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 data from the American Community Survey (ACS) and Quarterly Workforce Indicators (QWI), exploiting minimum wage variation across state borders and over time. An out-of-sample validation finds that the model produces reliable forecasts of commuting responses to city minimum wage hikes. Model simulations of local and universal minimum wage effects show how welfare varies with the minimum wage level. Low skill workers benefit from local wage increases up to $12.50/hour and high skill workers up to $15.50/hour. The greatest per capita welfare gain (including both workers and firms) is achieved by a universal minimum wage of $15.25/hour.

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

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1 Introduction

More than 40 cities passed their own minimum wage ordinances since 2010. In 22 of these, the minimum wage is set at $15 per hour or higher, which is more than twice the federal minimum wage.[1] These local minimum wages may have different impacts from the federal and state minimum wages that have been 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 earned 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.[3] Firms may also respond to higher minimum wages by adjusting their hiring strategies, which may benefit some workers but adversely affect others (Horton, 2017; Clemens, 2021). Although minimum wage policies are often considered to be anti-poverty policies, we show in this paper that local minimum wages can be potentially used as a sorting device to attract higher skill workers into an area and repel lower skill workers, which generates externalities on neighboring counties.

As emphasized in Robert Moffit's research, public policies, such as tax policies, welfare programs, and minimum wage laws, alter labor supply incentives. Using structural frameworks, Moffitt investigated the heterogeneous effects of both existing and hypothetical programs on welfare and inequality.[4] In this tradition, this paper studies the distributional and welfare effects of local and universal (federal) minimum wage policies, accounting for worker heterogeneity, mobility, and firms' labor demand. In particular, we develop and estimate a spatial general equilibrium job search model that integrates features of the Diamond-Mortensen-Pissarides framework ((Pissarides, 2000; Mortensen, 2005)) and of Flinn's (2006) model that includes minimum wages. By considering job search in a spatial context, we are able to compare the effects of both local and universal minimum wage policies. We present evidence on how local and universal minimum wage policies affect the welfare of high and low skill workers over a wide range of values, from $7.50 (the current federal minimum wage) to $20.00. We also show how our estimated model can be used to derive a minimum wage policy that is optimal under a social welfare criterion.

Our model assumes that the economy consists of two adjacent regions, similar to the cross-border

[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]Recent studies have shown that local minimum wages influence labor mobility.(e.g. Monras (2019); McKinnish (2017); Pérez (2022))

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

contiguous county pairs considered in Dube et al. (2016). Workers are differentiated by skill levels (college educated or not) and by geographic residence location. They receive job offers from local and neighboring county firms. Workers accept a local offer if its value exceeds the value of unemployment. When deciding whether to accept neighboring offers, workers require extra compensation to offset migration/commuting costs. 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 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 firm-worker match, which results in changes in the number of posted vacancies. We assume random search, which implies that heterogeneous workers within a location are contacted by firms at identical rates. An individual's productivity upon meeting a firm depends on by his/her skill level (high or low) and a random match quality component. The bargained wage is determined by a surplus division rule, subject to any minimum wage constraints, as in Flinn (2006).

Our spatial framework is motivated, in part, by previous studies that showed that an increase in the relative minimum wage between neighboring counties tends to decrease commuting. In this paper, we also examine how commuting and migration patterns across state borders respond to relative minimum wage changes. Our event-study analysis shows that relative minimum wage increases negatively impact commuting, with magnitudes varying by travel distance and by worker type. With a commuting band of 11 kilometers around a state border, we find that 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.

Our spatial job search model incorporates four channels through which local minimum wage changes affect low and high skill workers as well as firms. For workers, there are counterveiling employment and wage effects. Although a minimum wage increase dissolves marginally acceptable firm-worker matches (a *"disemployment effect"*), it also leads some workers in sustainable job matches to get a larger share of the match surplus (a "*wage enhancement effect*"). Commuting will decline if the disemployment effect on the future present discounted value of utility outweighs the wage enhancement effect. For firms, a local minimum wage increase reduces the incentive to post job vacancies, because it reduces the firms match surplus share (a "*share reduction effect*"). Finally, labor mobility alters the skill composition of workers. Our random search assumption implies that firms cannot 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 local firms' revenue, but also firms' revenues in neighboring areas. Importantly, 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).[5] We evaluate the model fit using both within-sample and out-of-sample fit criteria.

Our analysis yields five key results. First, our out-of-sample validation exercise uses the estimated model to predict commuting responses to city wage changes that were not used in the model's estimation and compares our predictions to corresponding commuting data. The model provides reasonable forecasts of how commuting responds to city-level minimum wage increases, despite the 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. We find 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 exhibit hump shapes for both high and low skill workers with peaks at different levels. Low skill workers' welfare peaks at a wage equal to \$12.50 and high skill workers peak at \$15.50. Third, we examine the sensitivity of our welfare calculations to assumptions on whether minimum wage costs are partly passed on to consumers through higher prices for goods and services. Adjusting 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. Fourth, following Hosios (1990), we construct a Benthamite social welfare function that includes all labor market participants (workers and firms). Under this social welfare function, the optimal local minimum wage is \$14.75.

Fifth, we use the estimated model to compare the effects of a local minimum wage policy to a universal one.[6] For a representative county pair, we calculate the welfare effects of a universal minimum wage hike (in both counties) and of a local minimum wage hike (in one county) over a range of values (from \$7.25 to \$20.00). The hump-shaped social welfare function peaks at a wage level of \$15.25, at which level the per capita welfare under a universal minimum wage policy is higher than under a local policy. This is because the universal minimum wage removes the incentive to arbitrage regional minimum wage differences, which saves on moving costs. Interestingly, our simulated optimal universal minimum wage aligns with the recently proposed federal minimum wage of \$15/hour.[7] This suggests a substantial poten-

[5] The migration and commuting flows come 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).

[6] As of July 6, 2017, 25 states passed laws preempting local minimum wages. 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.

[7] 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

tial improvement in per capita welfare if a new universal minimum wage at this level were implemented. However, at a higher minimum wage of $18.5/hour, per capita welfare is lower under a universal policy than under a local policy, due to greater disemployment effects.

Related Literature. This paper builds on a body of literature that examines minimum wage effects through the lens of equilibrium job search models. Eckstein and Wolpin (1990) study minimum wage effects in a Nash equilibrium model with workers that are homogeneous in productivity but heterogeneous in preferences for leisure and they are matched with heterogeneous firms. Their framework extends the model of Albrecht and Axell (1984) to incorporate endogenous job offer probabilities and measurement error in wages. Van den Berg and Ridder (1998) also derive an endogenous wage distribution within an alternative search framework that allows for heterogeneous workers, on-the-job search, and firing decisions (extending the Burdett and Mortensen (1998) framework). 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 match surplus division. Flinn shows that imposing a minimum wage could, in principle, enhance welfare on both the supply and demand sides of the market and that an increase in the minimum wage does not necessarily lead to greater unemployment.[8]

The previous search literature that incorporates minimum wages assumes a single labor market with a universal minimum wage and relies on time series minimum wage variation for identification. By considering job search in geographically distinct sub-markets, our study exploits additional cross-sectional minimum wage variation. We also use our model to explain data features not analyzed in earlier studies, such as how migration and commuting respond to regional wage disparities. Importantly, our spatial framework permits evaluation of both local and universal minimum wage policies with regard to effects on labor mobility, employment, migration/commuting, wages and welfare.[9] As previously noted, local minimum wages are an increasingly important and controversial feature of the U.S. labor market.

This paper also builds on the body of literature that uses spatial search frameworks to analyze labor mobility. For example, Coen-Pirani (2010) develop 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) develop a model with heterogeneous workers, search frictions, firm-worker match quality, human capital accumulation and endogenous migration between large, medium and small cities to explain

bill.

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

[9]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.

the positive relationship between worker wages and city size.[10] The framework closest to ours is Schmutz and Sidibé (2019), which develops and estimates a partial equilibrium model in which homogeneous workers face spatial frictions that make it harder to compete for distant jobs. To our knowledge, this is the first paper to assess the impact of local minimum wage policies within a spatial search and general equilibrium framework incorporating heterogeneous workers.[11]

Our paper also relates to recent studies analyzing how migration/commuting responds to local minimum wage changes. Several studies find that workers avoid moving to areas with higher minimum wages.[12] We show additionally that commuting elasticities depend on the distance around the border used to define the commuting zone.[13] A recent study by Pérez (2022) develops a spatial equilibrium model of location choice that he uses to study how commuting and residence locations respond to local minimum wage changes. His model does not, however, allow for ripple effects of the minimum wages over the entire wage structure, which we find to be empirically substantial.[14]

Our paper also relates to the literature that examines whether place-based tax policies have spillover externalities.[15] This is the first paper to investigate externalities in the minimum wage context. 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. 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 potential spillover effects.[16] In this paper, we find evidence of cross-border spillover effects and propose a

[10] Another related paper is 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.

[11] While Schmutz and Sidibé (2019) also considers local minimum wages in their counterfactual exercise, our results substantially diverge from theirs, likely due to their assumption of worker homogeneity and their exclusion of general equilibrium effects. They have acknowledged this limitation in their paper(p.31): "As such, our frictional model may be able to offer some answers, although the scope for analyzing optimal minimum wages is limited because of potentially large general equilibrium effect."

[12] Cadena (2014) shows that 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 shows that fewer low-skilled workers move toward states that increase minimum wages.

[13] Our result is consistent with Manning and Petrongolo (2017) who shows 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%.

[14] Cengiz et al. (2019) conclude that 40% of the total wage effects stems from the ripple effect of the minimum wage. Engbom and Moser (2021) also find that the minimum wage has far-reaching spillover effects on wages higher up in the distribution using Brazil data.

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

[16] For example, Kuehn (2016) shows that commuting spillovers may bias the effects of minimum wages in cross-border minimum

modeling framework that explicitly allows for them.

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

In this section, we develop a dynamic spatial search model where individuals live and work in one of two paired counties (j, j'). 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 supply in the neighboring county due to worker mobility, as described in detail below. Our model assumes job search takes place in county pairs. However, in the data, a county in one state may border on multiple counties in another state. At the end of this section, we will describe how our model of worker and firm behavior in pairs of counties handles such cases.

