare, including a different welfare measure. For the latter analysis, we measure welfare at a point in time (given the steady state assumption, it will be constant).

For this experiment, we consider a representative pair of symmetric counties where the parameters in both counties take the mean values of the random coefficient parameters. By assuming symmetric counties, we isolate the effects of local minimum wage hikes from other factors causing asymmetries between neighboring counties. The initial minimum wage levels in both counties, as well as the magnitude of local minimum wage increases, have a significant impact on the distributional effects. We assume that the initial hourly minimum wage in both counties is \$7.25 (the federal minimum wage level in 2022) and consider welfare changes that result when increasing the minimum wage in county 1 to levels ranging from \$7.25 to \$20.00. We show most results graphically. First, we show the changes in welfare for low skill and high skill workers living in different locations. Then, we consider how local economic conditions change (e.g. contact rates, the composition of heterogeneous workers). Finally, we show per capita welfare combining workers and firms.

Welfare effects for heterogeneous workers. Recall that workers were distinguished by their education type a and location j. Location heterogeneity has received little attention in the previous literature, because workers are often assumed to be ex-ante identical and in one market. The value of unemployment at different levels of minimum wage $V_u(a, j; m_1, m_2)$ can be interpreted as the ex-ante welfare of a worker with education type a and in location j when the minimum wage in counties 1 and 2 is m_1 and m_2.

Figure 5 depicts the ex-ante welfare when the minimum wage in county 1, m_1, varies while the minimum wage in county 2 remains fixed at \$7.25. The left panel depicts ex-ante welfare for low skill workers, while the right panel depicts ex-ante welfare for high skill workers. We use a red line to represent workers in County 1 (the county's minimum wage increases) and a blue line to represent workers in County 2 (the county that does not change the minimum wage). Countervailing effects of the minimum wage generate a hump shape in the welfare function for both types of workers. Raising the minimum wage raises workers' expected income by increasing the return on a match (the *wage enhancement effect*), but it also reduces

Figure 5: Welfare changes across heterogeneous workers under different minimum wage increases

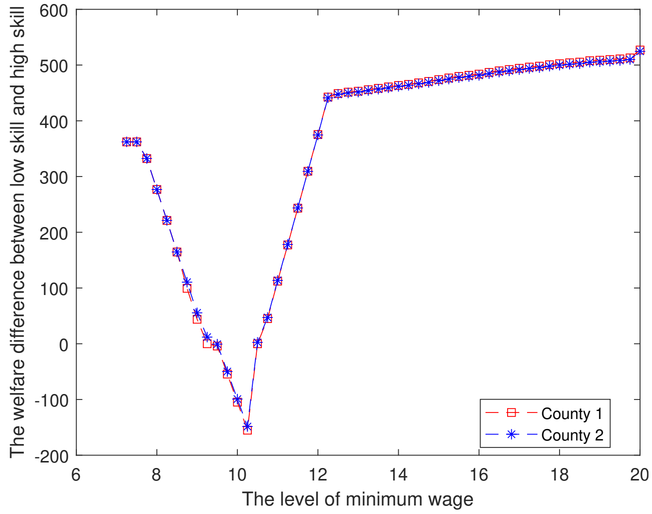


working opportunities, because some previously acceptable matches become unacceptable (the *disemployment effect*). When the local minimum wage in county 1 exceeds $\$10.75$, the latter effect dominates for low skill workers. The welfare function for high skill workers has a hump shape as well but it peaks later. Because the productivity distribution of high skill workers first-order stochastically dominates that of low skill workers, high skill workers have less of a *disemployment effect* at lower wage levels. The negative disemployment effect exceeds the wage enhancement effect at a higher minimum wage $m_1 = \$12.25$. Finally, we see that the welfare function of workers with the same education type in the two counties closely tracks each other. This is due to the fact that two labor markets are interconnected and workers receive job offers from both counties. However, the welfare disparities between workers of the same type reflect the home bias in terms of job opportunities.

Lastly, Figure 6 reports changes in inequality between high education and low education workers as the minimum wage increases in county 1. The inequality curve displays a U-shape and reaches its lowest point at $m_1 = 10.25$, slightly below the minimum wage level at which the low education type attains the highest average welfare. This result reveals that local minimum wage policy reduces inequality between high and low type workers only if the minimum wage is set at a modest level. The currently proposed $\$15$ minimum wage would actually increase the inequality, which is likely opposite to the intended policy effect.

There are some studies in the literature arguing that the cost of minimum wage increases are partly passed on to consumers. Consequently, wage benefits stemming from minimum wage increases may be partly offset by increases in the prices of goods and services. To allow for such potential pass-through

Figure 6: The inequality between high type and low type as minimum wage increases in county 1

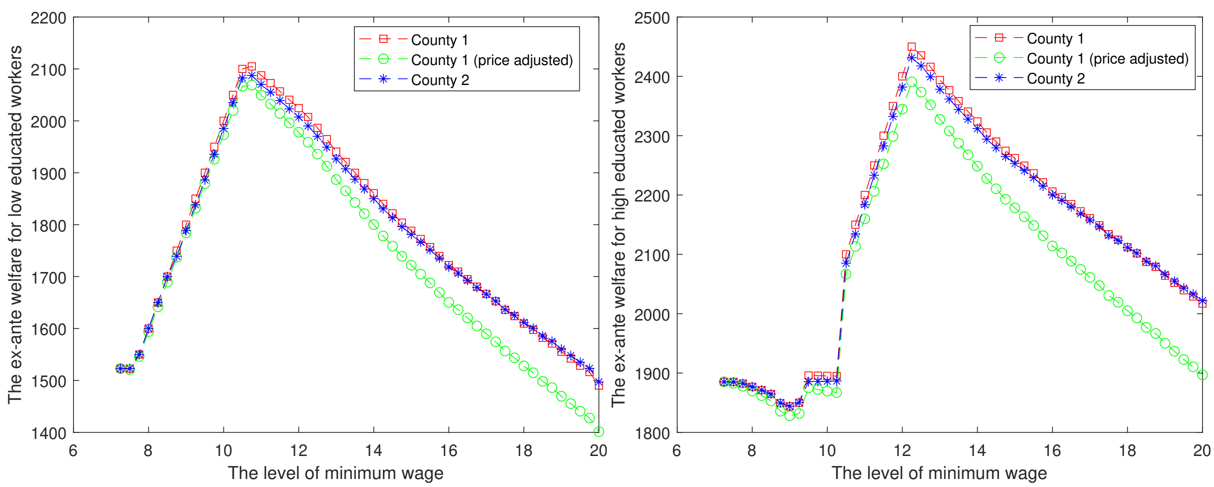


effects that erode the benefits of a wage increase, we redo the welfare analysis including an adjustment to worker wages based on the price elasticity estimates reported in Renkin et al. (2022). Their study finds that a 10% minimum wage hike translates into a 0.36% increase in the prices of grocery products.

