Minimum Wages and Spatial Equilibrium: Theory and Evidence

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This paper introduces a spatial equilibrium model that relates earnings, employment, and internal migration responses to minimum wage increases. Population moves to or away from regions that increase minimum wages depending on the labor demand elasticity and on the financing of unemployment benefits. The empirical evidence shows that increases in minimum wages lead to increases in wages and decreases in employment among the low skilled. The labor demand elasticity is estimated to be around 1, which in the model is in line with the migration responses observed in the data. Low-skilled workers tend to leave regions that increase minimum wages.

I. Introduction

After many years of research, there is still a heated debate on what the employment effects of minimum wages are (Card 1992a, 1992b; Card and Krueger 1994, 2000; Neumark and Wascher 2000; Dube, Naidu, and Reich 2007; Dube, Lester, and Reich 2010; Allegretto, Dube, and Reich 2011; Neumark,

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Salas, and Wascher 2014; Dube and Zipperer 2015). To evaluate the effect of minimum wages, most of these studies compare what happens to the employment rate of teenagers in states where minimum wages increase and states where they do not.[1] The controversies have revolved around the measurement of the relevant employment variables and about the appropriate control groups.

However, when the employment rate changes, two things can change. It can be that the number of employed workers changes or that the number of workers in the local labor market changes. The latter has usually been forgotten in previous studies. Yet a large literature in urban economics builds on the fact that workers are free to move—and they do so when local labor market conditions change (see, e.g., Rosen 1974; Roback 1982; Blanchard and Katz 1992; Carrington 1996; Glaeser 2008; Hornbeck 2012; Hornbeck and Naidu 2014; Monras 2015a). What happens, then, when in a multiregion economy with free labor mobility one of the regions introduces a minimum wage or increases the one already in place? In what direction do workers move?

Despite the simplicity of this question, I am not aware of any study that provides a complete answer.[2] This is the first contribution of this paper. In a simple Rosen-Roback spatial equilibrium model, I show that a region that increases its minimum wage—which may result in higher unemployment—becomes more attractive if the disemployment effects created by minimum wages are small relative to the increased wages. When the employment effects are large, I show that the region can still become more attractive. This is the case only when unemployment benefits are financed nationally and when the region that introduces minimum wages is sufficiently small—so that most of the unemployment benefits are effectively paid by workers outside the region. This aspect of the model highlights a novel interaction between public finance and the spatial equilibrium that has not been shown before. More generally and relevantly for empirical inspection, the model shows that there is a tight relationship between employment effects and migration decisions resulting from increases in minimum wages.

The second and arguably main contribution of this paper is to show that the data in the United States are well explained by this model. To test the implications arising from the model I depart from existing literature on mini-

[1] All of these papers use US data. Obviously, researchers have also evaluated the impact of minimum wages in other countries (see, e.g., Machin and Manning 1994). The spatial comparisons can be done only in some countries with region-specific minimum wages, like the United States and Canada (for studies using Canadian data, see, e.g., Brochu and Green 2013; Campolieti, Fang, and Gunderson 2005) .

[2] The model presented in this paper is related to classical models of minimum wages when there are covered and uncovered sectors (see Mincer 1976) and rural urban migration models with unemployment a la Harris and Todaro (1970). For a recent application of these models, see Cadena (2014). Relative to these, I consider different ways to finance unemployment benefits and how this influences some of the results.

mum wages and concentrate on prime-age low-skilled workers, defined as workers with at most a high school diploma. I show that minimum wages are binding for around 10% of this group of workers.[3] As in previous literature, I then combine all of the changes in the effective minimum wage at the state level between 1985 and 2012.[4] Using all of these events, I first show that prior to increases in minimum wages, the wages of low-skilled workers tend to decrease while low-skilled employment tends to increase. I interpret this as evidence that the timing of minimum wage changes is not entirely random—as implicitly assumed in previous papers. This observation is crucial for explaining the small employment responses estimated in some of the previous research. Second, I show that after minimum wage changes, the negative trend in wages becomes positive, while the positive trend in employment disappears.[5] This suggests that minimum wage laws have a positive impact on wages, as intended by the policy change, but also a negative impact on the employment of low-skilled workers. This allows me to identify the local labor demand elasticity.

This estimation strategy is related to the one proposed in the recent paper by Meer and West (2016). Relative to them, in this paper I show not only that the trend in wages and employment changes after the policy change but also that the trends prior to the policy changes have specific shapes. In particular, there is on average across all of the state-level increases in minimum wage between 1985 and 2012 a very clear positive trend in low-skill employment before the policy change that flattens out with the policy.[6]

My results suggest that employment reacts more than average wages, with an implied local labor demand elasticity of around 1. According to the model, this is entirely consistent with low-skilled population leaving states that increase minimum wages, which is what is observed in the data. A 1% reduction in the share of employed low-skilled population reduces the share of low-skilled population—irrespective of their employment status—by between 0.5% and 1%. I also show that these migration results are primarily

[3] To make it comparable to prior literature, I also show results on teen employment. It is worth emphasizing that the number of older, prime-age, low-skilled workers earning wages around minimum wage levels is larger than the total number of teenage workers. I document all of these points in detail below.

[4] The effective minimum wage is either the federal minimum wage or the state minimum wage, depending on which one is more binding.

[5] This is also somewhat visible in fig. 3 of Allegretto, Dube, and Reich (2011), although less than in this paper because of the 2-year time gaps they use. Concentrating on the entire pool of low-skilled workers strengthens this finding. I replicate some of their findings in app. B.

[6] This change in the trend leading to the average policy change is detectable even when I allow for state-specific linear trends detached from minimum wage policies, one of the contentious debates in the literature (see Neumark, Salas, and Wascher 2014). Meer and West (2016) would have detected it had they included leads to their econometric specification.

a consequence of fewer low-skilled workers moving toward states that increase minimum wages—in line with recent results on the response of internal migration during the Great Recession reported in Monras (2015a). It is worth emphasizing that this is a surprising and remarkable result: working-age population for whom the policy was designed leave or do not move to the states where the policy is implemented.

These wage, employment, and migration responses affect low-skilled workers and not high-skilled ones. The high-skilled workers can be thought of as a control group and the evidence concerning them as a placebo test that should give further credibility to the empirical strategy proposed in this paper and the overall findings reported. March Current Population Survey (CPS) data allow me to easily construct this group of workers using the observable education information and to show that their earnings are way above the typical level of minimum wages.

This paper is related to some recent work. A handful of papers have studied migration responses to minimum wage laws, concentrating on international migrants. For example, Cadena (2014) estimates that recent low-skilled foreign immigrants avoid moving to regions with higher minimum wages, which he relates to the disemployment effects of minimum wage increases. He estimates an implicit labor demand elasticity that is consistent with the estimates in this paper. Relative to Cadena (2014), I report direct estimates of both internal migration decisions and employment effects using a novel identification strategy.[7]

The immigration literature has also estimated local labor demand elasticities and has considered the internal migration responses of natives. If an (unexpected) inflow of low-skilled workers arrives in a particular local labor market exogenously, the wages of competing workers are expected to decrease if the local labor demand is downward sloping. Estimates on whether and how much wages decrease have been controversial, given that it is often hard to find episodes where immigrants move to particular labor markets for completely exogenous reasons. Early studies following Altonji and Card (1991) using immigration networks to build instrumental variable strategies usually estimate small wage decreases, often not distinguishable from zero (see also Card 2001, 2009). If native low-skilled workers and immigrants are close competitors, these studies would imply that increases in minimum wages would be followed by very large employment responses, which would contradict some of the findings in the minimum wage literature. Most of the immigration literature, however, looks at longer time horizons—usually a decade—than what has been the focus of the minimum wage literature. When looking at shorter time horizons in Monras (2015b), I found that local labor demand elasticities are in line with the one estimated in this paper and that the reason

[7] See also Giulietti (2014) and Boffy-Ramirez (2013) for similar investigations on immigration and minimum wages.

why over longer time horizons the elasticities are lower is driven, among other things, by internal migration.[8] These findings are also consistent with the recent reassessment of the impact of the Mariel boatlift immigrants (see Monras 2015b, appendix; Borjas 2017; Borjas and Monras 2017).

Taken together, this paper offers both new evidence and a new way of thinking about minimum wage laws in the context of a spatial equilibrium model. It argues that to properly understand the effect of minimum wages, it is crucial to think about the relevant group of workers affected by the policy change and the particular economic conditions of the years in which the policy is implemented and to take into account the fact that internal migration quickly reacts to changes in local labor market conditions. In what follows, I first introduce the model, and I then show the empirical evidence. I conclude by relating my findings to previous literature.

II. Minimum Wages in a Two-Region World

Assume an economy with two regions, which I denote by 1 and 2. The production function is identical in the two regions and combines land (denoted by K) and labor (denoted by L) to produce a final freely traded good. Land is a fixed factor of production, meaning that each region is endowed with $\bar{K}_i$ and land cannot be transferred across regions. The production function is constant returns to scale and defined by $Y_i = AF(K_i, L_i)$.[9] Labor, instead, is fully mobile. Without loss of generality, we can normalize the total population to 1: $P_1 + P_2 = 1$ (I use the notation L_i to denote workers in region i and P_i to denote population in i). Individuals value expected indirect utility. Expected indirect utility is simply the value of the wage rate when there is no unemployment. If workers are risk averse, this value is marginally decreasing in income. If there is unemployment, then the expected indirect utility is the unemployment rate times the value of unemployment benefits plus the employment rate times the value of wages. Risk aversion implies that workers prefer low unemployment rates for a fixed level of expected income. Land rents go to absentee landlords that I do not model explicitly.

The model has a number of simplifications. First, I do not consider the possibility of different amenity levels in the two regions. This can be easily incorporated. Second, I do not consider local product demands. If there was a nontradable sector, a share of consumption would be in locally produced goods. This may limit some of the potential employment losses that I discuss but, to the extent that not all consumption is local, does not limit the main

[8] These findings confirm some of the insights in the earlier immigration literature (see Borjas et al. 1997; Borjas 2003).

[9] In the context of the model, having one representative firm or many different firms with the same production function is irrelevant. Thus, the number of firms is an indeterminate outcome in this model. I, thus, abstract from considerations relating to the number of firms.

arguments of the paper. Third, in some cases home market effects could undo some of the results in the paper. If home market effects are sufficiently large, they could even imply that everyone would prefer to live in one of the two regions. I abstract in this paper from those and from standard "new economic geography" forces that lead to multiple equilibria. Fourth, I also abstract from congestion forces other than the ones coming from the labor market. These include, most prominently, housing costs. Introducing them does not change the main points of the model either. I prefer to show the main arguments of the model in a simple framework rather than obscuring them by incorporating all of the aforementioned complications.

A. Short-Run Downward-Sloping Labor Demand Curve

To derive the demand for labor in each region is simple. Denote by r_i and w_i the price of land and labor in each region. A representative firm maximizes profits:

$$\max AF(K_i, L_i) - r_i K_i - w_i L_i.$$

So,

$$AF_l(\bar{K}_i, L_i) = w_i \tag{1}$$

is the demand for labor in each region. The term F_l indicates the partial derivative of the production function with respect to labor or the marginal product of labor.