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 $a \in A = \{a_1, ..., a_n\}$.[17] Individuals' working and residential status are determined by the job search process. $U(a, j)$, $E(a, j)$, $C(a, j)$ and $M(a, j)$ denote 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, which is assumed to be an i.i.d. draw

wage studies, and Monras (2019) demonstrates how ignoring migration decisions can lead to an understatement of minimum wage effects on employment.

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

from $G_j(\theta)$, the cumulative distribution function (cdf) of matching quality in county j.[18] We assume that 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 county j firms, local workers receive such offers with an "effective" rate $s_j\lambda_j \leq \lambda_j$ while the neighbouring workers receive such offers with "effective" rate $(1-s_j)\lambda_j \leq \lambda_j$.[19] The value of unemployment for type a workers living in county j can be written as:

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

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 that is specified in the next section. The job acceptance decision is based a comparison of 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 incur additional moving costs $c(a,j) > 0$.[20] If $c(a,j) = 0$ and $s_j = 0.5$, then workers in county j and county j' would have 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 completely isolated markets. As pointed out by Schwartz (1973) and Greenwood (1975), moving costs combine both the psychic costs of losing local social connections and physical transportation costs that usually depend on distance. Section 4.1 will discuss the parametric specification of the moving and commuting costs.

The model assumes no on-the-job search.[21] Therefore, the worker who accepts a job with wage w will

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

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

[20] 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 $(\rho + \eta_j)c(a,j)$.

[21] Incorporating on-the-job (OTJ) search into our framework presents two primary identification challenges. First, integrating

not voluntarily quit. Existing matches are assumed to dissolve at a constant exogenous rate η_j. The value of employment, $V_e(w, a, j)$, has the the form:[22]

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

2.3 Bargaining with a minimum wage constraint

We next specify how the worker's wage 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.[23]

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

The bargaining weight α_j, which is allowed to vary by location, represents the relative strength of labor at that location and is strictly between 0 and 1.[24] 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:

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

This 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 by accepting employment, $\rho V_u(a, j)$.

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

OTJ search complicates the bargaining environment significantly. This complexity arises because an employed worker can simultaneously bargain with both their current employer and a potential outside poacher. Consequently, the worker's share of surplus is influenced not only by their bargaining power α, but also by the value of their last job, which serves as the outside option during wage negotiations with their current employer following a job transition. Additionally, accounting for both unemployed and employed job seekers complicates the matching function, as it necessitates decisions on how to measure the effective number of employed job seekers.

[22] 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 section 2.4.

[23] See related discussion in section 2.6

[24] 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.

with match quality $\theta^*(a, j)$ and staying unemployed.

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

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

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

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

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 to 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, denoted $\hat{\theta}(a, j)$

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

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

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

where $f_j(w|a, j)$ is the probability density function (pdf) of $F_j(w|a, j)$, $g_j(\theta)$ is the PDF of $G_j(\theta)$, and $\tilde{G}_j(\theta) = 1 - G_j(\theta)$ is the complementary function of the cumulative distribution function $G_j(\theta)$. $\tilde{\theta}(w, a, j) =$

$\frac{w-(1-\alpha_j)\rho V_u(a,j)}{a\alpha_j}$ denotes the matching quality whose bargained wage is equal to w. The observed wage distribution consists of a point m_j with mass $\frac{G_j(\hat{\theta}(a,j))-\tilde{G}_j(\frac{m_j}{a})}{\tilde{G}_j(\frac{m_j}{a})}$ and a continuous function (assuming $G_j(\theta)$ 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 $\rho V_u(a,j)$.[25] Lastly, 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 Acceptance strategies for neighboring offers and the migration/commuting decision

Next, we characterize workers' job acceptance and migration decisions upon receiving a neighboring county job offer. Our model assumes the following timing: (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 a comparison 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 a neighboring county offer, then the worker draws another preference shock and chooses whether to commute or migrate (as described 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 explain the different mobility patterns in the data, our model allows workers to choose whether to migrate or commute in response to neighboring county wage offers. After accepting an offer, workers can pay a lump-sum cost to migrate ($h=1$) and become a native worker in county j' or pay a commuting

[25] 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.

cost and become a commuter ($h = 0$).[26] As described in detail below, we assume that the choice-specific cost functions depend on the worker's ability type a, the physical distance between county j and j' and on amenity differences between the counties (captured by rental prices). The worker's mobility choice also depends on the relative value of employment in each of the two counties. The employment value for commuters is

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

and the employment value for migrants is

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

Let $cc_1(a, j)$ and $cc_0(a, j)$ denote the nonstochastic component of the net benefit from migrating or commuting from j to j'.[27] Workers choose their mobility option $h(a, j) \in \{0, 1\}$ that provides the greatest net benefit:

$$h(a, j) = \begin{cases} 0 & \text{if } cc_0(a, j) + \varepsilon_{a0} > cc_1(a, j) + \varepsilon_{a1} \\ 1 & \text{if } cc_0(a, j) + \varepsilon_{a0} \leq cc_1(a, j) + \varepsilon_{a1}. \end{cases} \tag{8}$$

The above decision also depends on unobserved choice-specific preference shocks ε_{a0} and ε_{a1} to allow for nonpecuniary factors that might affect migration/commuting decisions, such as the desire to live near high quality schools or close to relatives. Assuming ε_{ah} follows an i.i.d. type I extreme value distribution with a location parameter 0 and a scale parameter σ_a^c (that is common for matched pair counties). The probability of choosing option h, $h \in \{0, 1\}$, is:

$$Q_h(a, j) = \frac{exp(cc_h(a, j)/\sigma_a^c)}{exp(cc_0(a, j)/\sigma_a^c) + exp(cc_1(a, j)/\sigma_a^c)} \tag{9}$$

2.5 Workers' optimal strategies

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

[26] In reality, the commuting cost is recurring, but without loss of generality we can incorporate in the model its lump-sum equivalent.

[27] Section 4.1 will give the precise parametric specification of $cc_1(a, j)$ and $cc_0(a, j)$.

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 or migrate depending on equation 8.

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:[28]

$$
\begin{aligned}
a\theta^*(a,j) \quad = \quad & \underbrace{ab_j}_{\text{(1) Flow utility}} + \frac{s_j\lambda_j}{\rho+\eta_j}[\underbrace{\boldsymbol{I}\left(\theta^*(a,j) < \frac{m_j}{a}\right)(m_j - a\theta^*(a,j))\left(\tilde{G}_j(\hat{\theta}(a,j)) - \tilde{G}_j(\frac{m_j}{a})\right)}_{\text{(2) Local offer with wage } m_j} \\
+ \quad & \underbrace{\int_{\max\{\hat{\theta}(a,j),\theta^*(a,j)\}} a\alpha_j(\theta - \theta^*(a,j))dG_j(\theta)]}_{\text{(3) Local offer with wage } w_j > m_j} \\
+ \quad & \frac{(1-s_j)\lambda_{j'}}{\rho+\eta_{j'}}[\underbrace{\boldsymbol{I}(\theta^{**}(a,j) < \frac{m_{j'}}{a})(m_{j'} - a\theta^*(a,j'))\left(\tilde{G}_{j'}(\theta^{**}(a,j)) - \tilde{G}_{j'}(\frac{m_{j'}}{a})\right)}_{\text{(4) Neighbouring offer with wage } m_{j'}} \\
+ \quad & \underbrace{\int_{\max\{\hat{\theta}(a,j'),\theta^{**}(a,j)\}} a\alpha_j(\theta - \theta^*(a,j'))dG_{j'}(\theta)}_{\text{(5) Neighbouring offer with wage } w_{j'} > m_{j'}} \\
- \quad & \underbrace{(\rho+\eta_{j'})\left(\frac{a(\theta^*(a,j) - \theta^*(a,j'))}{\rho} + c(a,j)\right)\tilde{G}_{j'}(\max\{\hat{\theta}(a,j'),\theta^{**}(a,j)\})]}_{\text{(6) The unemployed value difference between staying/moving}}
\end{aligned}
\tag{10}
$$

with

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

In equation 10, 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

[28] The derivation of equation 10 can be found in Appendix A.3

staying and moving, which includes both the moving cost $c(a, j)$ and the change of the option value of being unemployed $a\theta^*(a, j) - a\theta^*(a, j')$.

The intuition underlying equation (10) is the following. 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, including both local and mobile workers that can be low or high skill, and they cannot distinguish type of worker prior to meeting them. 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 K_j vacancies in county j with constant cost ψ_j. The matching technology is assumed to be constant returns to scale.

Due to search efficiency frictions,, the number of unemployed workers (of all skill types) seeking jobs in county j is:

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

where $s_j U(a, j)$ denotes the "effective" number of unemployed workers of type a in county j searching locally, while $(1 - s_{j'})U(a, j')$ denotes the "effective" number of the unemployed workers of type a in county j searching for jobs in the neighboring county. For the matching function, we assume a Cobb-Douglas specification with constant returns to scale and total factor productivity equal to 1. 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. The parameter ω_j characterizes heterogeneity in the matching functions across labor markets j.

The number of vacancy posted in county j, K_j, is determined by the following free entry condition (see Appendix A.4 for detailed derivations):

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

$$
(1 - s_{j'}) U(a,j') \int_{\max\{\theta^{**}(a,j'),\frac{m_j}{a}\}} V_f(\theta,a,j) dG_j(\theta)\ ] \tag{11}
$$

where

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

A minimum wage increase in county j could affect a firm's incentives to post job vacancies for two reasons: (1) it reduces the firm's share of the total surplus as both $\int_{\max\{\theta^*(a,j),\frac{m_j}{a}\}} V_f(\theta,a,j)dG_j(\theta)$ and $\int_{\max\{\theta^*(a,j'),\frac{m_j}{a}\}} V_f(\theta,a,j)dG_j(\theta)$ monotonically decrease as m_j increases; (2) The composition of job seekers, $U(a,j)$ and $U(a,j')$, may change as a result of worker relocation in response to the minimum wage change.[29] This would also impact the firm's expected profit, but the sign is ambiguous.