Figure 7: Welfare changes across heterogeneous workers under different minimum wage increases (price adjusted)

(a) Welfare changes - low educated workers

(b) Welfare changes - high educated workers



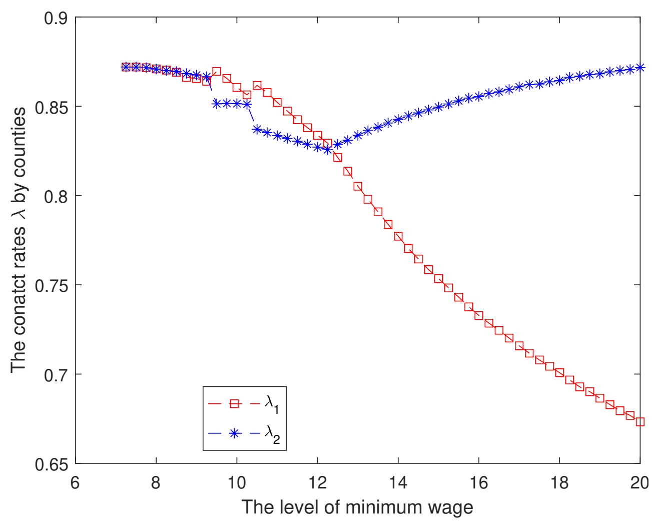
We plot the welfare function while accounting for this price pass-through channel in Figure 7. We assume that changes in the minimum wage in county 1 only affect price levels (purchasing power) in county 1 but not county 2, because previous research has shown that the pass-through effect is very localized.[45]

[45]For example, Allegretto and Reich (2018) found that price differences among restaurants that are one-half mile from either side of the policy border are not competed away, indicating that restaurant demand is spatially inelastic.

Our findings reveal that price increases caused by changes in the minimum wage account for a very small portion of the welfare changes. Although the price effect modestly reduces the welfare of both high and low-education workers in county 1, the optimal minimum wage level remains the same. Because of its small impact on the results, we do not adjust for potential pass-through effects in the following analysis.

Changes in local economic conditions We next consider how minimum wage changes affect firms' incentives to post job openings. Figure 8 depicts changes in contact rates (λ_1, λ_2) in both counties as the minimum wage in county 1 increases. There were two channels in our job search model through which the minimum wage influences the profitability of posting vacancies. First, as the minimum wage rises, firms receive less value per vacancy for the same match. This is because a higher minimum wage reduces the likelihood that a given match is acceptable while also making sustainable matches less profitable. This channel explains the monotonic decreasing pattern of the county 1 job contact rate, λ_1.

Figure 8: Contact rates under different minimum wages



Second, the job contact rate is also affected by the job seekers' skill composition. The random search assumption implies that firms are unable to screen workers' skill type when posting vacancies. Thus, the proportion of low-skill workers among job seekers will be negatively correlated with vacancies (per capita). When the minimum wage in county 1 is less than \$12.25, high type workers prefer to work in county 1 rather than county 2, because they receive a welfare gain from the higher minimum wage. As a result, the proportion of high education workers employed by firms in county 2 declines, reducing their incentives to post job openings. When the minimum wage exceeds \$12.25, high education workers begin to leave county 1 to avoid a welfare loss. As a result, the proportion of high education workers employed in county 2 begins to rise, providing firms with an incentive to post more job openings. In summary, the changing skill composition of local workers explains the U shape of county 2's contact rate, λ_2.

A Benthamite social welfare function Last, we consider an alternative social welfare function suggested by Hosios (1990) that applies to all labor market participants, including both workers and firms. In particular, we define the total welfare function as follows:

$$W_j(m_j) = \textstyle\sum_{a\in\{a_l,a_h\}}[\underbrace{L(a,j)\bar{V}_e(\theta,a,j,\theta^*(a,j))}_{\text{(1) Local employed workers}} + \underbrace{M(a,j')\left(\bar{V}_e(\theta,a,j,\theta^{**}(a,j')) - c(a,j')\right)}_{\text{(2) Migrants from neighbouring county}}$$
$$+\underbrace{C(a,j)\left(\bar{V}_e(\theta,a,j',\theta^{**}(a,j)) - c(a,j)\right)}_{\text{(3) Commuters to the neighbouring county}} + \underbrace{U(a,j)V_u(a,j)}_{\text{(4) Unemployed workers}} + \underbrace{E(a,j)\bar{V}_f(a,j)}_{\text{(5) Revenue from filled vacancies}}]$$

where (1) $L(a,j)$ is the population of local employed workers with $\bar{V}_e(\theta,a,j,\theta^*(a,j))$ denoting their average welfare. (2) $M(a,j)$ is the population of migrants who move from county j', with $\bar{V}_e(\theta,a,j,\theta^{**}(a,j'))-c(a,j')$ as their average net welfare. (3) $C(a,j')$ is the population of migrants who commute to work in county j', with $\bar{V}_e(\theta,a,j',\theta^{**}(a,j)) - c(a,j)$ as their average net welfare. (4) $U(a,j)$ is the population of local unemployed workers (all unemployed workers have same welfare level $V_u(a,j)$). (5) $E(a,j)$ is the total number of filled vacancies, with $\bar{V}_f(a,j)$ as average revenue per vacancy. We then calculate welfare per capita to control for the mechanical effect of population size on total welfare:

$$w_j(m_j) = \frac{1}{N_j}W_j(m_j)$$

where $N_j = \sum_{a\in\{a_l,a_h\}}(L(a,j) + M(a,j) + C(a,j))$ is the population of local residents in county j.

Figure 9: Per capita welfare by counties

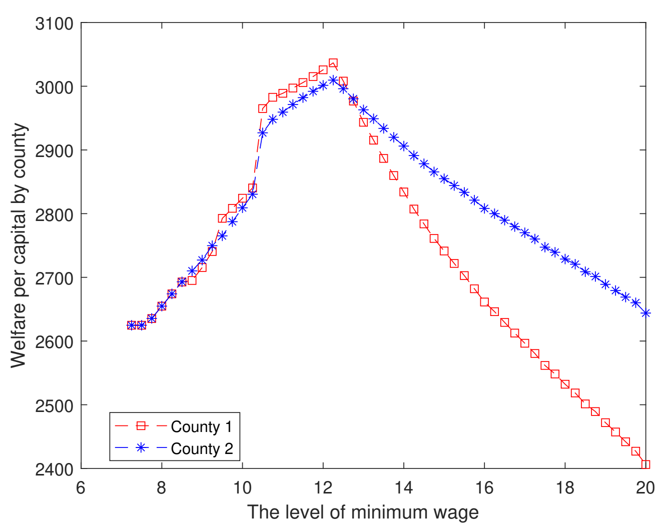


Figure 9 plots the welfare per capita in each county as the minimum wage in county 1 increases. With minimum wage increases in county 1, the welfare per capita in both counties depicts hump shapes with a single peak $m_1 = m_2 = \$12.25$. The changes in welfare per capita in county 2 constitute spillover externalities from county 1's local minimum wage policy. A minimum wage greater than $\$12.25$ in county 1 results in welfare loss for both local and neighboring workers due to the significant negative impact on employment opportunities. However, when compared to local workers in county 1, neighboring workers in county 2 are less affected because their job opportunities are less dependent on job offers from county 1. This explains why, when the minimum wage is raised above $\$12.25$, county 2 suffers less welfare loss than county 1.