This equation simply says that if more people move into one region, they exert downward pressure on wages. There are alternative ways to obtain this result (see, e.g., Blanchard and Katz 1992), but the main results of this paper do not depend on how I obtain this short-run local labor demand curve.[10]

B. Mobility Decision

Individuals' (indirect) utility in each region is given by

$$V_i = (u_i \cdot B_i^{\rho} + (1 - u_i) \cdot (1 - \tau_i)^{\rho} \cdot w_i^{\rho}) \quad \text{for } i \in \{1, 2\}. \tag{2}$$

This equation simply says that workers understand that (i) there is a certain probability (given by the unemployment rate) that they will not have a job and will receive instead the (per-worker) unemployment benefits (B) and (ii) there is a certain probability that they will work at the market wage rate (w) and will have to pay taxes (τ). I assume that the reservation wage is equal to zero and that unemployment benefits are below net wage rates. Risk aversion is captured by $\rho \in (0, 1)$. That is, for the same level of expected in-

[10] More generally, all that I need in the model is for the congestion forces to be stronger than the agglomeration forces.

come $((u_i \cdot B_i + (1 - u_i) \cdot (1 - \tau_i) \cdot w_i))$, workers prefer lower unemployment rates.[11]

C. Equilibrium

Two conditions define the equilibrium in this model. First, firms choose how many workers to hire in order to maximize profits. Second, workers are free to move. This means that in equilibrium workers need to be indifferent between living in region 1 or living in region 2. This is expressed as

$$(u_1 \cdot B_1^\rho + (1 - u_1) \cdot (1 - \tau_1)^\rho \cdot w_1^\rho) = (u_2 \cdot B_2^\rho + (1 - u_2) \cdot (1 - \tau_2)^\rho \cdot w_2^\rho). \tag{3}$$

Equation (3) simply says that the expected value of living in the two locations is, in equilibrium, the same. Note that where people live determines the wages prevailing in the two regions. That wages are decreasing in population implies that both regions have some workers.

D. Government Budget Constraint

So far, I have not specified how unemployment benefits are funded. In this paper, I consider two alternatives. Unemployment benefits in a particular region can be funded through taxes on workers in that same region or with taxes on workers from the entire country. This is expressed as follows.

Locally funded unemployment benefits.—Under this arrangement, local governments in each region face a separate budget constraint:

$$(P_i - L_i)B_i = \tau_i w_i L_i \quad \text{for } i \in \{1, 2\}. \tag{4}$$

This equation simply says that the total amount of unemployment benefits paid needs to be equal to the total amount of taxes raised in each region.

Nationally funded unemployment benefits.—Under this arrangement, the national government faces a national budget constraint:

$$(P_1 - L_1)B_1 + (P_2 - L_2)B_2 = \tau_1 w_1 L_1 + \tau_2 w_2 P_2. \tag{5}$$

This equation simply says that the total amount of unemployment benefits paid in both regions needs to be equal to the total amount of taxes raised in both regions. This means that certain policies will imply some net transfers of resources across space. I discuss this in detail later.

[11] To see this, we need to show that if $(\bar{u} \cdot \bar{B} + (1 - \bar{u}) \cdot (1 - \tau) \cdot \bar{w}) = (\underline{u} \cdot \underline{B} + (1 - \underline{u}) \cdot (1 - \tau) \cdot \underline{w})$ and $\bar{u} > \underline{u}$, then $(\bar{u} \cdot \bar{B}^\rho + (1 - \bar{u}) \cdot (1 - \tau)^\rho \cdot \bar{w}^\rho) < (\underline{u} \cdot \underline{B}^\rho + (1 - \underline{u}) \cdot (1 - \tau)^\rho \cdot \underline{w}^\rho)$. But this is a direct consequence of the concavity of the indirect utility function and the fact that B is assumed to be smaller than $(1 - \tau)w$.

E. Equilibrium without Minimum Wages

If there are no minimum wage laws in either of the two regions, local labor markets and the mobility decision determine the allocation of people across space. In equilibrium, the wage rate in each region is sufficiently low to ensure that no one is unemployed (given that the reservation wage is assumed to be zero). This means that the number of workers is the same as the number of people in each region ($P_i = L_i$). In this case, the mobility decision simplifies to $w_1^\rho = w_2^\rho$, and thus necessarily $w_1 = w_2$. Given the local labor demand (see eq. [1]), this implies that

$$F_l(\bar{K}_1, L_1^{\mathrm{FME}}) = F_l(\bar{K}_2, L_2^{\mathrm{FME}}), \tag{6}$$

where I use the superscript FME to denote this "free market equilibrium." To obtain the allocation of workers across space, we simply need to take into account that

$$L_2^{\mathrm{FME}} = 1 - L_1^{\mathrm{FME}}. \tag{7}$$

These two equations fully determine the allocation of workers and people across the two regions. Note that the population living in each region is increasing with the relative supply of land. To determine the wage levels in equilibrium, we just need to use $w_i^{\mathrm{FME}} = AF_l(\bar{K}_i, L_i^{\mathrm{FME}})$ and the implicit definition of the employment level L_i^{FME} given by equations (6) and (7).

In what follows, I study what happens to this equilibrium when minimum wages are introduced. I separately analyze the cases in which unemployment benefits are locally and nationally funded.

F. Locally Funded Unemployment Benefits

In this section, I analyze the case in which region 1 introduces a binding minimum wage and unemployment benefits are locally funded. In equilibrium, utilities need to be equalized across space $V_1 = V_2$. In region 2 there is no minimum wage, and thus there is no unemployment. This is simply a consequence of the fact that the labor market clearing in region 2 ensures that wages in region 2 are sufficiently low to employ everyone who decides to live in region 2 if their reservation wage is sufficiently low. Since there is no unemployment in region 2 and unemployment benefits are funded locally, $\tau_2 = 0$. Under these circumstances, the free mobility condition 3 simplifies to

$$(u_1 \cdot B_1^\rho + (1 - u_1) \cdot (1 - \tau_1)^\rho \cdot \underline{w}_1^\rho) = w_2^\rho,$$

where $\underline{w}_1$ denotes the binding minimum wage.

We can use the definition of unemployment rates, the fact that everyone is working in region 2 (so $P_2 = L_2$ and $P_1 + P_2 = 1$), and region 1's budget constraint ($B_1 = (L_1/P_1 - L_1)\tau_1\underline{w}_1$) to obtain

$$\underline{w}_1^\rho[u_1^{1-\rho}(1 - u_1)^\rho \tau_1^\rho + (1 - u_1)(1 - \tau_1)^\rho] = w_2^\rho. \tag{8}$$

This last equation implicitly defines the population in region 1 (P_1), since the level of employment is directly determined by the binding minimum wage. This equation shows that the expected utility in region 1 is the minimum wage weighted by the relative employment loss in region 1 as a consequence of the introduction of minimum wages. Thus, relative to the free market equilibrium, whether region 1 gains or loses population depends on whether the higher wages do not create too much unemployment.

To analyze this question further, it is convenient to define the local labor demand elasticity as $\partial \ln L_i / \partial \ln w_i = -\varepsilon_i$, which in a general production function is not necessarily a constant.

PROPOSITION 1: When unemployment benefits are financed locally, there is a threshold value of the labor demand elasticity (ε_1) above which region 1 loses population when minimum wages increase.

Proof: See appendix C.

This proposition and equation (8) highlight the following intuition. Suppose we start from a free market equilibrium and we raise minimum wages in region 1 just above the (free market) equilibrium wages. Then, whether region 1 becomes more or less attractive depends on the elasticity of the local labor demand. When the local labor demand is sufficiently inelastic, the lost employment is small, and thus expected utility increases in region 1 because of the higher wages. This attracts people from region 2 into region 1. On the other hand, if the local labor demand is sufficiently elastic, then the lost employment from the introduction of minimum wages is larger and employment effects do not compensate for the higher wage. This induces people to move from region 1 to region 2. And interesting special case arises when $\rho = 1$, that is, when workers are risk neutral. In that case, the threshold for population gains or losses is determined by whether the local labor demand elasticity is smaller or larger than 1; taxes are then simply a transfer from employed to nonemployed workers within the region and thus cannot affect the expected value of the region.

Importantly, this proposition says that if empirically we find a local labor demand elasticity above 1, the model has a clear implication: workers should leave regions that increase minimum wages.

G. Centrally Funded Unemployment Benefits

In this section, I analyze a case in which unemployment benefits are funded by the central government that imposes a common tax (τ) in both regions, as is the case in many countries. Note that this can also be used to think about cities that introduce a citywide minimum wage, as San Francisco and Seattle did recently and which New York is aiming to do.

In this case, the financing constraint is $(P_1 - L_1)B_1 = \tau\underline{w}_1 L_1 + \tau w_2 P_2$, and the derivations in the previous section change slightly.[12] Using the indifference condition for the location choice, we obtain

$$(u_1 \cdot B_1^\rho + (1 - u_1) \cdot (1 - \tau)^\rho \cdot \underline{w}_1^\rho) = (1 - \tau)^\rho \cdot w_2^\rho. \quad (9)$$

From equation (9) we can show that the introduction of minimum wages, departing from the free market equilibrium, has several consequences. First, expected utility in region 2 unambiguously decreases, since part of the wage is now used to pay unemployment benefits in region 1. In region 1 there are now two groups of workers. Employed workers may see their net wage increase or decrease, depending on whether the newly set minimum wage increases more than the newly set taxes. Given that taxes are the same in the two regions, whether taxes increase more than wages depends on the level of unemployment benefits and the size of region 1 relative to region 2. The second group is the unemployed. This second group of workers in region 1 loses, relative to the free mobility equilibrium, if unemployment benefits are below the free mobility wage rate ($B_1 < w_1^{\mathrm{FME}}$).[13] Overall, it is not clear whether region 1 becomes more or less attractive. It basically depends on how much better off employed workers in region 1 are and how much unemployment minimum wages create. With nationally funded unemployment benefits, region 1 is more likely to become attractive if unemployment benefits are high, if region 1 is small relative to region 2, and if the local labor demand is inelastic.

To see the importance of the unemployment benefits, it is useful to first think what would happen if they were zero. In this case, equation (9) simplifies to equation (8), previously discussed. As before, the only thing that then matters is the local labor demand elasticity. It is only when there are unemployment benefits that there is an extra effect coming from the taxes in region 2 used to pay unemployment benefits in region 1.

When unemployment benefits are not zero, there is a net transfer of value from region 2 to region 1. If this is sufficiently high, which depends on how high minimum wages and unemployment benefits are set and how small region 1 is relative to region 2, then no matter what the local labor demand elasticity is region 1 can become more attractive. It is worth highlighting, though, that this is a disequilibrium result. It is only when we move from the no minimum wage free market equilibrium to the new minimum wage equilibrium that this can arise. In general, when there are already minimum

[12] As before, there is no unemployment in region 2 since region 2 does not introduce minimum wages.

[13] In general, I only consider situations in which $B_i < (1 - \tau_i) \cdot w_i$. This simply limits the unemployment benefits to be below the net wage.

wages in place, the labor demand elasticity determines population gains or losses. To summarize:

Proposition 2: When unemployment benefits are financed nationally, region 1 may gain population if unemployment benefits are sufficiently high, irrespective of the local labor demand elasticity. In general, however, region 1 gains or loses population depending on the local labor demand elasticity. That is, there is a threshold value of the labor demand elasticity (ε_1) above which region 1 loses population when minimum wages increase.

Proof: See appendix C.

III. Empirical Evidence

In this section, I use all of the changes in the effective minimum wage that took place between 1985 and 2012—that is, both the state and federal level changes—to show how average wages, employment, and migration respond to this policy change. There are 441 events in which a state experienced a binding change to its minimum wage, sometimes because the state decided to change the state minimum wage law and sometimes because the federal increase was binding. I use all of these events to build my identification strategy. I consider 3 periods before and 3 periods after each change and do not consider them outside these time windows. I describe this strategy in detail in what follows. Before describing this empirical strategy, I describe the data that I use.