The contact rate in county j, λ_j, is determined by the tightness of local labor market:

$$
\lambda_j := \frac{M_j}{N_j} = \left(\frac{K_j}{N_j}\right)^{1-\omega_j} \tag{12}
$$

This concludes our description on the spatial search general equilibrium model. A detailed definition of the model's steady-state spatial equilibrium is given in the appendix, section A.5.

2.7 How the model accommodates multiple bordering counties

The theoretical model described above assumes two bordering counties. However, in our data, a county in one state may border on multiple counties in another state. For example, suppose county A in one state borders on two counties, B and C, in another state. Among 418 counties used in the estimation, 121 counties are adjacent to multiple counties. In estimating the model, we treat counties A and B and counties A and C as separate pairs. In the data, when we measure the number of migrants and commuters in county A, we cannot distinguish whether they come from counties B or C, which can lead to some measurement error. Alternatively, one could aggregate counties B and C and regard them as one unit. However, workers in counties B and C will generally have different reservation wages, for example, if they have different education levels and reside different distances from county A. Due to different characteristics, the rate at which workers in B or in C accept the posted wage offers from firms in A and choose to either commute

[29] Using ACS and the Burning Glass vacancy data, Clemens et al. (2021) show some evidence that firms may replace low-skilled workers by some slightly higher-skilled workers following minimum wage hikes.

or migrate will generally differ. Differences in worker composition and in local labor market conditions between counties B and C provide valuable sources of variation for identifying the model coefficients.

3 Data and descriptive analysis

City-level minimum wage ordinances are a fairly recent phenomenon. As of 2020, 42 municipalities enacted local minimum wage laws, with more than half of these enacted after 2013. Cities are of particular interest due to their large populations, but the number of cities with local minimum wage laws is still too limited to be the basis for estimating our search model parameters. Partly for this reason, we base our model's estimation rather on a sample of cross-state-border county-pairs, following a design originally proposed by Dube et al. (2010, 2016). Our model's identification/estimation exploits both cross-sectional, state-level minimum wage differences (across borders) as well as time series variation. After estimating the model, we use the model to predict commuting responses to city minimum wage ordinances and compare the predictions to the data. This provides a way of validating the model out-of-sample. After finding the forecasts are reasonably accurate, we use our estimated model to analyze the effects of both local and universal minimum wages of varying magnitudes.

We next describe the multiple datasets that are used in estimating the model. In this section, we also report evidence from an event study analysis examining how migration and commuting patterns in close proximity to state borders respond to cross-border-state changes in minimum wages.

3.1 Data and sample construction

To estimate our model, we use data from the Quarterly Workforce Indicators (QWI) and from the American Community Survey (ACS). In addition, we analyze data from the Longitudinal Employer-Household Dynamics Program's Local Origin and Destination Employment Statistics (LODES) to get a detailed look at how migration/commuting in close proximity to state borders responds to changes in minimum wages.[30]

QWI data: The QWI contains information on job stocks and flows as well as average earnings broken down by industry, worker demographics, employer age, and size for each county. QWI comes from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata.[31] It has near-universal coverage of worker-employer information, covering 96% of private-sector jobs. The worker demographic information, which includes age, sex, race/ethnicity, and education, permits analysis of the

[30]The LODES data are not used in estimating the model.

[31]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.

composition of workers in particular local labor markets or industries.[32] Lastly, QWI has labor flow information, including hires, separations, and turnovers, which is critical, because the studies have found that the effects of minimum wage hikes are most directly seen on job turnovers rather than on stocks.[33] We analyze data from years 2005-2015.[34]

ACS data: We use the 2005-2015 ACS data to measure commuting and migration flows between counties. Commuters are defined as people whose place of work differs from their place of residence, whereas migrants are defined as individuals 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.[35]

LODES data: We use the LODES data to analyze how cross-border commuting responds to minimum wage changes. According to Manning and Petrongolo (2017), distance is a key factor determining worker preferences across jobs. Therefore, minimum wage effects may be most apparent for workers residing close to state borders. For each pair of census blocks (referred to as "origin-destination census block pairs"), the LODES data includes counts of workers living in one census block and working in another. We use this information to derive a cross-border commuting flow measure within a band that stretches a short distance on both sides of state lines.[36] We find that workers who live within a narrower commuting band respond more to minimum wage changes in neighboring counties than workers who live further away. We also incorporate distance between counties in estimation of the spatial search model.

3.2 Minimum wage differences among border county pairs

Similar to Dube et al. (2010, 2016), we divide all U.S. counties into counties that border another state (border counties), and counties that do not (interior counties). Out of 3,124 counties, 1,139 are border

[32] 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.

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

[34] 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.

[35] 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.

[36] 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 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%

counties and we construct 1,181 unique county pairs.[37] Between 2005 and 2015, the border county pairs experienced 332 minimum wage adjustments (see Table A.6 in appendix C). 78 resulted from either the federal minimum wage law or the Fair Minimum Wage Act of 2007, and the other 164 events were due to state ordinances. From 2005 and 2015, all counties (except for those in Iowa) increased their local minimum wage at least three times.[38] In a given year, about half of the counties that comprise the pairs differ in terms of minimum wages, with mean differences of about 10% and substantial heterogeneity (see Table 1).

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

We next use the LODES data to examine how migration and commuting respond to minimum wage changes in close proximity to state borders. According to Kneebone and Holmes (2015), a typical commuting distance is 7 miles (11 kilometers), so we define our baseline sample as individuals living within 11 kilometers of the state boundary. As a robustness check, we also do calculations doubling the commuting band width. We exclude from our analysis sample county pairs that do not have a sufficient number of cross-state commuters.[39] Figure 1 shows the included counties and the associated number of commuters that they receive from cross-border counties.[40]

We obtain the relative shares of commuters versus migrants from the American Community Survey

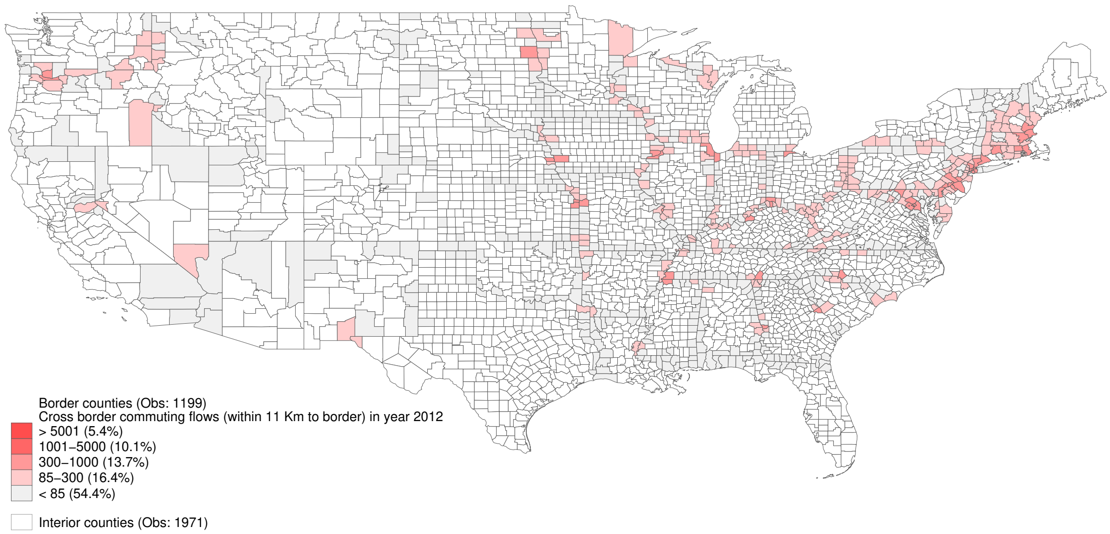
[37] Counties may border more than one county in the adjacent state, resulting in more pairs than border counties.

[38] The Fair Minimum Wage 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).

[39] These are typically border counties with low population density or ones where workers have barriers that make commuting difficult (for example, the Nevada-Utah border). Alaska and Hawaii are also excluded. We restrict our sample to the pairs with at least 85 low wage ($\leq$ \$3,333 per month) commuters. 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.

[40] Figure A.2 shows the included counties that send more than the threshold number of cross-border commuters.

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.

(ACS) data. To focus on workers potentially most affected by minimum wage changes, we limit our sample to individuals age 16 to 30 who are not in the military.[41] We divide this sample into two education groups: low (no college) and high (some college). Our spatial search model distinguishes between migrants (who move out of a county to a neighboring county in another state) and commuters who work in neighboring counties. As seen in Table 2, border counties have higher migration and commuting rates than interior ones. Also, more educated workers have higher rates of migrating and commuting.

Local labor market outcomes. We use the QWI data to obtain four key quarterly variables that describe local labor market characteristics: average monthly earnings, employment, hiring rates, and job separation rates. [42] 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.

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

[42]To make the QWI sample more comparable to the ACS sample, we restrict workers' ages to be between 19-34. 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 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 (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: Statistics are based on ACS data. The last column gives the proportion of migrants and commuters in the local population.

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.

3.3.1 Estimated elasticities in response to relative minimum wage changes

We next analyze how migrating/commuting responds to relative minimum wage changes using the following panel data model:

$$\log y_{wht} = \beta_0 + \beta_1 \log \frac{MW_{s(w),t}}{MW_{s(h),t}} + \tau_{c(w,h)} + \delta_t + \epsilon_{wht}. \tag{13}$$

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). $\frac{MW_{s(w)t}}{MW_{s(h)t}}$ is the ratio of the minimum wage in state $s(w)$ to which county w belongs and the neighboring state $s(h)$ to which county h belongs. We control for potential unobservables by including county-pair fixed effects $\tau_{c(w,h)}$ as well as time effects δ_t. β_1, gives the elasticity of labor flows

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 $\frac{MW_{st}}{MW_{st}}$). 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.

y_{wht} with respect to changes in the relative minimum wage ratio.