6.2 Universal (federal) minimum wages vs. local minimum wages

As seen above, one county adopting a local minimum wage of $\$15$ generates substantial negative externalities on its neighboring county. One possible way to mitigate such spillovers is to adopt a uniform minimum wage across both counties. In reality, 27 states have passed laws preempting of local minimum wage laws to avoid a "patchwork" of wage levels within a state. The federal government has also considered raising the federal minimum wage to $15 per hour to reduce the geographic variation in minimum wages across states.

Figure 10: Per capita welfare under local and universal (federal) minimum wages

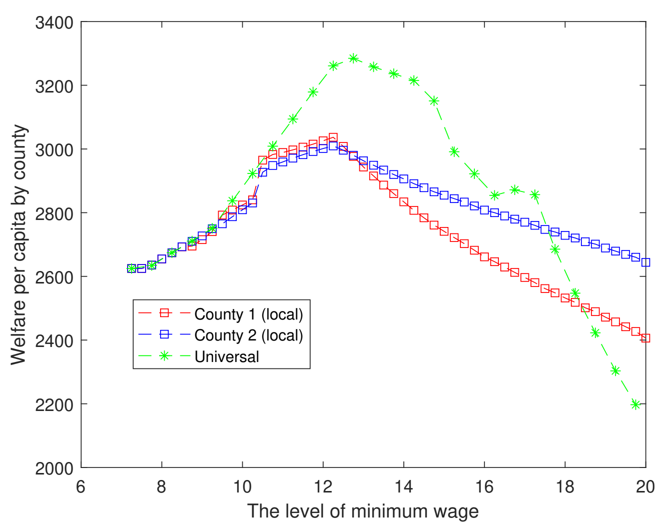


Figure 10 compares per capita welfare under local minimum wage regulation and under universal regulation ($m_1 = m_2$). The increase in m_2 in conjunction with m_1 produces two offsetting effects when compared to the "local minimum wage" case. On the one hand, it lowers moving costs because workers no longer have incentives to arbitrage minimum wage differences across counties. On the other hand, the expansion of the minimum wage coverage to two areas instead of one dissolves some previously acceptable matches. The welfare per capita under universal minimum wage policy also has a hump shape, with 12.75 being the optimal level. Compared with the optimal minimum wage under the local policy, the optimal minimum wage under universal policy is expected to be higher, because a universal minimum wage reduces migration/commuting costs. For the same reason, the welfare level associated with the optimal minimum wage is higher under the universal minimum wage policy. For example, at the current proposed federal minimum wage of $15, per capita welfare under the universal minimum wage policy is higher than under a local minimum wage policy in both counties. When the minimum wage is even higher ($m > \$18$), however, the per capita welfare is lower under the universal minimum wage policy than under a local policy. This is because at such high wage level, the cost of losing acceptable matches outweighs the benefits of reducing moving costs.

7 Conclusions

This paper develops a spatial job search model to study the effects of both local and universal (federal) minimum wage policies. In the model, firms endogenously choose where to post vacancies. Workers, differentiated by their education level and location, decide whether to search in a local or neighboring county job market and, upon getting offers, whether to accept them and whether to commute or migrate.

Our model captures four important effects associated with the minimum wage increases. First, conditional on being employed, a higher minimum wage reduces firms' match surplus and increases workers' wages. Second, a higher minimum wage also has a disemployment effect as it dissolves a fraction of previously acceptable matches that are no longer sustainable. The disemployment effect is more pronounced for low skill workers. Third, firms reduce their vacancy postings in response to minimum wage changes, because they receive a smaller share of the match surplus and vacancy postings are less profitable. Fourth, as workers reallocate themselves across the two counties, the geographic skill composition changes. This redistribution causes firms to further adjust their contact rates, in both the local county and the neighboring county. How these effects operating through different model channels combine to influence employment, welfare, mobility and commuting is an empirical question that we use our estimated model to address.

The empirical analysis yields a number of interesting findings. First, as a way of validating the model out-of-sample, we use the estimated model to forecast the impact of recent city-level minimum wage ordinances on commuting patterns. We find that changes in commuting flows close to city boundaries are within the range predicted by the model. Second, we use the estimated model to analyze the effect of local and universal minimum wage changes on worker and firm welfare. Model simulations show that low skill workers benefit from minimum wage increases up to $10.75, after which the disemployment effect outweighs the benefits of higher wages. High skill workers are more productive and are therefore less susceptible to having their matches dissolved in response to minimum wage hikes. Their welfare increases for wage levels up to $12.25. Interestingly, minimum wage increases, depending on the magnitude, can exacerbate inequality. Our results show that welfare inequality between high education and low education workers displays a U shape, reaching its smallest level when the minimum wage equals to $10.25.

Simulations based on our estimated structural model reveal how minimum wage impacts vary depending on the type of worker and depending on the magnitude of the minimum wage change. As described in the introduction, the minimum wage literature is characterized by a large number of studies reporting a wide range of estimates. Our analysis provides some insight as to the reasons for such variation. Even studies based on similar methodologies could be expected to arrive at different conclusions, depending on the analysis sample and magnitude of minimum wage changes being considered.

Lastly, we use the estimated model to compare the effects of local minimum wage increases to universal ones, an analysis that is motivated by the new state laws preempting local minimum wages. Again, we find a hump shape in welfare, with $12.75 being the value that maximizes per capita welfare (including all worker skill types and firms). If we simulate the effects of a universal $15.00 minimum wage level, as has been proposed by the US House of Representatives, we find that there is a substantial increase in welfare above that associated with the current minimum wage level. However, the greatest per capita welfare gains are achieved at a universal minimum wage of $12.75 rather than $15.00.

There are a few ways this analysis could be extended in future research. First, we consider welfare effects for representative border counties. Further investigation would be needed to determine whether the optimal universal minimum wage that we find would also be optimal for interior counties. Second, capital did not play a role in our linear production function. Recent papers incorporating capital with the putty-clay feature (e.g., (Sorkin, 2015; Aaronson et al., 2018; Hurst et al., 2021)) could perhaps be extended to a spatial context (if spatial capital data were available). Lastly, our model considers the implications of the local minimum wage policies on worker labor supply and firm labor demand in a setting where the local government is not a strategic player. Examining the competitive behavior of policy makers could provide insights as to why certain cities adopt high minimum wages.