A. Data Description, Summary Statistics, and Empirical Definition of the Low-Skilled Labor Market

This paper is based mainly on the widely used and openly available March files of the CPS, available in Ruggles et al. (2016). I combine these March CPS data with data compiled by Autor, Manning, and Smith (2015) on the minimum wage law changes (table 1 in their appendix).[14]

I mainly study the evolution of three outcome variables: average wages, shares of employed workers, and share of low-skilled population. I define low-skilled individuals as workers who have a high school diploma or less and are not in school. This is a commonly used definition. Card (2009) argues that these form a sufficiently homogeneous group, as they are probably very close substitutes in the local production function.

I call "composition-adjusted wages" the measure of wages that I use. Since the March CPS is just a repeated cross section of micro data, it is easy to first

[14] I assume the minimum wage for Colorado in 2010 to be \$7.28 instead of \$7.25, as they assume, since \$7.28 is still binding in 2010.

run a Mincerian regression allowing for the returns to skill to be specific to the low-skilled and high-skilled labor markets. This means that I run the following regression:

$$\ln w_i = \alpha + \beta X_i + \varepsilon_i, \tag{10}$$

where i indicates individuals, X_i are their individual characteristics, and w_i are their real weekly wages. These are computed using the yearly wage income and the amount of weeks worked. The yearly income information in the March CPS refers to the year prior to the survey year. In what follows I use the year of the wage, not the survey year. In equation (10) I include age, age squared, marital status, race dummies, and state and year fixed effects, as well as the interactions of those, with a dummy taking a value of 1 for low-skilled workers. The assumptions behind this procedure are that the return to these personal characteristics is equal across space and time but that different periods and different states may have different wage levels and the returns to skills are different in the high- and low-skilled markets. I can then use the residuals from this regression and aggregate them by skill and geography, which is what I call composition-adjusted wages. I run this Mincerian regression using March CPS data between 1962 and 2013, which is the longest time span available on IPUMS.[15] I run this regression using all full-time employed workers who have a nonzero weekly wage. Weekly wages are computed using the yearly income and the weeks worked. In appendix A I provide more details on how I construct all of these variables. By using this wage measure, I am effectively controlling for composition effects that may change from different CPS survey years.

To measure the number of employed workers, I simply compute the share of workers (aged 25–64) who are employed full time and part time according to the CPS and are not in school. To compute full-time employment I use information on the working activity of a worker during the week preceding the CPS survey. Full-time workers are defined as those who worked at least 40 hours in the week prior to the interview. I devote part of Section III.E to showing results using many alternative measures and subgroups of workers. Finally, I define full-time-equivalent employment as full-time plus one-half of part-time employment.

I distinguish high- and low-skilled workers using the high school diploma cutoff previously mentioned. I also use this cutoff to compute the share of working-age population who are low skilled irrespective of their employment status. This is my main migration variable, although I also look directly at in- and out-migration rates. The March CPS files identify the state of origin of households that changed homes during the preceding year. This allows

[15] Using fewer years does not change the results.

me to identify migration choices and compute both the 1-year in- and out-migration rates—that is, the share of individuals who were living in a different state and the share of individuals who move to a different state, respectively. This internal migration information is not available for 1995. Despite being able to observe this, I consider the share of low-skilled population to be my preferred measure of migration because it is available for a longer time span, which, given the frequency of the minimum wage changes, likely results in more precise estimates. The changes in the share of low-skilled workers are necessarily a consequence of changes in in- or out-migration rates of low-skilled workers, changes in in- or out-migration rates of high-skilled workers, or changes in the education of different cohorts of workers. If the latter is not very important, then the estimates of the in-migration and out-migration rates of low-skilled workers relative to high-skilled workers should be quantitatively similar to those of the changes in low-skilled population—as is indeed the case (see below).[16]

I define teenage workers as workers between 16 and 21 years old. There is some divergence in the literature on exactly who should be considered as a teenage/young worker. To inform my choice of who should be taken into account as a potential minimum wage earner, I plot in figure 1 the share of workers who have hourly incomes below the minimum wage of the following year's minimum wage. I compute this for every age group.

The graph in figure 1 shows that while it is true that the share of workers potentially affected by minimum wage changes is much higher for workers below 24 years old, a nonnegligible share of older low-skilled workers is also potentially affected. This figure also shows that the number of low-skilled workers below 24 years old is very small (as a share of the labor force).[17]

On average, around 10% of low-skilled workers are potentially affected by minimum wage changes. This share is almost zero for high-skilled workers, except for the younger ones.[18] This means that minimum wage laws are likely to affect the small fraction of teenage workers in the labor market (the main focus of much of the literature) and a much larger group of low-skilled workers: those who earn wages close to the minimum wage. Minimum wage laws are much less likely to affect the high-skilled labor market.[19]

[16] This is not surprising since the systematic differences in the level of education across states are captured by state fixed effects, while trends in education levels are captured by year fixed effects and state-specific linear time trends.

[17] Note that I do not use workers aged 22–24 in any of the estimates that I later report. Including these workers does not change any of the results in the paper.

[18] Young high-skilled workers who work full time and who have some form of college education are small in number.

[19] Figure A1 shows that the overall share of workers potentially affected by minimum wage changes fluctuates around 3% and 7% of the workforce during the years under study.

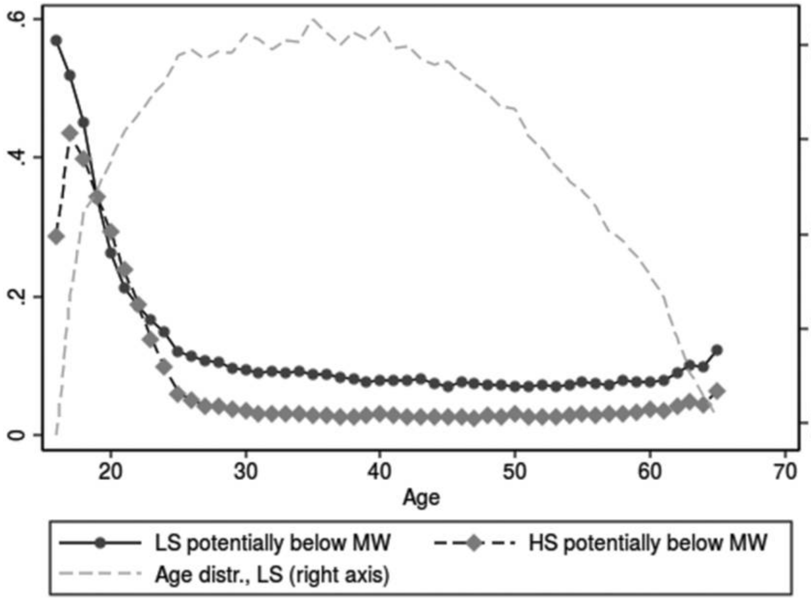

FIG. 1.—Descriptive statistics about how binding minimum wages are. The graph shows what share of the population had a weekly wage below the weekly earnings of a worker earning the minimum wage of the following year by age group, distinguishing between high- and low-skilled workers, measured by educational attainment. The light dashed line shows the age distribution of the population. HS = high skilled; LS = low skilled; MW = minimum wage.

Table 1 shows concrete statistics related to what is shown in figure 1. It shows that the share of workers who are between 16 and 21 years old and are full-time employed is quite low. Only 13% of teens are working full time, compared with almost 50% of low-skilled workers who are older than 25 years and compared with almost 60% of high-skilled workers. Table 1 also shows that the share of population who are low skilled (according to the definition used in this paper) is almost 50%. Thus, around half of the US population constitutes the labor market for low-skilled workers. Among those, around half work full time, while the others work part time or do not work. Among the ones who work full time, around 10% are close to or below the minimum wage of the following year. Among the teens, this share of potentially affected workers is much higher, around 60%, but they represent only slightly less than 13% of the population and are half as likely to be working full time as other low-skilled workers. Instead, teenagers are much more likely to work part time than older low-skilled workers. The table also shows other measures of interest for the results reported later, like the average in- and out-migration rates, which are around 3%; the average percent-

Table 1
Summary Statistics

Variable	Mean	SD	*N*
Share of low skilled who are employed, full time	.462	.051	1,249
Share of low skilled who are employed, part time	.215	.035	1,249
Share of low skilled who are employed, FTE	.569	.052	1,249
Share of teens who are employed, full time	.134	.046	1,249
Share of teens who are employed, part time	.329	.076	1,249
Share of teens who are employed, FTE	.299	.063	1,249
Share of high skilled who are employed, FTE	.694	.036	1,249
Share of low-skilled population	.471	.091	1,249
In-migration rate, low skilled	.029	.016	1,198
Out-migration rate, low skilled	.027	.03	1,198
Share of low-skilled population, aged 25–35	.447	.087	1,249
Share of population who are teens	.129	.015	1,249
Percentage change in minimum wage	.112	.056	1,249
Share year-states with a minimum wage change	.353	.478	1,249

NOTE.—This table shows different population and employment shares. Teenage workers are workers between 16 and 21 years old. Low- and high-skilled workers are workers between 25 and 65 years old below or above high school graduation. Full-time-equivalent (FTE) employment is full time plus one-half of the part-time workers.

age change in minimum wages across all 441 events, at 11%; and the frequency of minimum wage changes, which take place every 3 years on average.

B. Minimum Wage Policy Changes

In this paper, I consider minimum wage changes at the state level that are a result of either a state changing its minimum wage or the federal government changing the minimum wage to a level that is higher than the state one. Between 1985 and 2012 there were 441 such events. In 290 of these, the change in minimum wages was a result of the federal change, while in the remaining 151 occasions the change was a result of particular states changing their legislation. There have been 7 years between 1985 and 2012 when the federal government decided to increase the minimum wage. There are some states, like Texas, for which these are the only changes in minimum wage. As can be seen in table 2, there are many other states that have changed the minimum wages a lot more often.

Over time, there is some variation in the number of states that are affected by a minimum wage change. Years when the federal level changes, like 1990, 1997, and 2009, are years where the vast majority of US states see changes in their effective minimum wages, while in other years few states have policy changes. It is remarkable, however, that for every year there is at least one state effectively changing the minimum wage.

The average increase in minimum wages across all of these events was of around 11%, as is shown in table 1. Table 1 shows that the likelihood of having a change in the effective minimum wage in a given state during a particular year is around 35%. Thus, these are policy changes that are relatively

Table 2
Frequency of Change in Minimum Wages between 1985 and 2012

State	Changes	State	Changes	Year	Changes
Alabama	7	New Hampshire	10	1985	1
Alaska	6	New Jersey	7	1986	1
Arizona	9	New Mexico	6	1987	5
Arkansas	7	New York	8	1988	7
California	7	North Carolina	7	1989	9
Colorado	9	North Dakota	7	1990	47
Connecticut	15	Ohio	9	1991	50
Delaware	8	Oklahoma	7	1992	3
District of Columbia	9	Oregon	14	1993	1
Florida	12	Pennsylvania	7	1994	2
Georgia	7	Rhode Island	11	1995	1
Hawaii	8	South Carolina	7	1996	3
Idaho	7	South Dakota	7	1997	48
Illinois	11	Tennessee	7	1998	47
Indiana	7	Texas	7	1999	3
Iowa	7	Utah	7	2000	5
Kansas	7	Vermont	19	2001	6
Kentucky	7	Virginia	7	2002	6
Louisiana	7	Washington	17	2003	7
Maine	16	West Virginia	7	2004	6
Maryland	7	Wisconsin	8	2005	10
Massachusetts	11	Wyoming	7	2006	14
Michigan	7	Total	441	2007	26
Minnesota	9			2008	38
Mississippi	7			2009	41
Missouri	8			2010	36
Montana	10			2011	10
Nebraska	7			2012	8
Nevada	9			Total	441

NOTE.—This table shows how many times a state changed its effective minimum wage between 1985 and 2012 and how many states changed their effective minimum wages in all of these years.

common. This should provide enough power to estimate how particular outcome variables respond to such policy changes. The rest of the paper uses these events to empirically evaluate the effect of these policy changes on average wages, employment, and migration.