We estimated various versions of specification (13) using both the LODES and ACS data. For the sake of brevity, LODES results are shown here and ACS results are shown in Appendix B.2. 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 low wage category (equivalent to hourly rate $7.82 for a full time worker (160h/month)), which we expect to be the most responsive of the three groups to minimum wage changes.

The estimates show that the migration/commuting flows responds to relative increases in the local increases in the minimum wage. 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 commuting flows decrease by 1.248%, 0.827% and 0.407% in the low, middle, and high wage categories.[43] To explore whether distance 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.

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

[43]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 commuting response is greater for individuals residing close to state borders.

(2019)) In appendix B.1 , we explore whether there are "pre-trends" in commuting flows occurring before the minimum wage changes, for which we do not find any evidence. Appendix B.1 also shows event-study results disaggregated by education level, which indicates that low wage workers' commuting patterns are the most responsive to minimum wage changes.

4 Estimation of the spatial search model

4.1 Parameterization

To implement the spatial search model described in section 2, we first group workers into two skill types, a_h and a_l, where high type are those with some college and low type are those with no college. The type proportions are p_h and p_l. We assume that moving costs depend on the worker's type a, the physical distance $d_{jj'}$ between the counties, a cost of living difference $\gamma_j - \gamma_{j'}$, and on whether the worker chooses to migrate or commute, denoted by $h \in \{0, 1\}$.

(14)

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

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 (2.4) and (2.4)) when the worker chooses to commute rather than migrate.[44] β_{hj} measures the relative openness of labor market j, which is county-specific and can vary depending on whether the worker commutes or migrates (h). The impacts of physical distance on costs are captured by β_{0d} and β_{1d}.[45] The coefficients β_{0a} and β_{1a} represent additional costs paid by high type workers. We assume that differences in moving and commuting costs across different county pairs can be related to differences in local amenities, which we measure using regional housing rental price differences ($\gamma_j - \gamma_{j'}$).

As discussed in Flinn and Heckman (1982), it is necessary to assume a parametric distribution for the matching quality $G_j(\theta)$ 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.[46] Given these assumptions, the economy is characterized by the vector S which

[44] 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.

[45] 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)).

[46] A similar assumption is made in Flinn (2006) and Flinn and Mullins (2015).

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.

combines a set of general parameters, common across all counties, and a set of county-specific parameters.

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

To incorporate county-level heterogeneity while keeping the number of model parameters parsimonious, we impose a random coefficient structure on the county-specific parameters

$$\Theta_j(n) \in \left\{b_j(n), \bar{\theta}_j(n), s_j(n), \psi_j(n), \beta_{0j}(n), \beta_{1j}(n)\right\}$$

These correspond to the unemployment benefit, the mean of the match quality distribution, 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.

Because paired counties are geographically close, we allow the parameters in the $\Theta_j(n)$ and $\Theta_{j'}(n)$ vectors to be correlated within pairs by assuming that each of the components is bivariate normally distributed. Specifically, we make the following distributional assumptions:

$$\begin{aligned}
\begin{pmatrix} b_j \\ b_{j'} \end{pmatrix} &\sim N\left(\begin{bmatrix} \mu_b \\ \mu_b \end{bmatrix}, \begin{bmatrix} \sigma_b^2 & \rho_b\sigma_b^2 \\ \rho_b\sigma_b^2 & \sigma_b^2 \end{bmatrix}\right) \\
\begin{pmatrix} \bar{\theta}_j \\ \bar{\theta}_{j'} \end{pmatrix} &\sim N\left(\begin{bmatrix} \mu_\theta \\ \mu_\theta \end{bmatrix}, \begin{bmatrix} \sigma_\theta^2 & \rho_\theta\sigma_\theta^2 \\ \rho_\theta\sigma_\theta^2 & \sigma_\theta^2 \end{bmatrix}\right) \\
\begin{pmatrix} \log\psi_j \\ \log\psi_{j'} \end{pmatrix} &\sim N\left(\begin{bmatrix} \mu_\psi \\ \mu_\psi \end{bmatrix}, \begin{bmatrix} \sigma_\psi^2 & \rho_\psi\sigma_\psi^2 \\ \rho_\psi\sigma_\psi^2 & \sigma_\psi^2 \end{bmatrix}\right) \\
\begin{pmatrix} \beta_{0j} \\ \beta_{1j} \end{pmatrix} &\sim N\left(\begin{bmatrix} \mu_{\beta0} \\ \mu_{\beta1} \end{bmatrix}, \begin{bmatrix} \sigma_{\beta0}^2 & \rho_\beta\sigma_{\beta0}\sigma_{\beta1} \\ \rho_\beta\sigma_{\beta0}\sigma_{\beta1} & \sigma_{\beta1}^2 \end{bmatrix}\right) \\
\log\left(\frac{s_j}{1-s_j}\right) = \log\left(\frac{s_{j'}}{1-s_{j'}}\right) &\sim N\left(\mu_s, \sigma_s^2\right)
\end{aligned}$$

These random coefficient joint distributions are fully characterized by 16 parameters: 6 means, μ_Θ; 6 variances, σ^2_Θ; and 4 correlations, ρ_Θ. The search efficiency s_j and $s_{j'}$ is assumed to be the same.[47]

4.2 Identification

As previously noted, the modeling framework that is closest to ours is that of Flinn (2006), which develops a search model with homogeneous workers and one labor market that is used to analyze minimum wage effects. This paper extends Flinn (2006) by incorporating two worker types and allowing workers to search and firms to post offers in two geographically connected markets. Flinn (2006) shows that under a log-normal assumption on the matching quality distribution, the model parameters are 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, and the vacancy cost ψ is also identified when the matching technology ω is Cobb-Douglas.

In our model, workers search in both their local labor market and a neighboring labor market with potentially different efficiency levels (denoted by s_j and $1 - s_j$). The reservation wages for local jobs and neighboring jobs differ; 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 parameter identification in our set-up.

We begin with the parameters obtained directly from the multiple data sources, summarized in Table 5. First, we obtain the labor share α_j as the average payroll share of firms' revenues at the county level obtained from the Economy Wide Key Statistics (EWKS), which is the U.S. government's official five-year measure of American business and the economy.[48] Second, we obtain the matching technology parameter ω_j from a market tightness measure k_j, defined as the state-level ratio of job demand to labor supply (constructed from the Conference Board Help Wanted OnLine (HWOL)).[49] Third, the job destruction rate η_j is measured as the ratio of total separations to total number employed (from QWI data). Fourth, the share of high/low educated workers (p_j^h and 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 observe the centriod distance within any county pairs $d_{jj'}$ and the local

[47] This assumption eliminates workers' incentives to move in order to arbitrage differences in search efficiency.

[48] 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.

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

minimum wage m_j series, which is provided in Dube et al. (2016) but adjusted using the 2015 CPI.

We now consider identification of the remaining model parameters that not directly observed, including the low and high 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. Plugging $a\theta^*(a,j) = \rho V_u(a,j)$ into (3) expresses the bargained wage as:

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

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

$$w(a,\theta,\theta^*) = \begin{cases} m_j & \theta \in [\frac{m_j}{a}, \hat{\theta}(a,\theta^*)] \\ a(\alpha_j\theta + (1-\alpha_j)\theta^*(a,j)) & \theta > \hat{\theta}(a,\theta^*) \end{cases} \tag{15}$$

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 derived directly from data. A wage offer for a worker in location j is determined by three values: the worker's 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:

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

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

Similarly, we can identify $\{a, \theta^{**}(a,j)\}$ from the wage distribution of mobile workers. Notice that we assume the same wage determination protocol (equation (15)) for both local workers and mobile workers. 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 variance of the wage distribution for mobile workers:[50]

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

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

[50] 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.

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

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

Given $c(a,j)$ and observed proportions of commuters/migrants $Q_0(a,j)$ and $Q_1(a,j)$, the moving costs $cc_0(a,j)$ and $cc_1(a,j)$ are identified based on equation (9).

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

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

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

4.3 Estimation and selection of moments

The model is estimated by the method of moments (MOM), a natural approach for combining moments from multiple databases. The moments used and the associated parameters are shown in Table A.1 and A.2 in the Appendix A.6. Note that we incorporated commuting and migration elasticities from regression (13) as extra moments (the lower panel in Table A.2). These auxiliary moments are not required for identification. 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 data features.

5 Empirical results

5.1 Model fit

The estimated model reproduces many features of the data at both the county level (Table 6) and at the national level (Table 7). As seen in Table 6, 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 than in the data. Lastly, our model simulations reproduce the observed positive relationship between commuting patterns and rental costs. However, while the simulation reveals a negative correlation between migration patterns and housing rental costs,

Table 6: Model fit: county level statistics

Empirical moments	County j		County j'	
	Data	Sim	Data	Sim
Employment rate: mean	0.847	0.831	0.855	0.832
Employment rate: std	0.085	0.042	0.067	0.043
Proportion of migrants: mean (low edu)	0.074	0.141	0.078	0.140
Proportion of migrants: std (low edu)	0.082	0.119	0.099	0.119
Proportion of commuters: mean (low edu)	0.094	0.107	0.100	0.107
Proportion of commuters: std (low edu)	0.102	0.102	0.124	0.102
Proportion of migrants: mean (high edu)	0.102	0.128	0.107	0.128
Proportion of migrants: std (high edu)	0.103	0.107	0.119	0.107
Proportion of commuters: mean (high edu)	0.114	0.118	0.120	0.118
Proportion of commuters: std (high edu)	0.114	0.102	0.134	0.102
Correlation between migrants and distance	-0.109	0.003	-0.117	0.003
Correlation between commuters and distance	-0.106	-0.012	-0.114	-0.012
Correlation between migrants and rent cost	0.020	-0.016	0.031	-0.023
Correlation between commuters and rent cost	0.010	0.021	0.043	0.034

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

the data indicates a positive correlation.

Model simulations also exhibit the pattern that high education workers have much higher wages than low education workers, as is true in the data. 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, the estimated model captures the negative minimum wage elasticities for both commuters and migrants. Local minimum wage hikes deter both commuters and migrants from other areas. Lastly, the model simulations show that low educated commuters exhibit greater responsiveness to the minimum wage changes than high educated commuters.