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A Appendix: Derivations

A.1 Derivations of $V_u(a, j)$ and $V_e(w, a, j)$

We start by considering an unemployed worker's job search problem. Consider the length of a period to be ϵ. Then the discount factor would be $\frac{1}{1+\rho\epsilon}$. The value function of an unemployed worker has the following expression:

$$\begin{aligned} V_u(a,j) &= (1+\rho\epsilon)^{-1}[&& ab_j\epsilon + s_j\lambda_j\epsilon \underbrace{\int_{m_j}^{\infty} \max\{V_e(w,j), V_u(a,j)\} dF(w|a,\theta,j)}_{\text{A local offer arrives}} \\ &+ && (1-s_j)\,\lambda_{j'}\epsilon \underbrace{\int_{m_{j'}}^{\infty} \max\{V_e(w,j') - c(a,j), V_u(a,j)\} dF(w|a,\theta,j'))}_{\text{A neighbouring offer arrives}} \\ &+ && +(1 - s_j\lambda_j\epsilon - (1-s_j)\,\lambda_{j'}\epsilon)V_u(a,j) + o(\epsilon)] \end{aligned}$$

Multiplying $1 + \rho\epsilon$ then subtracting $V_u(a, j)$ from both sides, we get

$$\begin{aligned} \rho\epsilon V_u(a,j) &= ab_j\epsilon + s_j\lambda_j\epsilon \underbrace{\int_{m_j}^{\infty} \max\{V_e(w,j), V_u(a,j)\} dF(w|a,\theta,j)}_{\text{A local offer arrives}} \\ &+ (1-s_j) \quad \lambda_{j'}\epsilon \underbrace{\int_{m_{j'}}^{\infty} \max\{V_e(w,j') - c(a,j), V_u(a,j)\} dF(w|a,\theta,j'))}_{\text{A neighbouring offer arrives}} \\ &+ \quad -(s_j\lambda_j\epsilon + (1-s_j)\,\lambda_{j'}\epsilon)V_u(a,j) + o(\epsilon) \end{aligned}$$

Dividing both sides by ϵ and taking limits $\epsilon \to 0$, we arrive at

$$\begin{aligned} \rho V_u(a,j) &= ab_j + s_j\lambda_j \underbrace{\int_{m_j}^{\infty} \{V_e(w,j) - V_u(a,j)\}^+ dF(w|a,\theta,j)}_{\text{A local offer arrives}} \\ &+ (1-s_j) \quad \lambda_{j'} \underbrace{\int_{m_{j'}}^{\infty} \{V_e(w,j') - c(a,j) - V_u(a,j)\}^+ dF(w|a,\theta,j'))}_{\text{A neighbouring offer arrives}} \end{aligned}$$

The value of employment with wage w is

$$V_e(w,a,j) = (1+\rho\epsilon)^{-1}\{w\epsilon + \eta_j\epsilon V_u(a,j) + (1-\eta_j\epsilon)V_e(w,a,j) + o(\epsilon)\}$$

Multiplying $1 + \rho\epsilon$ then subtracting $V_e(a, j)$ from both sides, we get

$$\rho\epsilon V_e(w,a,j) = w\epsilon + \eta_j\epsilon V_u(a,j) - \eta_j\epsilon V_e(w,a,j) + o(\epsilon)$$

Dividing both sides by ϵ and taking limits $\epsilon \to 0$, we arrive at

$$V_e(w,a,j) = \frac{w + \eta_j V_u(a,j)}{\rho + \eta_j}$$

A.2 Solving for the bargained wage equation without the minimum wage constraint

Following the same derivation procedure, the firm's value for a match with wage w, $V_t^f(w,a,\theta,j)$, is (we assume that the effective discount fact $\rho + \eta_j$ is the same as worker's):

$$V_f(w,a,\theta,j) = \frac{a\theta - w}{\rho + \eta_j}$$

Then the Nash bargaining $\hat{w}(\theta,a,j)$ (without considering a possible binding minimum wage) is:

$$\begin{aligned} \hat{w}(a,j,\theta) &= \arg\max_w (V_e(w,a,j) - V_u(a,j))^{1-\alpha_j} V_f(w,a,\theta,j)^{1-\alpha_j} \\ &= \arg\max_w (\tfrac{w+\eta_j V_u(a,j)}{\rho+\eta_j} - V_u(a,j))^{1-\alpha_j} (\tfrac{a\theta - w}{\rho+\eta_j})^{\alpha_j} \\ &= \arg\max_w (\tfrac{w - \rho V_u(a,j)}{\rho+\eta_j})^{1-\alpha_j} (\tfrac{a\theta - w}{\rho+\eta_j})^{\alpha_j} \\ &= \alpha_j a\theta + (1-\alpha_j)\rho V_u(a,j) \end{aligned} \tag{21}$$

A.3 The derivation of fixed point system of $\theta^*(a,j)$ and $\theta^{**}(a,j)$

We start from the expression of unemployed value $V_u(a,j)$, equation 1:

$$\begin{aligned} \rho V_u(a,j) &= ab_j + s_j\lambda_j \underbrace{\int_{m_j}^{\infty} \{V_e(w,j) - V_u(a,j)\}^+ dF(w|a,\theta,j)}_{\text{A local offer arrives}} \\ &+ (1-s_j) \quad \lambda_{j'} \underbrace{\int_{m_{j'}}^{\infty} \{V_e(w,j') - c(a,j) - V_u(a,j)\}^+ dF(w|a,\theta,j'))}_{\text{A neighbouring offer arrives}} \end{aligned}$$

Now, we replace the term $V_e(a,j,\theta)$ in the above equation using the following step-wise function:

$$V_e(a,j,\theta) = \begin{cases} \frac{m_j + \eta_j V_u(a,j)}{\rho+\eta_j} & \theta \in [m_j, \hat{\theta}(a,j)) \\ \frac{\alpha_j(a\theta - \rho V_u(a,j))}{\rho+\eta_j} + V_u(a,j) & \theta \in [\hat{\theta}(a,j), \infty) \end{cases}$$

Then we replace $\rho V_u(a,j)$ with its equivalent definition $a\theta^*(a,j)$ then get:

$$
\begin{aligned}
a\theta^*(a,j) \quad = \quad & ab_j + \tfrac{s_j\lambda_j}{\rho+\eta_j}[\underbrace{\boldsymbol{I}\left(\theta^*(a,j) < \frac{m_j}{a}\right)(m_j - a\theta^*(a,j))\left(\tilde{G}(\hat{\theta}(a,j)) - \tilde{G}(\frac{m_j}{a})\right)}_{\text{Local offer with wage } m_j} \\
+ \quad & \underbrace{\int_{\max\{\hat{\theta}(a,j),\theta^*(a,j)\}} a\alpha_j(\theta - \theta^*(a,j))dG(\theta)]}_{\text{Local offer with wage } w_j > m_j} \\
+ \quad & \tfrac{(1-s_j)\lambda_{j'}}{\rho+\eta_{j'}}\underbrace{[\boldsymbol{I}(\theta^{**}(a,j) < \frac{m_{j'}}{a})(m_{j'} - a\theta^*(a,j'))\left(\tilde{G}(\theta^{**}(a,j)) - \tilde{G}(\frac{m_{j'}}{a})\right)}_{\text{Neighbouring offer with wage } m_{j'}} \\
+ \quad & \underbrace{\int_{\max\{\hat{\theta}(a,j'),\theta^{**}(a,j)\}} a\alpha_j(\theta - \theta^*(a,j'))dG(\theta)}_{\text{Neighbouring offer with wage } w_{j'} > m_{j'}} \\
- \quad & \underbrace{(\rho + \eta_{j'})\left(\frac{(a\theta^*(a,j) - a\theta^*(a,j'))}{\rho} + c(a,j)\right)\tilde{G}(\max\{\hat{\theta}(a,j'),\theta^{**}(a,j)\})]}_{\text{The unemployed value difference between staying/moving}}
\end{aligned}
$$