C. Empirical Strategy and Graphical Evidence

It is difficult to show the raw data around these 441 changes taking place in different states and different time periods. This would require a lot of different graphs, especially if we want to consider various outcome variables. However, I can easily show the average effect of all of these events in one graph per outcome variable. To do so, I use the following regression:

$$y_{st} = \alpha + \sum_{k=-3,k\neq 0}^{k=3} \delta_k \cdot \text{event}_{k,st} + \delta_t + \delta_s + \varepsilon_{st}, \tag{11}$$

where y_{st} is the (log of the) outcome of interest and $\text{event}_{k,st}$ is a dummy that takes a value of 1 if in state s and at time $t - k$ there was a change in the effective minimum wage; δ_t and δ_s denote year and state fixed effects, and ε_{st} is the error term. I consider only 3 periods before the year when the minimum wage changes and 3 periods after it.[20] It is worth noting that by using pre-event and postevent dummies I am not imposing particular functional forms on how minimum wage changes may be influencing the outcome variables. What I report is, thus, the pooled average over all of these events. Later, in Section III.E, I introduce some functional form assumptions to leverage the different intensities in the change of the minimum wage across all of these different events.

The estimates δ_k capture the average of the outcome variable across all states that changed the minimum wage k periods before (if k is negative) or after (if k is positive) all of the events, controlling for common shocks and statewide invariant characteristics. These averages are weighted by the size of each state. It is simple to plot these coefficients in a graph. The estimates are relative to the year of the change in the minimum wage, which is the omitted category in the regression. It is important to note that on some occasions a state increases its minimum wage in two (or more) consecutive years. I code these as the year of the event (and thus the omitted category in the graph). It is important to keep this in mind, since the year 1 can represent either a true year after the change in minimum wages or 1 year after a series of consecutive changes in minimum wages.[21] Similarly, year 0 of the event represents both a year that experiences a new change in minimum wages and a year that experiences a new change after already having had a change in the preceding year.

With the state fixed effects, I remove variation at the state level that does not change over time, such as certain amenities or the geographic location of the state. With the year fixed effects, I remove common shocks to the entire US economy. When in the regression tables I also include state-specific linear year trends, I remove systematic trends in the evolution of the outcome variable of interest that may be different across states.

The estimates of these event-period dummies are shown in figure 2 for four outcome variables: average low-skilled (composition-adjusted) wages, share of full-time-equivalent employment among low-skilled workers, share of low-skilled population, and share of full-time-equivalent employment among teenage workers.[22] The first graph shows the evolution of low-skilled

[20] Given the frequency of the minimum wage changes, I am somewhat constrained in the number of pre- and postperiods that I can hope to estimate. I have tried various lengths, and the results are very similar to the ones I report.

[21] In app. sec. D3 I show that excluding the events with consecutive changes in minimum wages do not affect my estimates.

[22] As a reminder, the share of full-time-equivalent employment is the number of workers employed full time plus one-half of those who are part-time employed divided by the working age population.

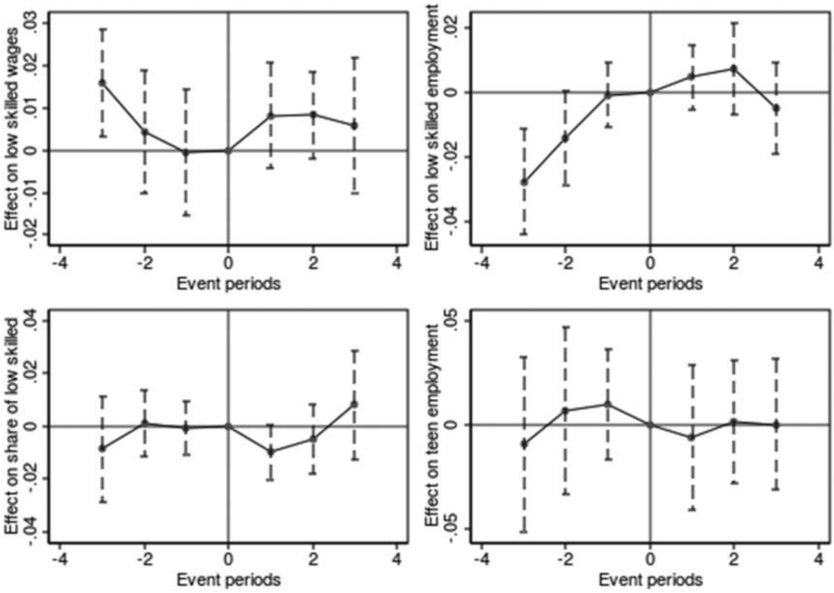

FIG. 2.—Wages, employment, and migration responses to minimum wage increases. The four graphs show the estimate "event" dummies from regression 11 for four different outcome variables: average (composition-adjusted) low-skilled wages, full-time-equivalent low-skilled employment shares, share of low-skilled population, and teenage employment. The dotted vertical lines show 95% confidence intervals of robust standard errors clustered at the state level.

wages around changes in minimum wage laws. Two things stand out. First, prior to the policy changes, average wages seem to be moderately declining. Second, this trend seems to change in the year when a minimum wage increases and particularly during the following year. I interpret this as evidence that the changes in policy did affect the wages of low-skilled workers. It is also evidence that minimum wage change policies tend to be implemented in periods of moderately declining low-skilled wages.

Similar considerations apply when analyzing what happens to the share of low-skilled workers who are (full-time-equivalent) employed.[23] There is a clear positive trend leading to the policy change. This trend is completely reversed when minimum wages increase. It is worth emphasizing that this is a trend leading to the policy change common to all of the events after controlling for state fixed effects and time fixed effects and, later in the tables, state-specific linear year trends. This can be interpreted as evidence that minimum wage changes tend to happen during periods when low-skilled wages decline and low-skilled employment is strong. If policy makers anticipate that aug-

[23] In Sec. III.D and Sec. III.E I show that there is some heterogeneity in the results when distinguishing full-time and part-time employment.

menting minimum wages will curb employment creation and are concerned about both unemployment and average wages, then it is natural that policy makers implement these policy changes precisely during these periods of declining wages and strong low-skilled employment.

The third graph shows what happens to migration, something that I explore in more detail in figure 4. In it we see how the share of low-skilled working age population does not seem to have a particular trend before the change in minimum wages and how it drops right after. This suggests that there is a migration reaction, presumably to the employment effects caused by the minimum wage changes. It is worth noting that systematic differences in cohort size and education attainment across states are controlled for with state and year fixed effects; later in the tables they are controlled for with state-specific linear year trends. The final graph shows the evolution of teenage employment. While if anything it seems that the series exhibits patterns similar to that of the low-skilled employment series, the main conclusion I draw from this graph is that there is too much noise in teenage full-time-equivalent employment to obtain strong conclusions.

In all, figure 2 suggests that controlling for preevent trends is extremely important (over and above the state and year fixed effects and the state-specific linear year trends). I argue in this paper that we can evaluate the effect of a policy by looking at the average changes in trends around the policy change episodes. This is a valid identification strategy if in the absence of the policy change the different outcome variables would have evolved following the linear trend implied by the periods preceding the policy change. To better illustrate this identification strategy, figure 3 allows for specific linear trends leading to the policy change and highlights the results under the aforementioned identification assumption. More explicitly, to build figure 3 I fit (and remove) a linear trend in the 3 periods preceding the policy change.

The results shown in figure 3 are clear. Once I allow for a linear trend preceding the policy change (so that the average is around zero in the 3 periods before the event), it is easy to observe, first, that average low-skilled (composition-adjusted) wages increase. This is evidence suggesting that the average (log) wages of low-skilled workers increase after an increase in minimum wages (which is presumably one of the intentions of the policy). Second, the (log) share of full-time-equivalent employed low-skilled workers decreases. In fact, figure 3 suggests that the decline in low-skilled employment is of a similar order of magnitude than the increase in average wages. This is evidence that suggests that the local labor demand elasticity is around 1. As I argued in the model, a sufficiently high local labor demand elasticity implies that the share of low-skilled population will decrease. This is what the third graph in figure 3 shows. The last graph in the figure shows that similar patterns seem to emerge for teenage workers, although I later show that the there is an important difference in employment outcomes between younger and older workers that becomes clear when distinguishing between full-time and part-time employment.

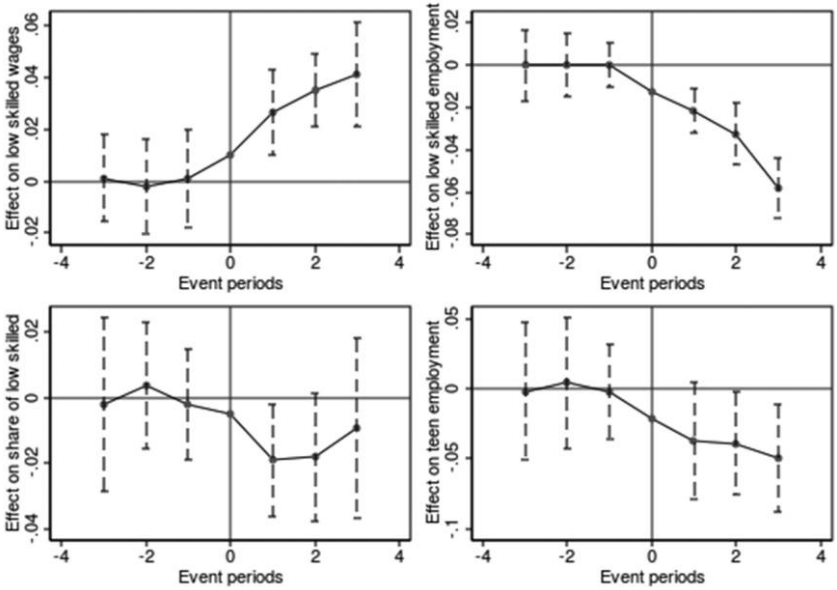

Fig. 3.—Wages, employment, and migration responses to minimum wage increases. The four graphs show the estimate "event" dummies from regression 11 for four different outcome variables: average (composition-adjusted) low-skilled wages, full-time-equivalent low-skilled employment shares, share of low-skilled population, and teenage employment. The dotted vertical lines show 95% confidence intervals of robust standard errors clustered at the state level.

In figure 4 I investigate migration responses in more detail.[24] Allowing for a pretrend prior to the policy changes, figure 4 shows how much in-migration and out-migration rates explain the evolution of the share of low-skilled population. In the top left graph, I show how the low-skilled in-migration rate—that is, the share of population who were living in a different state in the previous year—declines with the policy changes. That is, low-skilled workers avoid moving to states that increase minimum wages. Instead, the low-skilled out-migration rate, shown in the top right graph, seems to stay stable or if anything increase slightly. The bottom two graphs of figure 4 show the difference in in- and out-migration rates between low- and high-skilled workers. Relative to high-skilled workers, it is clear that in-migration rates of low-skilled workers decline after the policy change and out-migration rates, if anything, increase. In all, this is very suggestive evidence that internal migration responds according to the predictions of the model.[25]

[24] As explained in Sec. III.A, in-migration rates cannot be computed for 1995, and thus the estimates are based on a smaller sample.