5.2 Parameter estimates

Table 8 shows estimates of both the general parameters and the county-specific moving cost equation parameters (see Equation 14). The pair of means of the matching quality distribution, $(\bar{\theta}_j, \bar{\theta}_{j'})$, follow a bivariate log-normal distribution. Its parameters include a mean of $\mu_{\bar{\theta}} = 0.808$, a correlation $\rho_{\bar{\theta}} = 0.013$, and a standard deviation $\sigma_{\bar{\theta}} = 0.239$. Additionally, the standard deviation of the matching quality distribution, denoted as σ_G, is estimated to be 0.654. The unemployment values $\left(b_j, b_{j'}\right)$, are estimated to be similar across paired counties, with a high correlation $\rho_b = 0.959$ and a low standard deviation $\sigma_b = 0.327$. In contrast, the vacancy cost ψ varies considerably across counties. Its mean value is 202, which is equivalent to $32,320 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.

Table 7: Model fit: average across counties (national) statistics

Empirical moments	Data	Sim
Average hourly wage (high edu)	14.70	14.62
Average hourly wage (low edu)	10.04	10.14
S.D. of (log) hourly wage distribution (high edu)	0.550	0.541
S.D. of (log) hourly wage distribution (low edu)	0.510	0.618
S.D. of mean wage distribution across county (high edu)	2.42	4.25
S.D. of mean wage distribution across county (low edu)	2.54	1.90
Wage diff between local and mobile (high edu)	1.73	1.82
Wage diff between local and mobile (low edu)	0.98	1.03
Commuting elasticity (high edu)	-0.214	-0.080
Commuting elasticity (low edu)	-0.442	-0.299
Migration elasticity (high edu)	-0.613	-0.130
Migration elasticity (low edu)	-0.294	-0.367

The mean value of the search efficiency parameter s_j is 0.694, which mimplies that a typical worker receives roughly one-third the number of neighboring job offers as local offers. This magnitude is consistent with Manning and Petrongolo (2017), who note that the effective labor market for job seekers is quite local. We find that 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 ($a_h = 15.99$ vs. $a_l = 10.18$). When comparing mobility costs, migrating is more costly ($\beta_1 = 0.749$) than commuting ($\beta_0 = 0.258$), which can explain why the fraction of commuters is on average larger than the fraction of migrants.

The lower panel in Table 8 reports estimates of the additional parameters that enter into the estimated moving cost functions $cc_h(a, j)$. Both β_{0a} and β_{1a} have a positive signs, indicating that workers with more education face higher costs to be mobile workers than workers with less education. The next two coefficients, $\beta_{0\gamma}$ and $\beta_{1\gamma}$ specify how moving costs depend on local housing rental prices, used to proxy for local amenities. The positive sign for $\beta_{0\gamma}$ and $\beta_{1\gamma}$ indicates the commuting/migration costs are higher for workers coming from areas with high rental costs. The coefficients β_{0d} and β_{1d} account for distance costs. 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 are estimated to be similar for high- and low-education workers. Table 9 shows quantiles of the estimated ex-ante moving costs ($c(a, j)$) for workers differentiated by education levels and locations. The cost is on average about \$4,400 for low educated workers and \$10,700 for high educated workers. These costs would typically include the time and expense associated with commuting and the relocation costs associated with migration.(See, e.g., Schwartz (1973), Greenwood (1975)) Our estimated

Table 8: Model parameter estimates

General parameters				
Parameters	Notation	Mean μ	S.D. σ	Corr. ρ
Matching quality: mean	$\bar{\theta}$	0.808	0.013	0.239
		(0.021)	(0.017)	(0.778)
Matching quality: std	σ_G	0.654	-	-
		(0.0014)	-	-
Unemployed flow utility	b	-4.635	0.327	0.959
		(0.118)	(0.067)	(0.190)
Search efficiency	s	0.694	0.190	-
		(0.030)	(0.054)	-
Vacancy cost	ψ	202	267	0.082
		(1.263)	(1.369)	(0.057)
High type productivity	a_h	15.99	-	-
		(0.216)	-	-
Low type productivity	a_l	10.18	-	-
		(0.365)	-	-
Commuting cost (constant term)	β_0	0.258	1.105	-0.171
		(0.582)	(0.230)	(1.159)
Migration cost (constant term)	β_1	0.749	0.552	-
		(1.020)	(0.778)	
Additional moving and migration cost equation parameters $cc_h(a, j)$				
	Commuting ($h = 0$)		Migration ($h = 1$)	
Additional cost for high education	β_{0a}	3.57	β_{1a}	4.03
		(2.203)		(2.516)
Local amenities (rental cost)	$\beta_{0\gamma}$	0.252	$\beta_{1\gamma}$	0.179
		(1.639)		(1.649)
Distance cost	β_{0d}	0.502	β_{1d}	0.170
		(0.994)		(1.247)
Scale of preference shock (low type)	σ_l^c	1.797		
		(2.440)		
Scale of preference shock (high type)	σ_h^c	1.844		
		(2.373)		

Note: Standard errors in parentheses.

Table 9: Moving costs between county pairs

	Lump-sum ex-ante moving cost (unit: $)			
	Low educated		*High educated*	
	County j	County j'	County j	County j'
10th	3057	2965	9321	9232
25th	3613	3560	9847	9818
Median	4223	4191	10489	10436
75th	5082	5036	11376	11287
90th	6154	6029	12400	12307
Mean	4456	4392	10714	10650
Std	1294	1298	1297	1302

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.

moving costs are much lower than some cost estimates reported in the 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, our analysis is based on a relatively young sample of workers who are most likely to be impacted by minimum wage laws and who typically have lower moving costs.

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

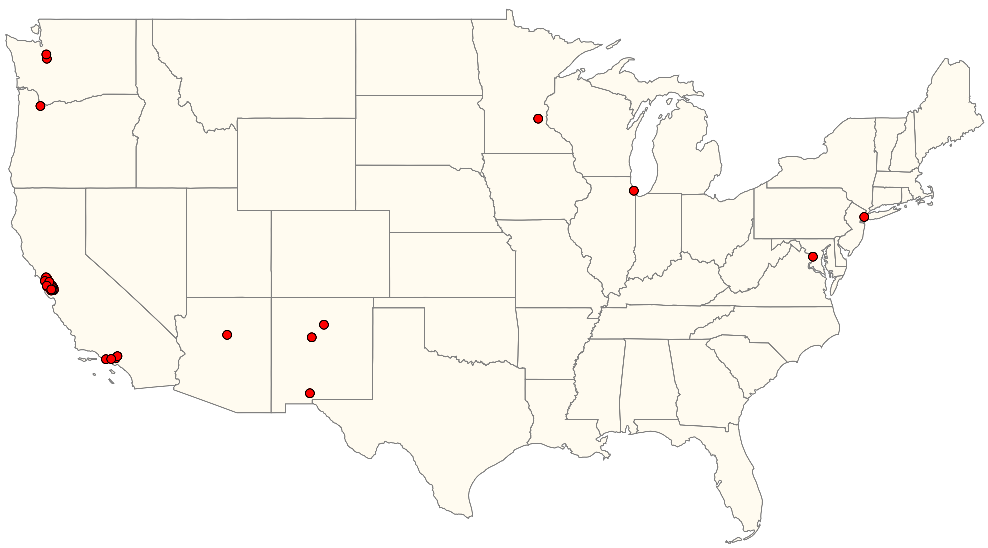
As previously noted, we do not exploit wage variation around cities in estimating the model, because the sample of cities that implemented minimum wage laws is relatively modest in size. However, as an out-of-sample validation exercise, we use our estimated model to predict how commuting responds after cities pass minimum wage ordinances. According to Figure 2, 37 cities from ten states have their own minimum wages in 2019, which range from $9.20 to $16.30. We compare the commuting elasticities predicted by our model to those calculated from the LODES data (up to 2019), which were not used in estimation.[51] We focus on workers living within 22 kilometers of the city (in the suburbs), and we use the following formula to calculate their commuting elasticity in response to relative minimum wage changes:

(16)
$$E_k = \frac{\log C_{k,t} - \log C_{k,t-1}}{\log \frac{MW_{k,t}}{MW_{s(k),t}} - \log \frac{MW_{k,t-1}}{MW_{s(k),t-1}}}.$$

[51] 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.

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 $\frac{MW_{k,t}}{MW_{s(k),t}}$ 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 $\frac{MW_{k,t}}{MW_{s(k),t}}$ change at least 2% between two years. We focus on low-wage workers (as reported in the LODES wage categories), because they are the most susceptible to minimum wage changes (see Table 4).

Figure 2: Cities with minimum wage ordinances in year 2019



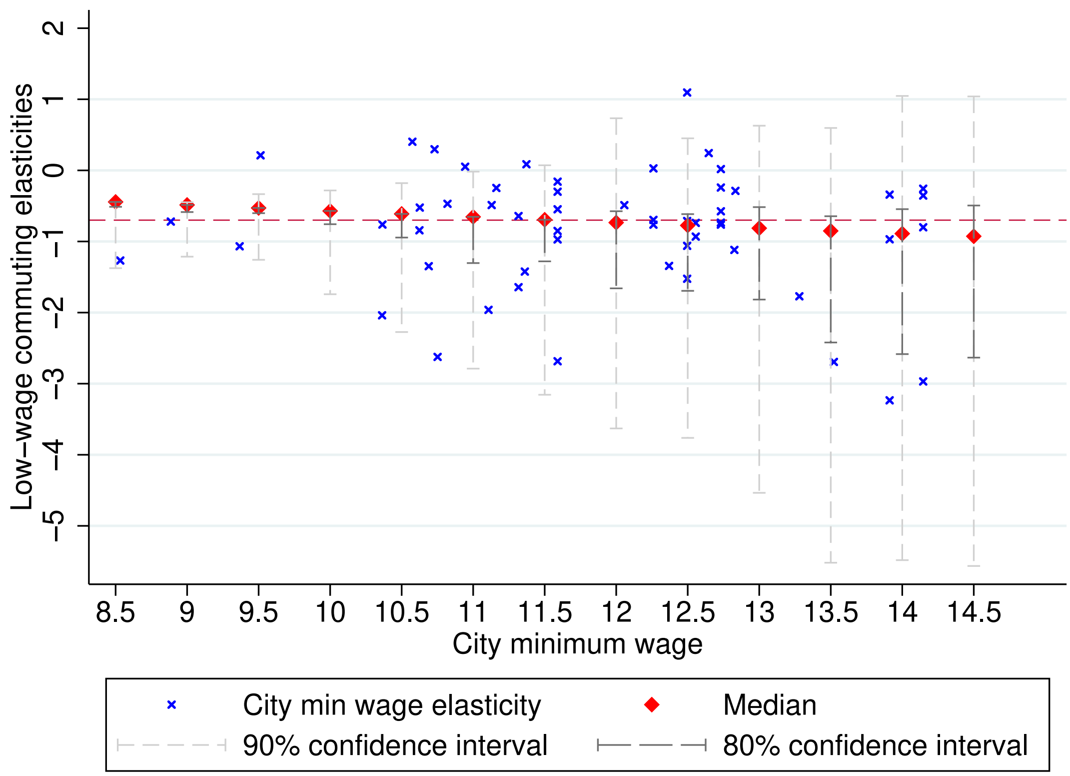
Note: This figure is reproduced based on Dube and Lindner (2021) and shows the cities having minimum wages above the state-level one in year 2019.