A.4 Analytical expressions for the moments used in estimation

We next provide the analytical expressions that we use as model-derived moments and the corresponding data elements. The GMM estimator minimizes the weighted average of the distances between the model-derived moments and the corresponding data moments. As described in the paper, we use an optimal weighting matrix. Also, our analysis assumes that each time period is a steady state. We therefore treat the multiple time periods from our panel as multiple independent observations. For ease of notation, the moments described below do not have a time subscript. Also, in generating the data-derived moments, we obtain the random coefficients for the county pairs by simulation. A separate simulation is performed to obtain the weighting matrix (the inverse of the variance-covariance matrix).[46]

1. *Employment rates:* We first solve for the number of employed workers in locations j and j': $\{E(a,j), E(a,j')\}$ can be solved from the following equations that are linear in E:

$$
\lambda_j\left(s_j\left(N(a,j) - E(a,j)\right)\tilde{G}(\max\{\theta^*(a,j), \tfrac{m_j}{a}\}) + (1-s_{j''})\left(N(a,j') - E(a,j')\right)\tilde{G}(\max\{\theta^{**}(a,j'), \tfrac{m_j}{a}\})\right) = E(a,j)\eta_j
$$
$$
\lambda_{j'}\left(s_{j'}\left(N(a,j') - E(a,j')\right)\tilde{G}(\max\{\theta^*(a,j'), \tfrac{m_{j'}}{a}\}) + (1-s_{j'})\left(N(a,j) - E(a,j)\right)\tilde{G}(\max\{\theta^{**}(a,j), \tfrac{m_{j'}}{a}\})\right) = E(a,j')\eta_{j'}
$$

Then, the employment rate is then calculated by $\frac{E(a,j)}{N(a,j)}$ and $\frac{E(a,j')}{N(a,j')}$. The moments are the differences between the average employment rates across counties and standard deviation of employment rates implied by the model and the corresponding quantities in the data.

2. *Proportion of migrants:* The proportion of migrants implied by the model is

$$
\frac{M(a,j)}{E(a,j)} = \frac{(1-s_j)\lambda_{j'}\left(N(a,j) - E(a,j)\right)P_1(a,j)\tilde{G}(max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}))}{E(a,j)}
$$

[46]Based on 300 simulations.

The moments minimize the distances between the average proportion across the counties and the standard deviation of the proportion implied by the model and the corresponding data quantities.
3. *Proportion of commuters:* The proportion of commuters implied by the model is

$$\frac{C(a,j)}{E(a,j)} = \frac{(1-s_j)\lambda_{j'}\left(N(a,j)-E(a,j)\right)P_0(a,j)\tilde{G}(max\{\theta^{**}(a,j),\frac{m_{j'}}{a}\})}{E(a,j)}$$

The moments minimize the distances between the average proportion across the counties and the standard deviation of the proportion implied by the model and the corresponding data quantities.
4. *Correlation between commuters and distance/rent costs:*

$$corr(\sum_a C(a,j), d_{jj'}), corr(\sum_a C(a,j), \gamma_j)$$

5. *Correlation between migrants and distance/rent costs:*

$$corr(\sum_a M(a,j), d_{jj'}), corr(\sum_a M(a,j), \gamma_j)$$

We minimize the distance between the above four correlations obtained from the model and the same correlations in the data.
6. *Average hourly wage:*

$$\bar{w}(a) = \frac{\sum_j \left(E(a,j)-C(a,j)-M(a,j)\right)\int_{\theta^*(a,j)} w(a,\theta,\theta^*)dG(\theta) + \sum_j \left(C(a,j)+M(a,j)\right)\int_{\theta^{**}(a,j)} w(a,\theta,\theta^*)dG(\theta)}{\sum_j E(a,j)}$$

We minimize the distances between the mean and standard deviation of the average hourly wage (across counties and education types) implied by the model and the corresponding data quantities.
7. *Wage difference between local and mobile workers:*

$$\sum_j \left(\int_{\theta^{**}(a,j)} w(a,\theta,\theta^*)dG(\theta) - \int_{\theta^*(a,j)} w(a,\theta,\theta^*)dG(\theta)\right)$$

We minimize the distance between the average (across counties) local and mobile wage disparity generated from the model and that observed in the data.
8. *Commuting elasticity and migration elasticity:* We obtain the commuting and migrating elasticities from the model by increasing the minimum wage by \$1.

$$\frac{\log(C(a,j)|m_{j'}=m+1) - \log(C(a,j)|m_{j'}=m+1)}{\log(m_{j'}=m+1) - \log(m_{j'}=m)}$$

$$\frac{\log(M(a,j)|m_{j'}=m+1) - \log(M(a,j)|m_{j'}=m+1)}{\log(m_{j'}=m+1) - \log(m_{j'}=m)}$$

where m is the current minimum wage at county j'. We minimize the distances between the average (across counties) elasticities generated from the model and those observed in the data.

B Preliminary regression results (online)

B.1 Commuting and migration evidence from ACS data

When using ACS data, we divide workers into two groups by their education levels: no college and some college. Lastly, we restrict the samples to the younger workers (below age 30) in comparing the results from these two datasets.

We next use the ACS data for two purposes. First, we use it to validate some of the estimates obtained from the LODES data. Second, ACS contains information on both commuters and migrants, so we can examine how migration responds to minimum wage changes. Workers are restricted to be 16 to 30 and between 2005 to 2015. Similarly to LODES data, we limit our analysis to county pairs with sufficient numbers of mobile workers. In particular, we include county pairs if the number of cross-border commuters and migrants is greater than 1.5 percent of the local population and the distance of centroids between two counties is smaller than 44 kilometers. We estimate the regression for three worker groups. Besides the whole sample, we also examine two subsamples based on worker's education levels: lower education group (high school graduates or less) and higher education group (some college or above).

Table A.1 shows the estimates In response to a 1% hike in relative minimum wages, the flow of commuters decreases by 0.401% for all young workers in the ACS sample, which is close to the estimate based on the LODES sample (see column (4)). This comparison shows that the significant negative commuting responses to minimum wage changes are consistent across data sources. When the sample is divided by education level, the estimates remain negative but become statistically insignificant. In estimating our structural model, we fit moments pertaining to commuting elasticities that are derived from LODES rather than ACS data. The lower panel of table A.1 provides estimates of the elasticity of migration in response to minimum wage changes, which are generally imprecisely estimated. Some prior studies found that workers migrate away from areas where the minimum wage is increased.Cadena (2014); Monras (2019) Our estimates do not rule out this possibility.