[25] In app. sec. D1 I show that moving decisions are intimately linked to the labor market.

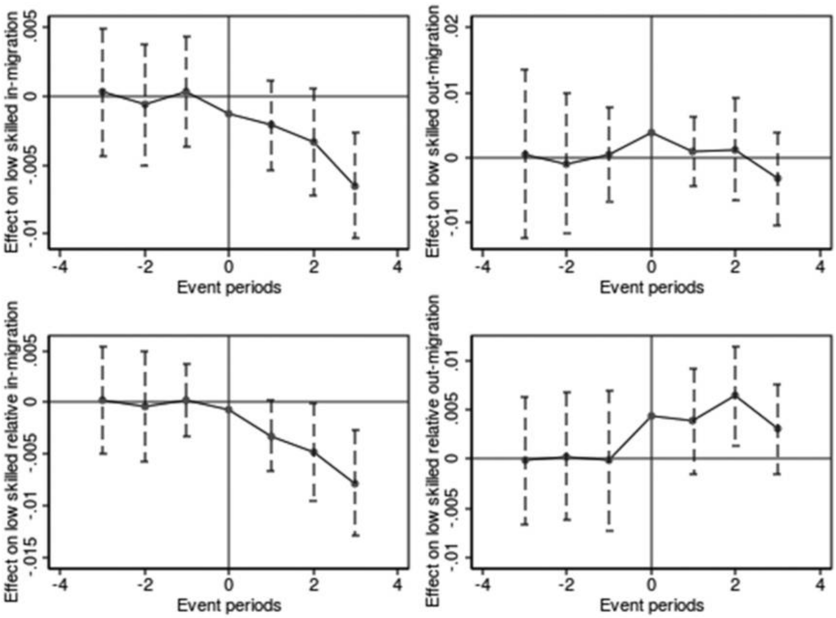

FIG. 4.—Migration responses to minimum wage increases. The four graphs show the estimate "event" dummies from regression 11 for four different outcome variables: low-skilled in-migration rate, low-skilled out-migration rate, low-skilled in-migration rate relative to high-skilled in-migration rate, and low-skilled out-migration rate relative to high-skilled out-migration rate. The dotted vertical lines show 95% confidence intervals of robust standard errors clustered at the state level.

Figure 5 shows that this evolution of wages and employment is exclusive to low-skilled workers. That is, if I repeat the exact same graphs but use high- instead of low-skilled workers, we see that there are almost no trends prior to the policy change and, more importantly, that there are no changes to these following the policy change.[26]

D. Estimates, Elasticities, and Discussion of the Findings

The previous graphs are meant to explain my identification strategy and show why I obtain the results that I do in the regressions. To quantify the effects displayed in the graphs, I use the following regression:

$$\begin{aligned} y_{st} = \alpha &+ \beta_1 \text{Posttreatment}_{st} + \beta_2 \text{Period Zero}_{st} + \beta_3 \text{Preevent trend}_{st} \\ &+ \beta_4 \text{Postevent trend}_{st} + \delta_t + \delta_s + \delta_s \cdot t + \varepsilon_{st}, \end{aligned} \tag{12}$$

[26] These graphs are raw data. The detrended graphs show similar patterns.

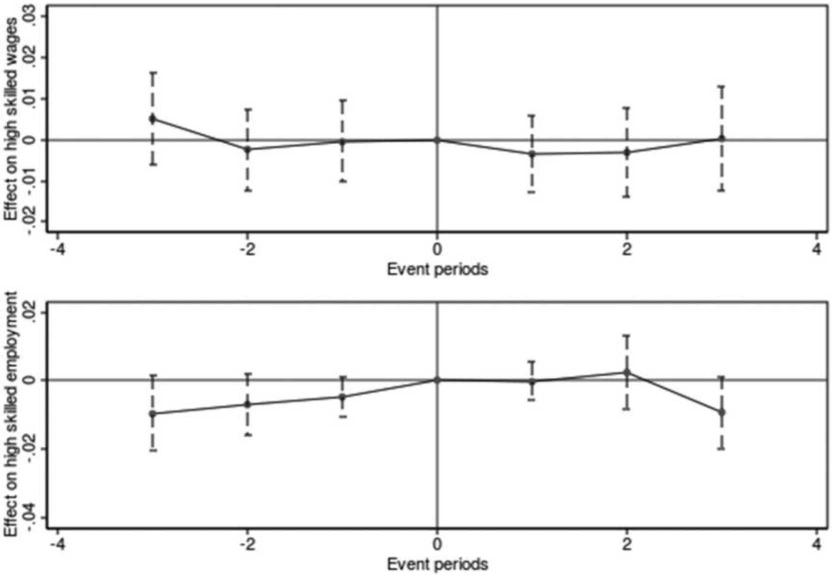

FIG. 5.—Wages, employment, and migration responses to minimum wage increases. The two graphs show the estimate "event" dummies from regression 11 for two different outcome variables: average (composition-adjusted) high-skilled wages and full-time-equivalent high-skilled employment shares. The dotted vertical lines show 95% confidence intervals of robust standard errors clustered at the state level.

where "Posttreatment" is simply a dummy variable taking a value of 1 for the 3 years after the change in minimum wages and taking a value of 0 for the 3 years before the change—including the year the change takes place. The variable "Period Zero" is simply a dummy variable taking a value of 1 in the year when the policy changes. I include this variable because as I explained before, the policy changes during the period 0, so there are parts of the year with the policy change in place and parts without it. Also there are some events coded as zero that are the second year of consecutive changes in minimum wages. The variable "Preevent trend" is a linear trend during the 3 periods before the policy change takes places. This should control for the linear preevent trend observed in figure 2. The variable "Postevent trend" allows for a change in the trend after the policy change takes place. This could be a result of the policy or simply a change in the trend that is unrelated to the event. Finally, I include year and state fixed effects. This should account for systematic (time-invariant) differences across states and common shocks affecting the overall US economy. In some of the models I also include state-specific linear year trends ($\delta_s \cdot t$). This should account for different linear evolutions of the outcome variables that are systematically different across states.

To make my identification strategy more transparent, I also report results on the simpler regression

$$y_{st} = \alpha + \beta_1 \text{Posttreatment}_{st} + \delta_t + \delta_s + \varepsilon_{st}, \tag{13}$$

which is essentially the same as equation (12) but without allowing for specific changes to trends around the events. Note that this is a simple event-type strategy. When combined with an appropriate control group, this is also the basis of standard difference-in-differences strategies widely used in the literature since Card and Krueger (1994). To obtain unbiased estimates of the effect of the policy change (β_1 in eq. [13]), it would have to be the case that the are no systematic trends leading to the policy changes. Figures 2 and 3 suggest that this is not the case.

The results are shown in table 3. In it I show four different estimates, which are labeled model 1, model 2, model 3, and model 4. Model 1 shows the estimates of running the simpler regression in equation (13). As we can anticipate by looking at figure 2, the estimates from this model are always around zero. These estimates are essentially comparing the first 3 preevent periods with the 4 periods following the policy change. Given the pretrends shown in figure 2, we can anticipate slightly positive estimates of wages and employment and slightly negative estimates of the share of low-skilled population. This is exactly what I obtain for model 1 in table 3.

The second model or set of estimates uses equation (12). I report the estimate $\beta_1 - \beta_3$. This assumes that there is a preevent trend that changes after the policy change. These estimates are the estimates in figure 3 but where the possible change in trend in the "postperiod" is not assumed to be part of the effect of the policy. Under these assumptions, the results are clear. The average increase in minimum wages of around 11% (see table 1) translates into a 2.7% increase in average wages. Given that the share of low-skilled population potentially affected by the minimum wage is around 10% (see fig. 1), an estimate of around 2.7% implies that there are some, but not substantial, spillovers across the entire wage distribution. Suppose that this 10% is the only group affected be the policy change and their wages increase by exactly 11%. Then 10% of the workers have an increase in wages of 11%, which means that the average increase for all low-skilled workers is around 1.1% (not too far from the estimated 2.7%).[27] These relatively small spillover effects on wages of workers not directly affected by minimum wages are in line with what is documented in Autor, Manning, and Smith (2015).

This increase in average wages translates into a decrease in the share of low-skilled workers who are full-time-equivalent employed of around 2%. This implies a local labor demand elasticity close to −1, as also shown in the

[27] In reality, there may be affected workers whose wage increase is larger than the 11% increase in minimum wages.

Table 3
Effect of Minimum Wage Changes on Low-Skilled Wages, Employment, and Migration

	Model 1: Fixed Effects	Model 2: Pretrend	Model 3: Change Trend	Model 4: State Trends
Effect on low-skilled wages	.006	.027	.026	.029
Standard error	(.004)	(.013)	(.012)	(.011)
p-value	[.163]	[.041]	[.029]	[.011]
Effect on share of low-skilled employed, FTE	.007	−.016	−.020	−.019
Standard error	(.004)	(.009)	(.009)	(.009)
p-value	[.051]	[.096]	[.022]	[.030]
Effect on share of low-skilled employed, full time	.007	−.024	−.032	−.032
Standard error	(.006)	(.012)	(.013)	(.013)
p-value	[.246]	[.052]	[.014]	[.015]
Effect on share of low-skilled population	−.004	−.028	−.019	−.015
Standard error	(.005)	(.012)	(.011)	(.011)
p-value	[.513]	[.018]	[.078]	[.174]
Effect on share of teen employed, FTE	−.003	−.039	−.035	−.027
Standard error	(.013)	(.032)	(.027)	(.026)
p-value	[.820]	[.220]	[.185]	[.311]
Effect on share of teens employed, full time	.000	−.018	−.014	−.001
Standard error	(.018)	(.038)	(.033)	(.033)
p-value	[.985]	[.642]	[.662]	[.982]
Implied local labor demand elasticity, FTE		−.582	−.757	−.667
Implied local labor demand elasticity		−.873	−1.218	−1.116
Implied migration sensitivity		1.168	.600	.458

NOTE.—This table reports four models. The first controls for year and state fixed effects and compares 3 years before and 3 years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a possible change in postevent trend around the policy change. Model 4 is the same as model 3 but controls for state-specific linear trends. Robust standard errors clustered at the state level are reported. More details can be found in the text. FTE = full time equivalent.

table, and an elasticity of employment to minimum wage changes of around −.2 (in line with part of the literature). When concentrating on full-time employment these estimates are even larger at around 3%, which imply even larger estimates of the local labor demand elasticity, also reported in the table. These relatively large local labor demand elasticities may imply, according to the model, that the share of low-skilled population could decrease.[28] In model 2 of table 3, I estimate that the decrease in the share of low-skilled population is around 2.8%, which implies a sensitivity of internal migra-

[28] Note that in all of the robustness checks displayed in app. sec. D3, the implied local labor demand elasticity is larger than the one reported in the main text.

tion[29] to employment changes of around 1. All of these estimates are significantly different from zero at the 5% confidence level (also shown in the table). Instead, the −1.8% estimate for the change in the share of teenage workers who are full-time-equivalent employed is of the same order of magnitude as the estimate on older workers but is not statistically different from zero at the 10% confidence level. These estimates are, as I show later, a consequence of decreases in part-time employment among this group of workers. When considering only teenagers employed full time, estimates are smaller and not distinguishable from zero.