Our validation exercise uses the estimated model to simulate the commuting elasticities for minimum wage increases ranging from \$8.50 to \$15. Specifically, we calculate the predicted commuting elasticity for each county pair at each proposed wage level. The predicted elasticities by minimum wage level are then compared to the city-level elasticities (calculated from the LODES data using equation (16)). Figure 3 shows the comparison. The blue crosses show the elasticities derived from the city data. Commuting by workers in the lowest wage category decreases in 46 of 55 city-year observations, with an average elasticity of around -0.84. These patterns corroborate our previous findings that a higher local minimum wage deters commuters from neighboring areas. Figure 3 also shows the predicted elasticities for lower education commuters obtained from simulating the model, varying the minimum wage from \$8.50 to \$14.50.[52] The red diamonds represent the median estimated elasticities (across county-pairs), with the dark grey and light gret long-dash vertical lines indicating the 80% confidence and 90% confidence intervals. The city-level elasticities fall within the 90% confidence interval of the predicted elasticity distribution. As seen in the figure, actual

[52]All real values of city minimum wages are below \$14.50 measured by 2015 US dollars.

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 are cities in the San Francisco Bay Area). Overall, our estimated model provides reasonable predictions of commuting patterns in response to city-level minimum wage ordinances.

Figure 3: 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 Distributional effects of local and universal minimum wage policies

6.1 Effects of local minimum wage increases

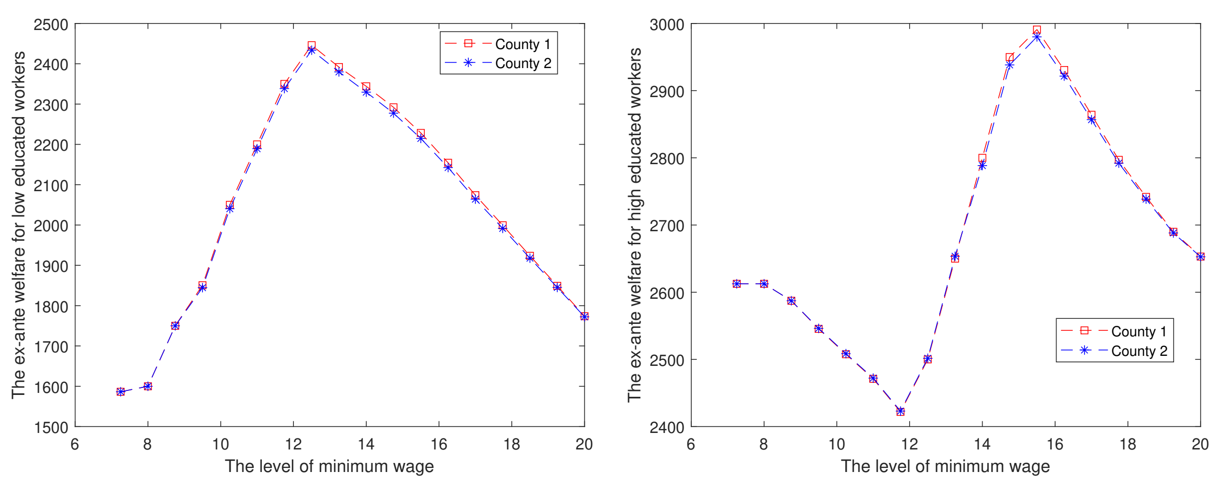
In this section, we use the estimated model to examine the welfare and distributional effects of local minimum wages. We first look at how the minimum wage affects workers differently based on their skill level a and location j, using the ex-ante value of unemployment as our welfare measure. We then investigate the impact on total welfare. 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 that could 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. In our model, workers are distinguished by their education type a and their location j. 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 4 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 and right panels show welfare levels for low and high skill workers. We use a red line to represent workers in County 1, the county for which the minimum wage increases, and a blue line to represent workers in County 2, the county with the fixed minimum wage.

Figure 4: Welfare changes across heterogeneous workers under different minimum wage increases

(a) Low educated workers (b) High educated workers



Countervailing effects of the minimum wage generate a hump shape in the welfare function for both types of workers. Increasing the minimum wage raises workers' expected income by increasing the return from a job match (the *wage enhancement effect*); but it also reduces work opportunities, because some previously acceptable matches are eliminated (the *disemployment effect*). When the local minimum wage in county 1 exceeds $\$12.50$, the latter effect dominates for low skill workers. The welfare function for high skill workers also has a hump shape but it peaks later. Because the productivity distribution of high skill workers first-order stochastically dominates that of low skill workers, high skill workers experience less of a *disemployment effect* at lower wage levels. The negative disemployment effect exceeds the wage enhancement effect at a minimum wage $m_1 = \$15.50$. Finally, we see that the welfare for workers in the same education class living in the two counties closely tracks each other due to the fact that two labor markets are interconnected and workers receive job offers from both counties. The small welfare disparities that we observe between similar workers living in different locations reflect a home bias in terms of job opportunities.

There are some studies in the literature arguing that the cost of minimum wage increases is partly passed on to consumers. (See, e.g., Clemens (2021) for a recent review.) Consequently, wage benefits stemming from minimum wage increases may be partly offset by increases in the prices of goods and services. To allow for potential pass-through 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. We plot the welfare function accounting for this price pass-through channel in Figure 5. 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 pass-through effects are very localized.[53] Our results show that price increases attributable to minimum wage changes account for a 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 minimum wage levels that maximize worker welfare remains the same. Because of its small effect on our welfare calculations, we do not adjust for potential pass-through effects in the subsequent analysis.

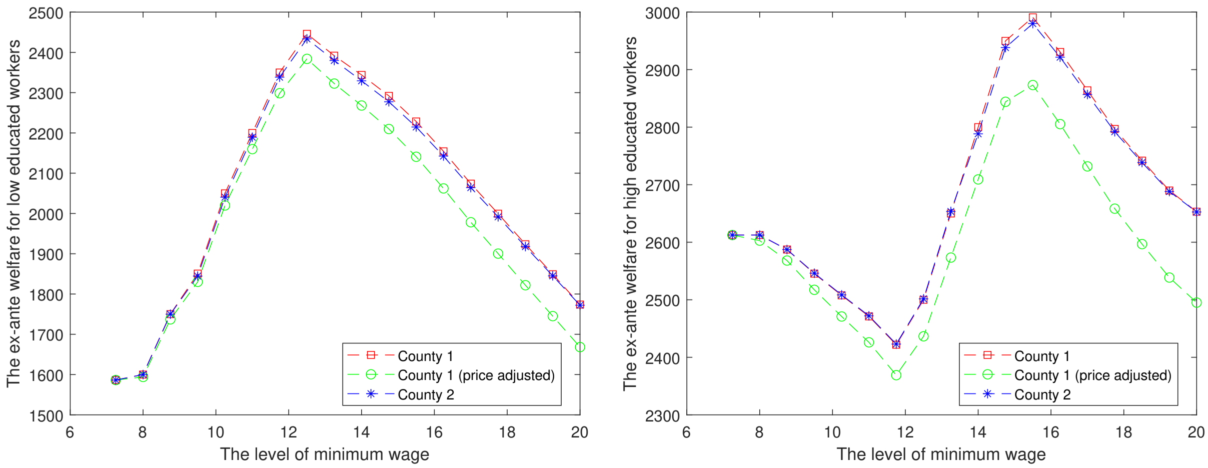
Effects of minimum wage changes on firms' vacancies We next consider how minimum wage changes affect firms' incentives to post job openings. Figure 6 shows how contact rates (λ_1, λ_2) in both counties change as the minimum wage in county 1 increases. In our job search model, there are two

[53]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.

Figure 5: Welfare changes across heterogeneous workers under different minimum wage increases (price adjusted)

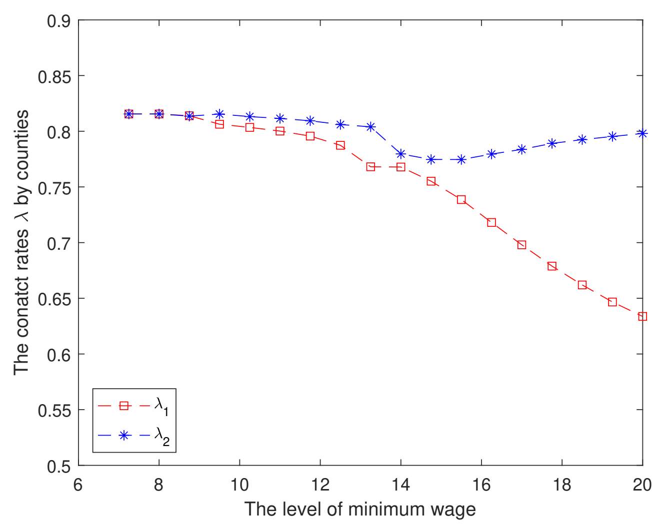
(a) Low educated workers

(b) High educated workers



channels through which the minimum wage influences the profitability of posting vacancies. First, as the minimum wage increases, firms receive less value per vacancy. This is because a higher minimum wage reduces the likelihood that a given match is acceptable and also makes sustainable matches less profitable. For these reasons, the contact rate λ_1 monotonically decreases in the minimum wage in county 1.