B.2 The disemployment effect of local minimum wage hikes

In this section, we show additional evidence that the increase of outflows in response to a minimum wage increase is caused by the decline of local working opportunities. Following Dube et al. (2007) and Dube et al. (2016), we run the following regression:

$$\log y_{c,t} = \beta_0 + \beta_1 \log MW_{s(c),t} + \beta_2 X_{c,t} + \phi_c + \eta_{p(c),t} + \epsilon_{c,t} \tag{22}$$

where $y_{c,t}$ refers to the local labor market variables, including earnings, employment, separations and hires, in county c and period t. $X_{c,t}$ is the log of the total local population. The coefficient β_1 is the primary variable of interest representing the elasticity of y_{it} with respect to the local minimum wages. Table A.2 reports two regressions which only differ in their specification of the time-fixed effect. In Column (1), we restrict the time fixed effect to be common across all county pairs ($\eta_{p(c),t} = \eta_t$) and we find statistically significant disemployment effects in response to local minimum wage changes. The estimated elasticity of employment stock is -0.156. Meanwhile, the elasticities of employment flows are also substantial with minimum wage increases. The hire elasticity and separation elasticity are -0.190 and -0.156, both of which are statistically significant. The fact that the separation elasticity is larger than the hire elasticity is consistent with the negative effect of minimum wage on employment stock. However, when we account for the pair-specific time fixed effect (to control for time-varying, pair-specific spatial confounders), the esti-

Table A.1: Commuting and Migration Flows in Response to Minimum Wage Ratio Changes: ACS

	ACS ($age < 30$)			LODES ($age < 30$)
	(1)	(2)	(3)	(4)
Mobile workers	Low educated	High educated	All workers	All workers
Commuters	-0.455	-0.304	-0.401*	-0.432***
	(0.289)	(0.249)	(0.215)	(0.130)
	[3,703]	[3,727]	[3,857]	[3,809]
Migrants	-0.062	-0.473	-0.090	
	(0.304)	(0.402)	(0.312)	
	[3,622]	[3,607]	[3,701]	
Controls:				
Common time effects	Y	Y	Y	Y
Pair specific fixed effects	Y	Y	Y	Y

Note: The table reports coefficients associated with the log of relative minimum wage ratio ($\log \frac{MW_{st}}{MW_{st}}$*) on the log of the dependent variables noted in the first column. All regressions include both county-pair fixed effects and year fixed effects. Columns (1)-(3) provide estimates for mobile workers between 16-30 based on pseudo county-level variation constructed by ACS PUMA between year 2005-2015. Column (4) uses LODES data, workers younger than 30. Robust standard errors, in parentheses, are clustered at the the paired-county levels. * for 10%. ** for 5%, and *** for 1%. Sample sizes are reported below the standard error for each regression.*

mates for the hire elasticity and separation elasticity are not distinguishable from zero. we attribute this change to the existence of spatial spillover effect. After the local county increases its own minimum wage, unemployed workers may seek their jobs in the neighboring county (either by migration or by commuting), which causes disemployment in the neighboring county. As a result, this spillover effect generates a common trend between the counties in one pair. When this pair-specific co-movement is teased out by pair-specific time effect, the estimates of local disemployment effect become less substantial.

C Sample construction appendix (online)

C.1 Minimum wage policies between 2005-2015

In this section, we will describe changes of minimum wage policies at all levels. Table A.3 provides the changes in minimum wages on both the state and federal levels.[47] Between 2005 and 2015, there was only one change to federal minimum wage law, the Fair Minimum Wage Act of 2007.[48] While 78 changes in minimum wage resulted from the Act, the other 164 events were due to state ordinances. Table A.3 highlights two important patterns. First, at least 5 states change their effective minimum wage every year. Second, there is significant variation in how often states change their minimum wages. For example, Georgia only changed its minimum wage three times in line with federal minimum wage policy. On

[47] David et al. (2016) document all minimum wage law changes between 1979-2012. Our table differs slightly from David et al. (2016) because we extend the sample through 2015 and include DC. Additionally, we have corrected errors in the minimum wages of Pennsylvania and Colorado.

[48] The Act raised the federal minimum wage in three stages: to \$5.85 60 days after enactment (2007-07-24), to \$6.55 one year after that (2008-07-24), then finally to \$7.25 one year after that (2009-07-24).

Table A.2: Minimum wage elasticity for employment stocks and flows

y_{it}	(1)	(2)
Hires	**-0.156*****	0.012
	(0.017)	(0.045)
	84,140	83,280
Separations	**-0.190*****	-0.024
	(0.017)	(0.022)
	84,120	83,246
Employment	**-0.068*****	**-0.039****
	(0.017)	(0.017)
	84,140	83,280
Earnings	**0.056*****	-0.016
	(0.015)	(0.015)
	84,140	83,280
Controls		
County fixed effect	Y	Y
Common time effects	Y	
Pair-specific time effects		Y
Centriods <75mi	Y	Y

*Data source: 2005-2015 Quarterly Workforce Indicator (QWI). This table reports the elasticity of the labor market outcomes listed in the first column. The regression sample is restricted to the counties from 964 county-pairs whose centriods are within 75 miles and includes all workers whose age is between 14-34. Robust standard errors, in parentheses, are clustered at the the paired-county level. * for 10%. ** for 5%, and *** for 1%.*

the contrary, its neighbor, Florida, makes the most minimum wage adjustments, changing 11 times.[49] Overall, the effective minimum wage increases $0.54 per change on average, but with substantial variation (Table A.4). The largest change ($1.90) happened in Michigan in 2005, while the smallest increment ($0.04) happened in Florida in 2010.

One limitation is the scarcity of city-level minimum wage ordinances. Before 2012, only five localities had their own minimum wage laws. As of 2019, 37 counties and cities have passed local minimum wage ordinances. Table A.5 provides the name of these cities and their associated minimum wage levels in year 2009. Due to limited data, we estimate the baseline model using state-level minimum wage variation but focus on the county-level labor market outcomes. Then, the effect of the city-level minimum wage will be inferred using contiguous border county pairs.

C.2 Construction of LODES analysis sample from the raw database

We use the Longitudinal Employer-Household Dynamics Program's Local Origin and Destination Employment Statistics (LODES) version 7.5, which counts the number of workers who live in one census block and work in another, spanning most states from 2002 to 2019. These census block pairs are known as origin-destination pairs. We use data from 2005 to 2015, with the origin census block in one state and the destination census block in another. The only missing state-year combinations are Massachusetts from 2005 to 2010 and District of Columbia from 2005-2009. We further exclude Alaska and Hawaii from our analysis because they are remote states with few commuters to other states.

We concentrate on private-sector employees who commute to their primary jobs. We further restrict our attention on the origin-destination pairs located within a band that stretches 11 kilometers on each side of state borders. As a robustness check, we also do calculations doubling the width to 22 kilometers. The LODES data classifies workers into three wage categories: less than $1,250 per month, between $1,250 and $3,333 per month, and more than $3,333 per month. We label these categories as low, middle, and high wage workers, respectively. We aggregate commuters from these origin-destination pairs to commuters between two counties. Then, we narrow our analysis sample to cross-border county pairs with a sufficient number (> 85) of cross-state low-wage commuters.

The counties included in the sample and their associated number of cross-boarder commuters are shown in Figure 1 and Figure A.1. 1 shows the included counties that received more than the threshold number of cross-border commuters, while Figure A.1 shows the included counties that sent more than the threshold number of cross-border commuters.