The third model also uses equation (12), and I report the estimate $\beta_1 - \beta_3 + \beta_4$, which is my preferred one. This assumes that the policy change also has an effect on the postevent trends. This, as one can anticipate from figure 3, results in similar estimates for wages and employment and slightly lower estimates on migration (as can be seen in the graph, migration seems to enter in a slightly increasing trend after the policy change). The estimate of the implied local labor demand elasticity is again around 1 and consistent with the estimate on internal migration predicted by the model.

Finally, I estimate a fourth model that includes state-specific linear year trends in equation (12)—on top of the trends around the event that I have been discussing extensively. I report in this column the same coefficient that I reported in column 3. All of the results are unchanged relative to column 3. This is also true if I reported the coefficients reported in column 2.[30] This means that the results in this paper do not depend on controlling for state-specific linear year trends and that what matters is to take into account the trends around the event window. This is important given the recent debates over this issue reported in Dube, Lester, and Reich (2010) and Allegretto, Dube, and Reich (2011) and responded to by Neumark, Salas, and Wascher (2014). It is also worth mentioning that with the March CPS data I use in this paper I can replicate the discussion in Dube, Lester, and Reich (2010) and Neumark, Salas, and Wascher (2014), and I obtain very similar results. Results of this replication are reported and briefly discussed in appendix B.

In table 4 I investigate the migration responses in more detail, following the analysis in figure 4. The first row replicates the estimates on the share of low-skilled population shown previously. This should serve as the reference. The second column investigates whether the share of low-skilled population responds more strongly for workers between 25 and 35 years old. These are the workers who are more likely to migrate, as can be seen in fig-

[29] Defined as the percentage change in the share of low-skilled population for a percentage change in the share of full-time low-skilled employed workers.

[30] The results on migration are in fact statistically different from zero at higher confidence levels when not including the postevent slightly upward trend that can be seen in fig. 3.

Table 4
Effect of Minimum Wage Changes on Migration

	Model 1: Fixed Effects	Model 2: Pretrend	Model 3: Change Trend	Model 4: State Trends
Effect on share of low-skilled population	−.004	−.028	−.019	−.015
Standard error	(.005)	(.012)	(.011)	(.011)
p-value	[.513]	[.018]	[.078]	[.174]
Effect on share of low-skilled population, 25−35	−.006	−.037	−.027	−.020
Standard error	(.008)	(.017)	(.015)	(.014)
p-value	[.443]	[.034]	[.077]	[.172]
Effect on low-skilled in-migration	−.001	−.001	−.002	−.003
Standard error	(.001)	(.003)	(.003)	(.003)
p-value	[.611]	[.816]	[.541]	[.385]
Effect on low-skilled out-migration	−.001	.002	.001	.001
Standard error	(.002)	(.005)	(.005)	(.005)
p-value	[.634]	[.646]	[.794]	[.815]
Effect on low-skilled relative in-migration	−.003	−.002	−.003	−.004
Standard error	(.002)	(.004)	(.004)	(.004)
p-value	[.106]	[.652]	[.425]	[.348]
Effect on low-skilled relative out-migration	−.001	.006	.005	.005
Standard error	(.002)	(.005)	(.006)	(.006)
p-value	[.517]	[.296]	[.408]	[.359]

NOTE.—This table reports four models. The first controls for year and state fixed effects and compares 3 years before and 3 years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a possible change in postevent trend around the policy change. Model 4 is the same as model 3 but controls for state-specific linear trends. Robust standard errors clustered at the state level are reported. More details can be found in the text.

ure D1. The estimates suggest that the migration response for this more "mobile" people is indeed stronger.

In the last four rows, I investigate the potentially different response of in- and out-migration rates. Note that this separates the potential reasons why the share of low-skilled population is moving into four variables (in- and out-migration rates for high- and low-skilled workers). The table shows that both in-migration rates of low-skilled population decreased and, if anything, out-migration rates of low-skilled workers increased. The second row shows that the share of in-migrants decreased by around 0.2–0.3 percentage points, from a mean of around 3% (i.e., around a 10% decrease). The response of the out-migration rate is slightly lower, at around 0.1 percentage point, from a mean of around 3%.[31] The results are, if anything, stronger when we compare

[31] I do not take logs from the migration rates because there are some zeros. Thus, the coefficients represent the percentage point change rather than the percentage changes.

the response of internal migration of low-skilled population to that of high-skilled population, reported in rows 4 and 5.[32] In terms of magnitude they align well with the estimated effect on the share of low-skilled population. The share of low-skilled population is estimated to decrease by around 2%–3%. Given that the level of the share of low-skilled population is around 50%, this means that the share of low-skilled population decreases by around 1 percentage point. If we add the change in the relative in-migration rate and the change in the relative out-migration rate reported in rows 4 and 5, we obtain this 1 percentage point decrease. All of the results using migration rates are, however, imprecisely estimated. This should not come as a surprise given the data limitations in computing migration rates previously explained and given that with the same data we are estimating all of the parameters in equation (12) of four different outcome variables (in- and out-migration rates for high- and low-skilled population) instead of just one (share of low-skilled population).

Overall, tables 3 and 4 show suggestive evidence on internal mobility that is entirely consistent with the model and with the intended and unintended effects of the policy change. First, low-skilled wages increase when minimum wages increase. This increase in average low-skilled wages leads to a decrease in low-skilled employment. The implied local labor demand elasticity is estimated to be around -1, consistent with the estimates reported in Monras (2015b) using migration shocks, and imply that low-skilled workers may likely leave (on net) states that increase the minimum wage. Table 4 shows that this is indeed the case.

Table 5 serves as a placebo test. In this table I show the wage, employment, and migration estimates for the high-skilled workers. Consistent with figure 5, all of the estimates in this table are small and never statistically distinguishable from zero. These can be thought of as a control group or as a placebo exercise for the results of the low-skilled workers. Minimum wage changes should not affect the wages of high-skilled workers, since they are higher than the binding levels in the United States.

E. Robustness and Heterogeneity

1. Heterogeneity in Low-Skilled Employment

In this section I explore the response in employment of low-skilled workers to a minimum wage increase distinguishing part- and full-time employment and using alternative measure of employment. I also provide evidence that the unemployment benefits paid by the states increase after minimum wage

[32] Indeed, when looking into in-migration rates and out-migration rates for high-skilled workers we observe that in-migration rates slightly increase above trend while out-migration rates slightly decrease relative to the trend. These results can be seen in fig. D3.

Table 5
Effect of Minimum Wage Changes on High-Skilled Wages, Employment, and Migration

	Model 1: Fixed Effects	Model 2: Pretrend	Model 3: Change Trend	Model 4: State Trends
Effect on high-skilled wages	−.003	.001	.003	.003
Standard error	(.004)	(.009)	(.010)	(.010)
p-value	[.520]	[.916]	[.779]	[.774]
Effect on share of high-skilled employed, FTE	.000	.005	.002	.001
Standard error	(.003)	(.007)	(.007)	(.007)
p-value	[.916]	[.434]	[.831]	[.918]
Effect on share of high-skilled employed	.004	.009	.004	.003
Standard error	(.005)	(.010)	(.011)	(.011)
p-value	[.419]	[.343]	[.682]	[.758]
Effect on high-skilled in-migration	.002	.001	.001	.001
Standard error	(.001)	(.003)	(.003)	(.003)
p-value	[.131]	[.754]	[.708]	[.760]
Effect on high-skilled out-migration	.000	−.004	−.003	−.004
Standard error	(.002)	(.006)	(.006)	(.006)
p-value	[.888]	[.532]	[.567]	[.508]

NOTE.—This table reports four models. The first controls for year and state fixed effects and compares 3 years before and 3 years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a possible change in postevent trend around the policy change. Model 4 is the same as model 3 but controls for state-specific linear trends. Robust standard errors clustered at the state level are reported. More details can be found in the text. FTE = full time equivalent.

increases. All of these results are shown in table 6. The identification strategy and the display of the results is identical to that discussed in Section III.D. The message is clear. Given the overall identification strategy previously discussed, minimum wages lead to decreases in adult low-skilled full-time employment and increases in adult part-time employment. Among teenagers the estimates are less precise, but if anything minimum wage increases are followed by decreases in employment, which are more pronounced among the part-time teenage workers. None of this is found for high-skilled workers.

The first two rows of table 6 simply replicate the two equivalent rows of table 3 and should be useful as a reference point. The third row considers workers who did not work full time. I define these as part-time workers. When minimum wages increase, there are more part-time workers above 25 years old (than the linear pretrend would have predicted). Table 6 shows that the share of part-time workers increases by around 3.5%–5%.[33]

The fourth row counts as employed workers all those who are working irrespective of whether they work full or part time. The combination of the decrease in full-time employment of around 2.4%–3.2% (of an average of

[33] On average, 22% of low-skilled workers are employed part time; see table 1.

Table 6
Effect of Minimum Wage Changes on Employment, Various Measures

	Model 1: Fixed Effects	Model 2: Pretrend	Model 3: Change Trend	Model 4: State Trends
Effect on low-skilled wages	.006	.027	.026	.029
Standard error	(.004)	(.013)	(.012)	(.011)
p-value	[.163]	[.041]	[.029]	[.011]
Effect on share of low-skilled employed, full time	.007	−.024	−.032	−.032
Standard error	(.006)	(.012)	(.013)	(.013)
p-value	[.246]	[.052]	[.014]	[.015]
Effect on share of low-skilled employed, part time	.009	.034	.045	.049
Standard error	(.016)	(.031)	(.032)	(.031)
p-value	[.584]	[.278]	[.162]	[.122]
Effect on share of low-skilled employed, full and part time	.007	−.010	−.011	−.010
Standard error	(.004)	(.010)	(.009)	(.009)
p-value	[.057]	[.343]	[.204]	[.250]
Effect on share of teens employed, full time	.000	−.018	−.014	−.001
Standard error	(.018)	(.038)	(.033)	(.033)
p-value	[.985]	[.642]	[.662]	[.982]
Effect on share of teen employed, part time	−.012	−.107	−.103	−.107
Standard error	(.012)	(.040)	(.035)	(.034)
p-value	[.310]	[.008]	[.004]	[.002]
Effect on share of teens employed, full and part time	−.005	−.052	−.048	−.043
Standard error	(.012)	(.030)	(.026)	(.025)
p-value	[.679]	[.086]	[.059]	[.090]
Effect on share not employed among low skilled	−.013	.017	.018	.014
Standard error	(.008)	(.021)	(.019)	(.019)
p-value	[.092]	[.409]	[.342]	[.473]
Effect on share not employed among teens	−.006	.044	.039	.031
Standard error	(.010)	(.023)	(.021)	(.020)
p-value	[.570]	[.057]	[.064]	[.115]
Effect on unemployment benefits, state account	−.018	.145	.162	.169
Standard error	(.019)	(.063)	(.057)	(.055)
p-value	[.341]	[.021]	[.004]	[.002]

Note.—This table reports four models. The first controls for year and state fixed effects and compares 3 years before and 3 years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a possible change in postevent trend around the policy change. Model 4 is the same as model 3 but controls for state-specific linear trends. Robust standard errors clustered at the state level are reported. More details can be found in the text.

around 50% of the population) and an increase in the share of workers who are employed part time of around 3.5%–5% (of an average of 20% of the population) almost exactly cancels out. The point estimates are slightly negative (2.7×50 is larger than 5×20).