Figure 6: Contact rates under different minimum wages



Second, the job contact rate is also affected by job seekers' skill composition. Our assumption that firms engage in random search 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 \$15.50, high type workers prefer to work in county 1 rather than county 2, because the minimum wage provides a net welfare gain. As a result, the proportion of high education workers employed by firms in county 2 declines, which reduces incentives for county 2 firms to post job openings. When the minimum wage exceeds $15.50, however, high education workers begin to leave county 1 to avoid a welfare loss. The influx of high education workers in county 2 gives firms an incentive to post more job openings. In summary, the changing skill composition of county 2 workers in response to minimum wage changes in county 1 explains the U shape of county 2's contact rate, λ_2.

A Benthamite social welfare function Lastly, we consider an alternative social welfare function suggested by Hosios (1990) that incorporates all labor market participants, including both workers and firms. In particular, total welfare is defined as follows:

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

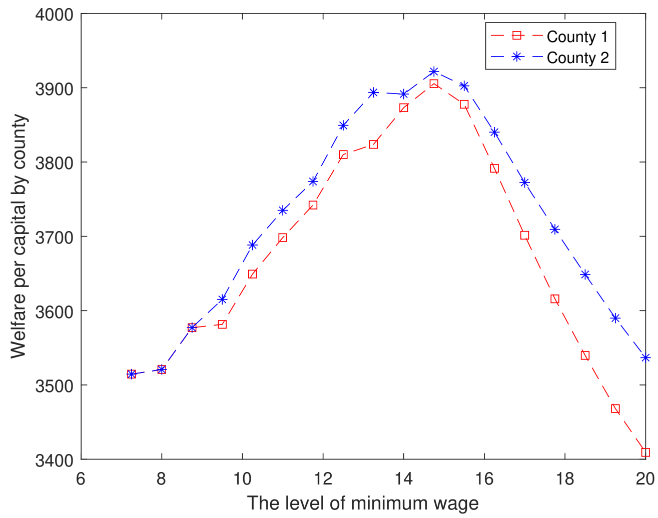
where (1) $L(a,j)$ is the population of local employed workers with $\bar{V}_e(\theta,a,j,\theta^*(a,j))$ denoting their average welfare. (2) $M(a,j)$ is the population of migrants who move from county j', with $\bar{V}_e(\theta,a,j,\theta^{**}(a,j')) - c(a,j')$ as their average net welfare. (3) $C(a,j')$ 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 calculate welfare per capita to account 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 7 plots the welfare per capita in each county as the minimum wage in county 1 increases. The welfare per capita in both counties exhibit hump shapes, with a single peak at $14.75. The changes in welfare per capita shown in the figure for 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. If we compare local workers in county 1 to neighboring county workers, we see that that neighboring county workers are less affected, because their job opportunities are less dependent on job offers from county 1.

Figure 7: Per capita welfare by counties

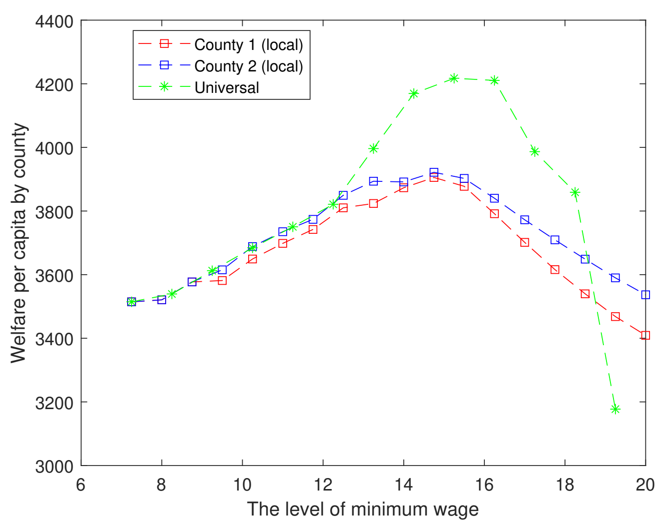


This explains why county 2 experiences less of a welfare loss in general compared to county 1.

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

As seen above, a county adopting a local minimum wage of $15 can generate substantial negative externalities on a neighboring county. A possible way to mitigate such spillovers is to adopt a uniform minimum wage across both counties. In fact, 27 states have passed laws preempting local minimum wage laws to avoid a "patchwork" of wage levels within a state. The federal government is also considering raising the federal minimum to $15 per hour to reduce minimum wage variation across states.

Figure 8: Per capita welfare under local and universal (federal) minimum wages



We use our estimated model to simulate the effects of local versus universal minimum wage policies on per capita welfare. Figure 8 compares welfare under local and under universal minimum wage 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 \$15.25 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. At the current proposed federal minimum wage of \$15, per capita welfare under the universal minimum wage policy is higher than under a local policy in both counties. When the minimum wage is even higher ($m \geq \$18.5$), 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 geographic 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 distinct effects 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 $12.50, 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 minimum wage levels up to $15.50.

Simulations based on our estimated structural model reveal how minimum wage impacts vary depending on the type of worker and depending on the minimum wage level. 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 and universal minimum wage policies, an analysis that is motivated by the recent state laws preempting local minimum wages. Again, we find a hump shape in welfare, with $15.25 being the value that maximizes per capita welfare (including all worker skill types and firms). Interestingly, our simulated optimal universal minimum wage closely aligns with the universal minimum wage of $15.00 recently proposed by the US House of Representatives. This finding suggests the potential for significant welfare gains if a universal $15.00 minimum wage policy were enacted.

There are a few ways this analysis could be extended in future research. First, we consider welfare effects for a sample of counties that border on state boundaries. 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:

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

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

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

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

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

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:

$$\begin{aligned}
\hat{w}(a, j, \theta) &= \arg\max\nolimits_w (V_e(w, a, j) - V_u(a, j))^{1-\alpha_j} V_f(w, a, \theta, j)^{1-\alpha_j} \\
&= \arg\max\nolimits_w \left(\tfrac{w + \eta_j V_u(a,j)}{\rho + \eta_j} - V_u(a, j)\right)^{1-\alpha_j} \left(\tfrac{a\theta - w}{\rho + \eta_j}\right)^{\alpha_j} \\
&= \arg\max\nolimits_w \left(\tfrac{w - \rho V_u(a,j)}{\rho + \eta_j}\right)^{1-\alpha_j} \left(\tfrac{a\theta - w}{\rho + \eta_j}\right)^{\alpha_j} \\
&= \alpha_j a\theta + (1 - \alpha_j)\rho V_u(a, j)
\end{aligned} \tag{17}$$

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:

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

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:

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

A.4 Solving the number of vacancy $K_(j)$ using free entry condition

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

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

Job seekers in different counties could 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.[54] The total number of matches created by the firms in county j is:

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

[54]It is important to note that the distribution of matching quality is characteristic of a specific location. Thus, local and mobile workers both derive their matching quality from the same distribution, $G_j(\theta)$, since they work in the same location j.

The firm's match value can be represented as:

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

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

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

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 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 equation:

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

A.5 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 $\boldsymbol{B}(\boldsymbol{R}_+)$ be the Borel $\sigma-$algebra of $\boldsymbol{R}_+$ and $\boldsymbol{P}(\boldsymbol{A})$, $\boldsymbol{P}(\boldsymbol{J})$ the power sets of $\boldsymbol{A}$ and $\boldsymbol{J}$, respectively. Let $\aleph = \boldsymbol{B}(\boldsymbol{R}_+) \times \boldsymbol{P}(\boldsymbol{A}) \times \boldsymbol{P}(\boldsymbol{J})$, and $\boldsymbol{M}$ be the set of all finite measures over the measurable space $(\boldsymbol{S_1}, \aleph)$.

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 2.5 and $\{Q_h\}_{h=0,1}$ is characterized by Eq. 9. The functions $\{V_u, V_e, \theta^*, \theta^{**}, Q_h\}$ are measurable with respect to $\aleph$.

2. The firm's problem: given the contact rate, wage and initial condition, V_f is solved by Eq. 2.6 and K_j is solved by Eq. 11.

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.

$$
\begin{aligned}
\underbrace{\lambda_j \left(s_j U(a,j)\tilde{G}_j(\max\{\theta^*(a,j), \frac{m_j}{a}\}) + (1-s_{j'})U(a,j')\tilde{G}_j(\max\{\theta^{**}(a,j'), \frac{m_j}{a}\}) \right)}_{\text{Inflow to } E(a,j) \text{(employed workers of type a in county } j\text{)}} &= \underbrace{E(a,j)\eta_j}_{\text{Outflow from } E(a,j)} \\
\underbrace{U(a,j) \left(s_j \lambda_j \tilde{G}_j(\max\{\theta^*(a,j), \frac{m_j}{a}\}) + (1-s_j)\lambda_{j'}\tilde{G}_{j'}(\max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}) \right)}_{\text{Outflow from } U(a,j) \text{ (unemployed residences of types a in county } j\text{)}} &= \underbrace{\left(E(a,j) - M(a,j')\right)\eta_j}_{\text{Inflow into } U(a,j)} \\
\underbrace{(1-s_j)\lambda_{j'}U(a,j)Q_1(a,j)\tilde{G}_{j'}(max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}))}_{\text{migrants from j to j'}} &= M(a,j) \\
\underbrace{(1-s_j)\lambda_{j'}U(a,j)Q_0(a,j)\tilde{G}_{j'}(max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\}))}_{\text{commuters from j to j'}} &= C(a,j)
\end{aligned}
$$

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

A.6 The method of moments estimator

The model parameters are estimated by the method of moments (MOM), a natural approach for combining moments from multiple databases. The moments used in estimation are shown in Tables A.1 and A.2. These moments have model-derived analytical expressions, shown in Appendix A.7. 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 (years 2005-2015). We select the county pairs using similar criteria as imposed in our 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.[55]
- 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

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

[55] This means the same county pair in two different periods would get separated draws of the county-level random coefficients.