C.3 Construction of the analysis samples from the raw ACS 2005-2015 PUMA databases

First, we merge the three raw ACS 2005-2007, 2008-2010 and 2011-2015 data files into one that contains all the relevant variables between 2005-2015. The raw ACS files are downloaded directly from the US Census Bureau, following https://www.census.gov/programs-surveys/acs/data/pums.html. From year 2012, the ACS starts to use the 2010 version of Public Use Microdata Areas (PUMAs). Therefore, we further use the 2000-2010 PUMA crosswalk (https://usa.ipums.org/usa/volii/puma00_{}puma10_{}crosswalk_{}pop.shtml) to map the 2010 PUMA definitions to 2000 PUMA definitions for all the years after 2010. The variables obtained from the raw database are reported in Table A.6. The wage measures are adjusted for inflation to be "2015 dollars" equivalent. we further put an age restriction $16 \leq age \leq 30$ on the population.

[49]Two changes happened in 2009.

Table A.3: Variation in State Minimum Wages (2005-2015)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Changes
Federal MW	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25	3
Alabama												3
Alaska	7.15	7.15	7.15	7.15	7.15	7.75	7.75	7.75	7.75	7.75	8.75	3
Arizona			6.75	6.90	7.25		7.35	7.65	7.80	7.90	8.05	8
Arkansas			6.25	6.25							7.50	4
California	6.75	6.75	7.50	8.00	8.00	8.00	8.00	8.00	8.00	9.00	9.00	3
Colorado			6.85	7.02	7.28	7.28	7.36	7.64	7.78	8.00	8.23	8
Connecticut	7.10	7.40	7.65	7.65	8.00	8.25	8.25	8.25	8.25	8.70	9.15	6
Delaware	6.15	6.15	6.65	7.15	7.15					7.75	8.25	5
D.C.	6.60	7.00	7.00	7.00	7.55	8.25	8.25	8.25	8.25	9.50	10.5	7
Florida	6.15	6.40	6.67	6.79	7.21		7.31	7.67	7.79	7.93	8.05	11
Georgia												3
Hawaii	6.25	6.75	7.25	7.25	7.25							3
Idaho												3
Illinois	6.50	6.50	7.00	7.63	7.88	8.13	8.25	8.25	8.25	8.25	8.25	5
Indiana												3
Iowa			6.20	7.25	7.25							2
Kansas												3
Kentucky												3
Louisiana												3
Maine	6.35	6.50	6.75	7.00	7.25	7.50	7.50	7.50	7.50	7.50	7.50	5
Maryland		6.15	6.15	6.15							8.25	4
Massachusetts	6.75	6.75	7.50	8.00	8.00	8.00	8.00	8.00	8.00	8.00	9.00	3
Michigan			7.05	7.28	7.40	7.40	7.40	7.40	7.40	8.15	8.15	4
Minnesota		6.15	6.15	6.15						8.00	9.00	5
Mississippi												3
Missouri			6.50	6.65	7.05				7.35	7.50	7.65	7
Montana			6.15	6.25	6.90		7.35	7.65	7.80	7.90	8.05	10
Nebraska											8.00	4
Nevada			6.24	6.59	7.20	7.55	8.25	8.25	8.25	8.25	8.25	5
New Hampshire												3
New Jersey		6.15	7.15	7.15	7.15				7.25	8.25	8.38	5
New Mexico				6.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	4
New York	6.00	6.75	7.15	7.15	7.15					8.00	8.75	6
North Carolina			6.15	6.15								3
North Dakota												3
Ohio			6.85	7.00	7.30	7.30	7.40	7.70	7.85	7.95	8.10	8
Oklahoma												3
Oregon	7.25	7.50	7.80	7.95	8.40	8.40	8.50	8.80	8.95	9.10	9.25	10
Pennsylvania			6.70	7.15	7.15							6
Rhode island	6.75	7.10	7.40	7.40	7.40	7.40	7.40	7.40	7.75	8.00	9.00	5
South Carolina												3
South Dakota											8.50	4
Tennessee												3
Texas												3
Utah												3
Vermont	7.00	7.25	7.53	7.68	8.06	8.06	8.15	8.46	8.60	8.73	9.15	10
Virginia												3
Washington	7.35	7.63	7.93	8.07	8.55	8.55	8.67	9.04	9.19	9.32	9.47	10
West Virginia			6.20	6.90	7.25						8.00	4
Wisconsin	5.70	6.50	6.50	6.50								4
Wyoming												3
Changes	12	17	47	45	47	5	9	8	10	18	24	242

Note: Two minimum wage changes happened in 2009 for Florida.

Table A.4: Summary Statistics of State-Level Effective Minimum Wage Changes (2005-2015)

Year	Counts	Mean	S.D.	Min	Max
2005	12	0.621	0.475	0.10	1.45
2006	17	0.605	0.463	0.15	1.85
2007	47	0.831	0.527	0.25	1.90
2008	45	0.541	0.285	0.10	1.35
2009	47	0.533	0.206	0.05	1.00
2010	5	0.548	0.234	0.04	0.70
2011	9	0.160	0.190	0.06	0.70
2012	8	0.315	0.032	0.28	0.37
2013	10	0.160	0.068	0.10	0.35
2014	18	0.362	0.321	0.10	1.00
2015	24	0.629	0.467	0.12	1.85
Total	212	0.538	0.370	0.04	1.90

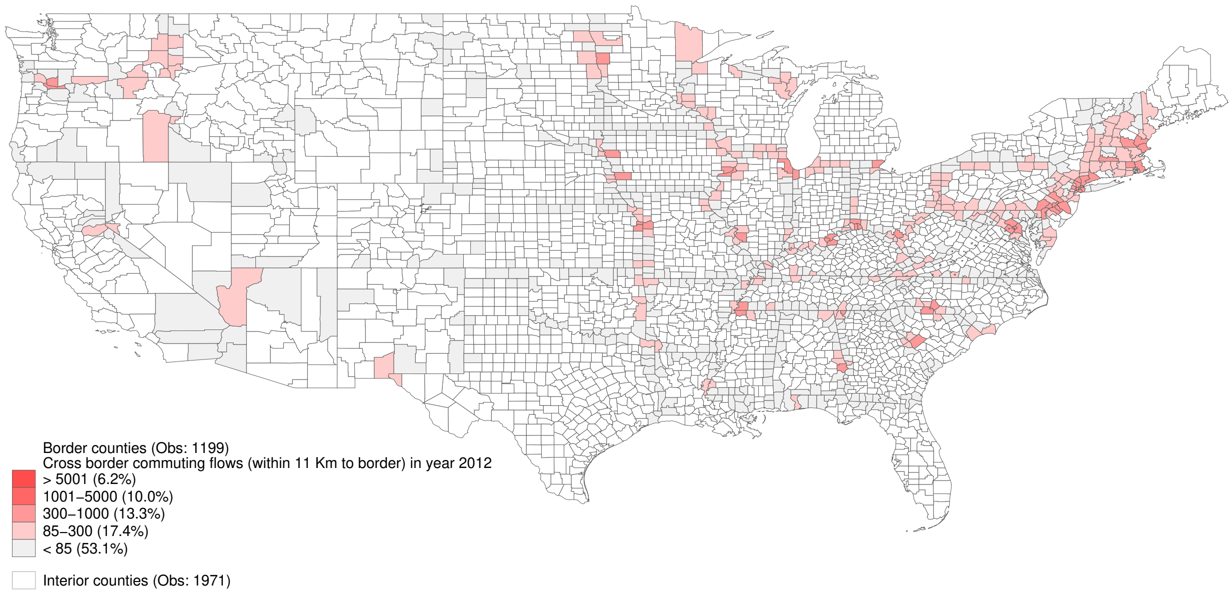
Note: All units are in nominal dollars.