Rows 5–7 repeat the same exercise but consider teenage employment exclusively. The results show that when I do not restrict my attention to teenage full-time employment (which is quite low) but also look at part-time employment (which is much higher), I increase the precision of my estimates (which can often be distinguished from zero), and these also become slightly more negative. For instance, it is interesting to see that the share of teens who are part-time employed decreases by around 10%.

Rows 8 and 9 consider the share of workers among the low skilled and teenagers, respectively, who are not working. Increases in minimum wages seem to slightly increase teenage nonemployment (and the estimate is significantly different from zero), while adult low-skilled nonemployment seems to increase slightly, but the estimates are very imprecise.

The last row of the table shows unambiguously that the unemployment benefits paid by the states increase after the increases in minimum wages. Given that the fluctuations in unemployment benefits are paid by the states, it is normal to find estimates that are considerably larger (around 15%–30% larger than what states were paying before the increase in minimum wage) than the employment or wage effects.

Taken together, table 6 provides evidence that, first, full-time employment decreases. Second, part-time employment among adult low-skilled workers seems to increase. Third, teenage employment seems to decrease, especially among part-time workers. All of this leads to increases in unemployment benefits paid by the states.

2. *Intensity of the Policy Change and Federal versus State-Level Changes*

Until this section I have identified the average effects of the changes in minimum wages on various outcome variables by pooling all of the events together and analyzing the changes in the trends leading to the events. Previous literature has used alternative strategies to document the effect of minimum wages. In particular, studies that use state-level panel data have often leveraged the fact that some increases in minimum wages are larger and the fact that some states have higher shares of workers potentially affected by minimum wage increases. I incorporate this into the analysis in this section. In this section I also investigate whether the findings in this paper depend on the variation coming from federal changes in the minimum wage or state-level changes.

To investigate all this, I enlarge my estimation equation in the following way:

$$y_{st} = \alpha + \beta_1 \text{Posttreatment} \times \text{intensity}_{st} + \beta_2 \text{Preevent trend} \times \text{intensity}_{st} + \delta_t + \delta_s + \varepsilon_{st}, \tag{14}$$

where "intensity" is defined as the percentage change in minimum wages affecting state *s* during the change occurring at time *t*. Note that intensity only varies across states for each event. The interaction of the Posttreatment dummy with this intensity measure captures the differential effect of the intensity of the policy change after the policy takes place. This is a continuous treatment variable. To account for potential pretrends leading to the policy, I use, as before, a specific linear trend leading to the event that may be potentially different given the intensity of the treatment. This is captured by the coefficient β_2. Note that this follows the ideas in model 2 shown in previous tables.[34]

I can further expand this specification by using the fact that the share of potentially affected workers is different across states and in different time periods. To leverage this variation I use the following equation:

$$
\begin{aligned}
y_{st} = {} & \alpha + \beta_1 \text{Posttreatment} \times \text{intensity} \times \text{share below minimum wage}_{st} \\
& + \beta_2 \text{Preevent trend} \times \text{intensity} \times \text{share below minimum wage}_{st} \\
& + \delta_t + \delta_s + \varepsilon_{st},
\end{aligned} \tag{15}
$$

where all of the variables are as before but where I compute for each event the share of workers that, given the wages in the preceding year, would be affected by the policy change. For each event, this variable varies across states. It is the same variable used to construct figure 1.

Finally, by interacting the variables in equations (14) and (15) with a dummy taking the value of 1 if the change in minimum wages is a result of a federal increase in minimum wages, I can easily observe whether federal changes have different effects from state-level changes. As mentioned before, it is worth noting that there are 290 events in which a state experiences a binding minimum wage change that is a consequence of a federal change in minimum wages, while 151 of the changes in effective minimum wages are related to state changes. Together, these are the 441 events that I used earlier to estimate the average wage, employment, and migration responses to minimum wage increases.

Table 7 reports the results for average low-skilled wages. The results are in line with what I reported earlier. First, in columns 1 and 2 I report the standard regression that others have run using the two continuous treatments introduced in equations (14) and (15), that is, without taking into account the trends leading to the policy change. In this case, using the continuous treatment lets us identify a positive effect of minimum wage increases on average low-skilled wages even when we do not take into account preevent trends.

In columns 3 and 4 I report results that control for the linear trend leading to the policy change. In this specification there is less of a systematic nega-

[34] I obtain similar results if I use models 3–5.

Table 7
Effect of Minimum Wage Changes on Average Low-Skilled Wages

	Low-Skilled Wages					
Variable	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)	Model 5 (5)	Model 6 (6)
Posttreatment × intensity	.120**		.141**		.132*	
	(.0526)		(.0601)		(.0738)	
Posttreatment × intensity × share		.830**		.914**		.920*
		(.317)		(.395)		(.495)
Preevent trend × intensity			−.0366		−.0386	
			(.0220)		(.0276)	
Preevent trend × intensity × share below minimum wage				−.141		−.189
				(.199)		(.230)
Preevent trend × intensity × federal change					.00878	
					(.0428)	
Postevent × intensity × federal change					.0243	
					(.0743)	
Preevent trend × intensity × share below minimum wage × federal change						.340
						(.326)
Postevent × intensity × share below minimum wage × federal change						−.0127
						(.508)
R^2	.331	.330	.336	.332	.337	.335
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

NOTE.—This table shows estimates of eqq. (14) and (15) using average low-skilled wages as a dependent variable. Standard errors are clustered at the state level.
* $p < .1$.
** $p < .05$.

tive linear trend before the policy change, as reflected in the small and insignificant coefficients on “Preevent trend × intensity” and “Preevent trend × intensity × share below minimum wage.” Columns 5 and 6 investigate whether there are systematic differences when the effective change in the minimum wage is a result of a federal-level change or a state-level one. That the interaction of both the posttreatment dummy and the linear preevent trend are small and indistinguishable from zero suggests that whether the policy change is implemented at the federal or state level makes no difference to the effect on wages. The results strongly suggest that increases in minimum wages have a positive effect on the average wage of low-skilled workers, as intended by the policy.

Table 8
Effect of Minimum Wage Changes on Employment

	Share of Low-Skilled Employment					
Variable	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)	Model 5 (5)	Model 6 (6)
Posttreatment × intensity	−.0336		−.0601		−.0648	
	(.0364)		(.0405)		(.0505)	
Posttreatment × intensity × share		−.198		−.468		−.512
		(.267)		(.307)		(.343)
Preevent trend × intensity			.0474***		.0359**	
			(.0151)		(.0150)	
Preevent trend × intensity × share below minimum wage				.453***		.344***
				(.111)		(.103)
Preevent trend × intensity × federal change					.0615**	
					(.0230)	
Postevent × intensity × federal change					.0211	
					(.111)	
Preevent trend × intensity × share below minimum wage × federal change						.754***
						(.191)
Postevent × intensity × share below minimum wage × federal change						.133
						(.739)
R^2	.743	.743	.745	.747	.747	.751
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

NOTE.—This table shows estimates of eqq. (14) and (15) using the share of employed low-skilled workers as a dependent variable. Standard errors are clustered at the state level.
** $p < .05$.
*** $p < .01$.

Table 8 reports the results for low-skilled full-time employment.[35] As before, columns 1 and 2 report simple difference-in-differences specifications that do not take into account possible linear trends leading to the policy change. This is what previous literature estimated. As in some of the previous literature, the estimated employment effects are small and nondistinguishable from zero. Figure 2, however, strongly suggests that there are very specific trends leading to the policy change. This is investigated in columns 3 and 4 by introducing a linear preevent trend interacted with the two continuous

[35] Results on full-time-equivalent employment are similar but less strong, as also happens with the main regressions.

measures of the treatment. As before, these preevent trends are strongly positive. This means that in places where a binding increase in minimum wages was implemented there were clear positive trends in employment, which flattened right when the policy change was implemented. This is the exact same result that we obtained before. In this case, it seems that the positive preevent trends are stronger for federal changes than for state-level changes, in contrast to what happened to average low-skilled wages, where heterogeneity is less pronounced.

Finally, I analyze in table 9 the responses of internal migration. Again, columns 1 and 2 investigate these responses without taking into account the possibility of there being specific preevent trends. In line with what is sug-

Table 9
Effect of Minimum Wage Changes on Internal Migration

	Share of Low-Skilled Population					
Variable	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)	Model 5 (5)	Model 6 (6)
Posttreatment × intensity	−.100**		−.121**		−.118***	
	(.0431)		(.0492)		(.0358)	
Posttreatment × intensity × share		−.599**		−.748**		−.732***
		(.294)		(.343)		(.258)
Preevent trend × intensity			.0372*		.0438*	
			(.0209)		(.0258)	
Preevent trend × intensity × share below minimum wage				.250		.298
				(.168)		(.199)
Preevent trend × intensity × federal change					−.0350	
					(.0405)	
Postevent × intensity × federal change					−.0149	
					(.0965)	
Preevent trend × intensity × share below minimum wage × federal change						−.330
						(.326)
Postevent × intensity × share below minimum wage × federal change						−.0479
						(.695)
R^2	.939	.939	.939	.939	.940	.939
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

NOTE.—This table shows estimates of eqq. (14) and (15) using the share of low-skilled population as a dependent variable. Standard errors are clustered at the state level.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

gested in figure 3, the trends in the evolution of the share of low-skilled population leading to the policy change are not pronounced though slightly positive. Thus, in line with what I reported earlier, states that see their minimum wage increase experience relative losses of low-skilled population. There is no observable difference between whether these changes are a result of a federal- or a state-level increase.

IV. Comparison of the Results to Prior Literature

In this section I compare my estimates of the local labor demand elasticity with previous estimates in the literature and to the debates on the effect of minimum wages on employment more directly.

First, a natural way to estimate the (inverse) of the local labor demand elasticity is to see what happens when more workers move into one region or city for exogenous reasons. The immigration literature has tried to use strategies that are close to this set up. Starting with Altonji and Card (1991), many papers have compared the labor market outcomes in regions—usually cities or states—that receive immigrants with regions that do not receive them (accounting for immigrants endogenous location choices; see Altonji and Card 1991).

Part of the literature on immigration that compares high- and low-immigration regions finds small wage effects (an early example is Card 1990).[36] If the economy is well described by a perfectly competitive model of the labor market and immigrants and natives are close substitutes, this suggests that the local labor demand is very elastic, so that large inflows of workers have small effects on wages.

In this case, increases in minimum wages should result in large employment effects. This is not what part of the literature on minimum wages finds. In their famous papers, Card and Krueger (1994, 2000) argue that the increase in minimum wages in New Jersey did not lead to employment losses in New Jersey relative to Pennsylvania. Similar findings are reported in Card (1992a, 1992b), Allegretto, Dube, and Reich (2011), Dube, Lester, and Reich (2010), and Dube, Naidu, and Reich (2007).[37] This would imply that the local labor demand is inelastic, that is, the employment effects are smaller than the wage effects. But if this is the case, the model presented earlier suggests that internal migration is particularly important since more people would be attracted to a region that introduces the minimum wage. Can we reconcile these two strands of empirical evidence?

In some previous research, I document that whether wages respond to immigrant inflows depends crucially on the time horizon that we use to eval-

[36] See also Card (2001) for another seminal contribution to this literature, and see Card (2009) for a recent literature review.

[37] These are contested findings; see Neumark, Salas, and Wascher (2014) for a longer discussion.

uate the wage effects (Monras 2015b).[38] Using the exogenous increase in net migration from Mexico resulting from the Mexican crisis of 1995 in combination with the networks instrument, Monras (2015b) estimates an inverse local labor demand elasticity of around -0.75 (i.e., labor demand elasticity equal to $1/0.75 = 1.33$), which is very similar to the one estimated here. Moreover, the migration responses reported in Monras (2015b) and this paper are in line with one another. Recently, Borjas (2017) and Borjas and Monras (2017) also reported estimates of the effects of the Mariel boatlift migrants that are in line with the estimates both in this paper and in Monras (2015b).