Table A.1: 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.7.

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 standard 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).)

A.7 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).[56]

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:

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

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

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.

[56] Based on 300 simulations.

Table A.2: National-level moments

Empirical moments	Value	Parameters identified by moment
Moments related to wage distribution		
Average hourly wage (high edu)	14.70	a_h
Average hourly wage (low edu)	10.04	a_l
S.D. of (log) hourly wage distribution (high edu)	0.550	μ_θ, σ_G
S.D. of (log) hourly wage distribution (low edu)	0.510	μ_θ, σ_G
S.D. of mean wage distribution across county (high edu)	2.42	$a_h, \mu_\theta, \sigma_\theta$
S.D. of mean wage distribution across county (low edu)	2.54	$a_l, \mu_\theta, \sigma_\theta$
Wage diff between local and mobile (high edu)	1.73	$\mu_{\beta 0}, \sigma_{\beta 0}, \mu_{\beta 1}, \sigma_{\beta 1}, \rho_\beta, \beta_{1a}$
Wage diff between local and mobile (low edu)	0.98	$\mu_{\beta 0}, \sigma_{\beta 0}, \mu_{\beta 1}, \sigma_{\beta 1}, \rho_\beta, \beta_{0a}$
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.7.

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

$$\frac{M(a,j)}{E(a,j)} = \frac{(1-s_j)\lambda_{j'}\left(N(a,j)-E(a,j)\right)Q_1(a,j)\tilde{G}_{j'}(max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\})}{E(a,j)}$$

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.

3. *Proportion of commuters:* The proportion of commuters implied by the model is

$$\frac{C(a,j)}{E(a,j)} = \frac{(1-s_j)\lambda_{j'}\left(N(a,j)-E(a,j)\right)Q_0(a,j)\tilde{G}_{j'}(max\{\theta^{**}(a,j), \frac{m_{j'}}{a}\})}{E(a,j)}$$

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 in county j:*

$$\bar{w}(a,j) = \frac{(E(a,j) - C(a,j) - M(a,j)) \int_{\theta^*(a,j)} w(a,\theta,\theta^*) dG_j(\theta) + (C(a,j') + M(a,j')) \int_{\theta^{**}(a,j)} w(a,\theta,\theta^*) dG_j(\theta)}{E(a,j) - C(a,j) - M(a,j) + C(a,j') + M(a,j')}$$

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:*

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

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 Regression results (online)

B.1 Pre-trends analysis using the LODES data

Following Freyaldenhoven et al. (2019), we modify equation 13 to incorporate leads and lags of up to three years of the relative minimum wage ratio:

$$\begin{aligned} \log y_{wht} = \beta_{-4+} \left(1 - \log \tfrac{MW_{s(w),t+3}}{MW_{s(h),t+3}}\right) + \textstyle\sum_{k=-2}^{3} \beta_{-k} \Delta \log \tfrac{MW_{s(w),t+k}}{MW_{s(h),t+k}} + \beta_{3+} \log \log \tfrac{MW_{s(w),t-3}}{MW_{s(h),t-3}} \\ + \tau_{c(w,h)} + \delta_t + \epsilon_{wht} \end{aligned} \tag{18}$$

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 A.1 plots the $\hat{\beta}_k$ estimated from the equation (18). 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 elasticity estimates 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 effect is mainly on low wage worker's commuting patterns.

B.2 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. We also restrict the sample 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.3 shows the estimates In response to a 1% hike in relative minimum wages, the flow of commuters decreases by 0.428% 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.3 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.3 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:

$$\log y_{c,t} = \beta_0 + \beta_1 \log MW_{s(c),t} + \beta_2 X_{c,t} + \phi_c + \eta_{p(c),t} + \epsilon_{c,t} \tag{19}$$

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.4 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 con-

Table A.3: 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	-0.443*	-0.214	-0.428*	-0.432***
	(0.258)	(0.278)	(0.220)	(0.130)
	[3,514]	[3,318]	[3,514]	[3,809]
Migrants	-0.294	-0.613	-0.333	
	(0.312)	(0.424)	(0.330)	
	[3,238]	[3,225]	[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.*

sistent 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 estimates 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.5 provides the changes in minimum wages on both the state and federal levels.[57] Between 2005 and 2015, there was only one change to federal minimum wage law, the Fair Minimum Wage Act of 2007.[58] While 78 changes in minimum wage resulted from the Act, the other 164 events were due to state ordinances. Table A.5 highlights two important patterns. First, at least 5 states change their effective minimum wage every

[57] 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.

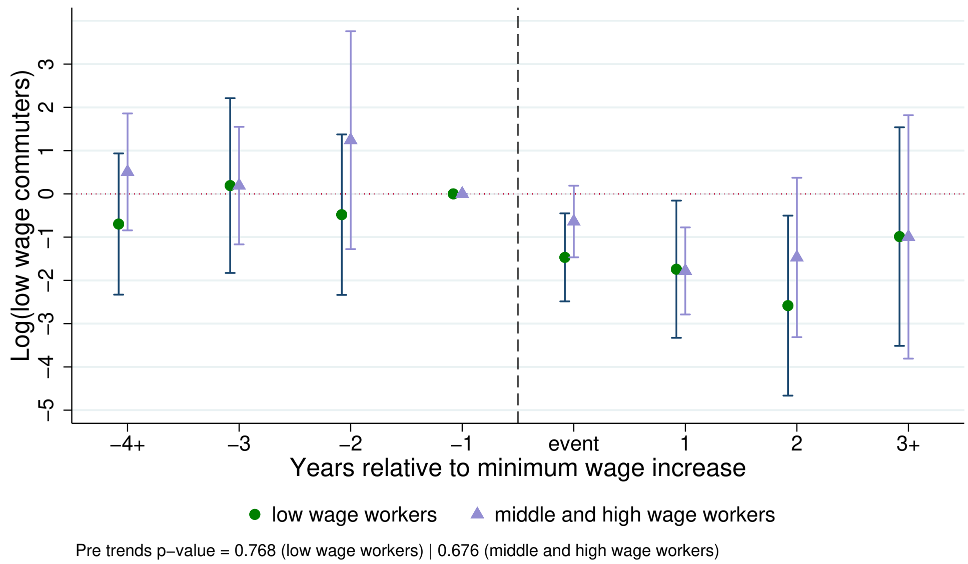
[58] The Act raised the federal minimum wage in three stages: to \$5.85 60 days after enactment (2007-07-24), to \$6.55 one year after that (2008-07-24), then finally to \$7.25 one year after that (2009-07-24).

Table A.4: 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%.*

Figure A.1: 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 $\beta_{-4+} = \beta_{-3} = \beta_{-2} = \beta_{-1} = 0$.

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 the contrary, its neighbor, Florida, makes the most minimum wage adjustments, changing 11 times.[59] Overall, the effective minimum wage increases \$0.54 per change on average, but with substantial variation (Table A.6). 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.7 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

[59]Two changes happened in 2009.

Table A.5: 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.6: 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

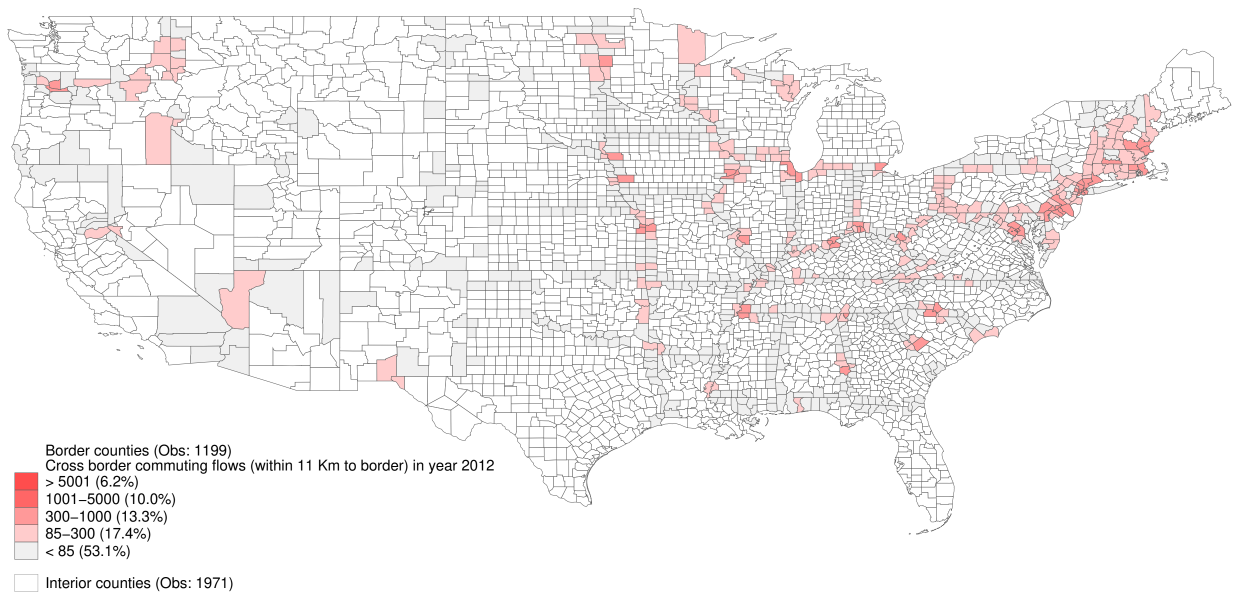
Note: All units are in nominal dollars.

Table A.7: 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	15.25	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	15.25	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	15.25	2016	34	Portland Urban Growth Boundary, OR	12.5	2017
16	Los Angeles, CA	15.25	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.2: 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.

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.2. 1 shows the included counties that received more than the threshold number of cross-border commuters, while Figure A.2 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.8. 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.

Table A.8: 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.9: 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.9. 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.9, 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.10 are calculated and used in this paper.

Table A.10: 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

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.

- **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)