Table A.5: City Minimum Wages

No.	City name	MW at 2019	Starting year	No.	City name	MW at 2019	Starting year
1	Flagstaff, AZ	12	2017	20	Santa Clara, CA	15	2016
2	San Jose, CA	15	2013	21	Berkeley, CA	15.59	2014
3	Belmont, CA	13.5	2018	22	Sunnyvale, CA	15.65	2015
4	Redwood City, CA	13.5	2019	23	San Leandro, CA	14	2017
5	Milpitas, CA	15	2017	24	Alameda, CA	13.5	2019
6	Palo Alto, CA	15	2016	25	Pasadena, CA	14.25	2016
7	Oakland, CA	13.8	2015	26	Washington, DC	14	2012
8	Mountain View, CA	15.65	2015	27	Chicago, IL	13	2015
9	Richmond, CA	15	2015	28	Portland, ME	11.11	2016
10	Emeryville, CA	16.3	2015	29	Minneapolis, MN	12.25	2018
11	Malibu, CA	14.25	2016	30	Albuquerque, NM	9.2	2007
12	Cupertino, CA	15	2017	31	Las Cruces, NM	10.1	2015
13	Los Altos, CA	15	2017	32	Santa Fe, NM	11.8	2004
14	San Francisco, CA	15.59	2004	33	New York City, NY	15	2017
15	Santa Monica, CA	14.25	2016	34	Portland Urban Growth Boundary, OR	12.5	2017
16	Los Angeles, CA	14.25	2016				
17	Fremont, CA	13.5	2019	35	Seattle, WA	16	2015
18	El Cerrito, CA	15	2016	36	SeaTac, WA	16.09	2014
19	San Mateo, CA	15	2019	37	Tacoma, WA	12.35	2016

Note: This table is reproduced based on Dube and Lindner (2021). All units are in nominal dollars. The Minimum wage only applies to transportation and hospitality workers within SeaTac city.

Figure A.1: Included Counties by the Number of Cross-Border Commuters They Sent in 2012



Note: Author's calculations from LODES. Highlighted counties are the ones included in the analysis. Colors represent the amount of commuters they send across the border in year 2012, i.e. the number of workers who live in the county and work in another county across the border.

Table A.6: Variables obtained from the raw ACS

Variables	Variable labels
serialno	Housing unit/GQ person serial number
puma	Public use microdata area code
st	State code
adjinc	Adjustment factor for income and earnings dollar amounts
agep	Age
pwgtp	Person's weight replicate
migpuma	Migration PUMA
migsp	Migration recode - state or foreign country code
powpuma	Place of work PUMA
powsp	Place of work - State or foreign country recode
schl	Educational attainment
esr	Employment status recode
wagp	Wages or salary income past 12 months
wkhp	Usual hours worked per week past 12 months
wkw	Weeks worked during past 12 months

Table A.7: Converting individual-level observations to county-level moments

Individual-level variables	County-level variables	Definition	RAW ACS
High type dummy	High type fraction	Education attainment is high school graduate or above	schl
Low type dummy	Low type fraction	Education attainment is high school dropouts	schl
Employment dummy	Employment rate by types (high and low)	(1) Employed at work and (2) employed with a job but not at work	esr
Hourly wage	Average hourly wage by types (high and low)	"Wages or salary income past 12 months"(wagp) divided by the product of "usual hours worked per week past 12 months"(wkhp) and "weeks worked during past 12 months"(wkw)	wagp, wkhp, wkw
Migrants dummy	The fraction of migrants by types (high and low)	Individuals who report a migration states (not N/A)	migsp
Commuters dummy	The fraction of commuters by types (high and low)	Individuals who report the place of work different from the place of residence	powsp
Labor force dummy	Labor force participation rate by type (high and low)	(1) Employed at work, (2) employed with a job but not at work and (3) unemployed	esr

Next, we convert the individual-level observations into county-level moments, reported in Table A.7. The biggest challenge in this process is that the basic geographic units for respondents in ACS is "Public Use Micro Areas"(PUMAs) rather than any jurisdiction geographic entity (i.e. county, city, etc.) in order to comply with census non-identifiable disclosure rule. Therefore, we instead construct the "pseudo" county-level statistics by the following two steps: (1) First, we construct the PUMA-level summary statistics from the corresponding individual-level variables. (2) Second, we impute the county-based measures from the corresponding PUMA-based measures following the crosswalk provided by Michigan Population Studies Center http://www.psc.isr.umich.edu/dis/census/Features/puma2cnty/. The new constructed county-level variables are reported in second column in Table A.7, while the original individual-level variables are displayed in first column.

Finally, we classify the counties by whether they are border counties (counties on state borders) and interior counties (counties not on state borders). Table 2 and the second panel in table 3 report conditional statistics both by educational types and by interior/borderline locations.

C.4 Constructing the analysis samples from the raw QWI 2005Q1-2015Q4 databases

The time series of county-level variables from QWI are directly obtained through LED extraction tool https://ledextract.ces.census.gov/static/data.html. The age group 19-21, 22-24, 25-34 are selected. The variables displayed in table A.8 are calculated and used in this paper.

C.5 Creating the merged sample using multiple data sources

In this session, we will discuss the final step in combining multiple data sources into the final completed sample. To begin, we will use QWI as our baseline data sample. Second, the ACS will be merged into QWI. Third, we will combine additional county-level moments from various data sources. Finally, we will apply several selection criteria to obtain our final sample.

Table A.8: County-level moments obtained from QWI

Variables	Definition	Raw QWI
Average monthly earnings	Average monthly earnings of employees who worked on the first day of the reference quarter.	EarnBeg
Employment	Estimate of the total number of jobs on the first day of the reference quarter.	Emp
Hire rate	The number of workers who started a new job at any point of the specific quarter as a share of employment	HirA/Emp
Separation rate	The number of workers whose job in the previous quarter continued and ended in the given quarter	SepBeg/Emp

- **Step 1: build the baseline data structure with pseudo ACS county-level data.** We create a balanced panel of all contiguous county-pairs between 2005-2015 using the ACS county level data we created in subsection C.3. The initial sample size is 12,518.

- **Step 2: merge with the QWI variables.** We then merge the baseline data with QWI quarterly data between 2005-2015 we created in subsection C.4. We average the quarterly data into the yearly data in the merged sample. (Obs. 11,858)

- **Step 3: merge additional other variables from several different databases.** We then merge several key variables from other data sources which are displayed in the following table 5. We then only keep the observation with no-missing values in all key variables. (Obs. 10,762)

- **Step 4: apply several selection criteria.** We only keep the observations with enough shares of both migrants and commuters. We also requires the distance between two counties in the county pair are close enough. In particular, we only include county pairs that are close with each other (centroids $\leq$ 44 km) and have sufficient numbers of mobile workers (the fraction of both migrants and commuters are more than 1.5%). (Final obs. 2,742)