It is important to highlight one key difference between the immigration and minimum wage literatures: the immigration literature has normally used census data and, thus, 10-year time gaps, while the minimum wage literature has focused on yearly data. Internal migration and other sources of spillovers across regions imply that these differences in time spans may result in very different estimates of the local labor demand elasticity.

Relative to the minimum wage literature, this paper both explains and expands previous results. On the one hand, I introduce an estimation strategy that takes into account the possible endogeneity of the timing of the policy changes. I show how this may downward bias the estimates on employment. This explains why I find more negative estimates than some of the prior literature. Not taking into account the trends leading to the policy changes underestimates the employment effects both for low-skilled workers and for teenage employment—especially part-time workers in the latter case. Moreover, I show how this strategy is not sensitive to controlling for state-specific linear time trends, as previous estimates using a panel of states and similar time spans seem to be (see the discussion in Allegretto, Dube, and Reich 2011, Neumark, Salas, and Wascher 2014, and app. B). It also potentially explains why influential studies like Card and Krueger (1994) may find no effects on employment or even slightly positive effects.

On the other hand, I expand prior literature on minimum wages by also analyzing employment outcomes of older workers. While older low-skilled workers are less intensively affected by minimum wages, it is also interesting to see what happens to this larger pool of workers who, moreover, may have fewer opportunities to leave jobs that pay around minimum wage levels.

V. Conclusion

To summarize, this paper provides two main contributions to the existing literature. First, the paper discusses the effects of minimum wages in a spatial equilibrium model. It shows the key role of local labor demand elasticity, and it helps in thinking about net labor flows between local labor markets. This is particularly relevant since many papers compare different local

[38] Given the rapid internal relocation responses, studies that use census data—and thus 10-year windows—are likely to miss most of the story.

labor markets to infer the effect of a wide range of policy changes without taking into account the responses of internal migration.

The model suggests that two things are important for the impact of minimum wage increases. First, in a world with two regions and no binding minimum wages, if a region decides to introduce minimum wages and the unemployment benefits are paid by the two regions together, the introduction of minimum wages leads to higher wages, lower employment, and maybe more low-skilled population even when the disemployment effects are large. This is the case only when unemployment benefits are effectively paid by the workers not affected by the policy. This highlights a novel interaction between public finance and internal migration that may be particularly relevant for thinking about city-level increases in minimum wages.

Second, when there are already minimum wages in place or when regions that introduce the minimum wage are sufficiently large, minimum wages lead to increases in wages, decreases in employment, and if the local labor demand elasticity is above 1, migration away from the region that increases its minimum wage, irrespective of how unemployment benefits are financed. This simply means that when employment effects are large relative to the effects on wages, regions that introduce minimum wages may become less attractive to the workers who should benefit from the policy change.

The second contribution of the paper is to provide empirical evidence that is in line with the model. In particular, using an event study design I compute that there are large internal migration responses away from states that increase minimum wages and that there is an estimated local labor demand elasticity of around 1. The paper tries to carefully explain why I obtain these results and why other papers have found different results when not taking into account the timing of when minimum wage increases tend to be introduced.

Appendix A

Data

In what follows I describe all of the variables from the March CPS files that I use in this paper. The source for these data is Ruggles et al. (2016). I also provide details on the other data set that I use.

A1. March CPS

High- and low-skilled workers.—High- and low-skilled workers are defined using the variable EDUC, with those who are high-school graduates and high-school dropouts defined as low skilled.

Weekly wage.—The weekly wage is computed using the variables INCWAGE and WKSWORK1. This is the total wage income of the previous year and the weeks worked in the previous year, respectively. Dividing total wage income by weeks worked yields weekly wages.

Hourly wage.—The hourly wage is computed using weekly wage divided by the usual hours worked UHRSWORK.

Employment status.—Employment status is computed using the variables EMPSTAT and HRSWORK. The main definition of workers employed full time are those whose EMPSTAT is equal to 10, 11, or 12 who worked 40 hours and were not in school (SCHOLL). For the share of full-time equivalents, I multiply the workers employed part time by one-half and add them to the full-time employed.

Weights.—The weights used are the variable WTSUPP. For the regressions, I use the Stata command analytic weights, using as weight the number of observations per cell.

Minimum wages.—Data on minimum wages are taken directly from Autor, Manning, and Smith (2015). A research assistant coded the minimum wage changes independently, obtaining almost the identical results.

A2. Unemployment Benefits Data

Unemployment benefits paid.—For the unemployment benefits paid I use data from the US Department of Labor. In particular, I use the benefits paid during the calendar year. Not reported in the paper, I also use other variables and the findings are in line with what was reported here. I obtain these data from http://www.oui.doleta.gov/unemploy/hb394.asp. The definitions of the variables are at http://www.oui.doleta.gov/unemploy/hb394/gloss.asp.

A3. Incidence of Minimum Wages

Figure A1 shows the share of workers potentially affected by minimum wage changes in each of the years of my sample. I distinguish between the share potentially affected by federal changes in minimum wages and the share potentially affected by the effective minimum wage—that is, taking into account both state and federal levels. In the main text I showed that low-skilled workers are a lot more likely to be affected by minimum wage changes than higher-skilled workers (see fig. 1). Figure A1 shows that the share of workers potentially affected by minimum wage tracks well the federal minimum wage. This is so because for a considerable fraction of states this is the binding minimum wage. This share of workers potentially affected by minimum wage fluctuates between 3% and 7% of full-time workers between 25 and 65 years old.

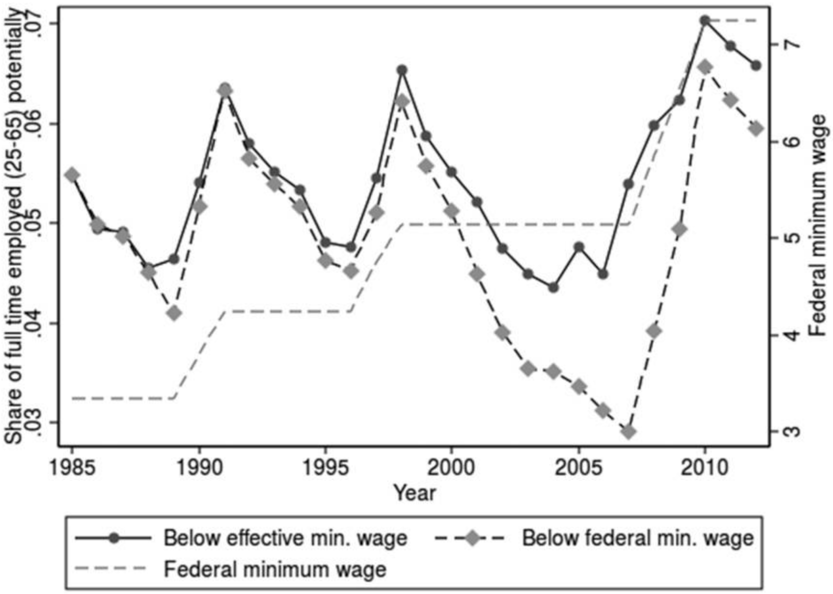

FIG. A1.—Share of workers potentially below the minimum wage. This figure shows the share of workers who at time t earn wages below the effective minimum wage of time $t + 1$.

Appendix B

Replication of Allegretto, Dube, and Reich (2011) Employment Results

Table B1 replicates the employment results in table 4 of Allegretto, Dube, and Reich (2011). In particular, I run the regression

$$\ln(\text{Share Employed}_{st}) = \alpha + \delta_s + \delta_t + \beta \ln \text{Minimum Wage}_{st} + \varepsilon_{st},$$

where s indicates states and t indicates years. When not using state-specific year trends I obtain a significant employment elasticity to minimum wage of -0.3 for teen employment and 0 for older low-skilled workers. This -0.3 estimate for teens disappears when I include state-specific year trends. This is shown in columns 1–4 of table B1. Columns 3 and 4 show that minimum wages do not seem to affect older low-skilled workers. In columns 5–8 I restrict the sample to the years used in the windows of the events used in this study. Columns 5 and 6 show that I also obtain the same results that Allegretto, Dube, and Reich (2011) obtain with my sample years. Columns 7 and 8 show the strong and statistically significant linear trends leading to the changes in minimum wages. The estimates of these positive preevent trends do not change with the inclusion or exclusion of state-specific linear year trends, as has been explained in the main text.

Table B1
Employment Effects of Minimum Wage Changes Using State Panel Regressions

	Share of Employment							
	Teens		All		Teens		All	
Variable	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	OLS (7)	OLS (8)
ln(Effective minimum wage)	−.281***	−.0256	−.0104	.0305	−.295***	−.0368	−.0724	−.0446
	(.0827)	(.115)	(.0457)	(.0416)	(.104)	(.112)	(.0455)	(.0358)
Preevent trend					.0143	.000729	.0143***	.0118***
					(.0105)	(.00728)	(.00421)	(.00340)
Postevent trend					−.00345	.00393	−.00253	−.00225
					(.00686)	(.00668)	(.00219)	(.00254)
Observations	1,428	1,428	1,428	1,428	1,249	1,249	1,249	1,249
R^2	.669	.730	.745	.821	.674	.732	.744	.819
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State trends	No	Yes	No	Yes	No	Yes	No	Yes

Note.—This table replicates table 4 in Allegretto, Dube, and Reich (2011) and the discussion in Neumark, Salas, and Wascher (2014) using employment from the March Current Population Survey data. OLS = ordinary least squares.
*** $p < .01$.

Appendix C

Proofs

To prove proposition 1 we can reexpress equation (8) as

$$\underline{w}_1^\rho[(P_1 - L_1)^{1-\rho}(L_1)^\rho \tau_1^\rho + (L_1)(1-\tau_1)^\rho] = w_2^\rho P_1,$$

which we can also express as

$$\underline{w}_1^\rho L_1\left[\left(\frac{u_1}{1-u_1}\right)^{1-\rho}\tau_1^\rho + (1-\tau_1)^\rho\right] = w_2^\rho P_1.$$

And we can totally differentiate the log of this expression:

$$\begin{aligned}\rho - \varepsilon_1 + \frac{1}{\Omega_1}\tau_1^\rho\frac{\partial(u_1/(1-u_1))^{1-\rho}}{\partial\ln\underline{w}_1} - \frac{\partial\ln P_1}{\partial\ln\underline{w}_1} &= \rho\frac{\partial\ln w_2}{\partial\ln\underline{w}_1}\\ &= \rho\frac{\partial\ln w_2}{\partial\ln L_2}\frac{\partial\ln(1-P_1)}{\partial\ln\underline{w}_1} = \frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}\frac{\partial\ln P_1}{\partial\ln\underline{w}_1},\end{aligned}$$

where $\Omega_1 = (u_1/1-u_1)^{1-\rho}\tau_1^\rho + (1-\tau_1)^\rho$.

So we need also to compute $(\partial(u_1/(1-u_1))^{1-\rho})/\partial\ln\underline{w}_1$:

$$\begin{aligned}\frac{\partial(u_1/(1-u_1))^{1-\rho}}{\partial\ln\underline{w}_1} &= (1-\rho)\left(\frac{u_1}{1-u_1}\right)^{1-\rho}\frac{\partial\ln u_1 - \partial\ln(1-u_1)}{\partial\ln\underline{w}_1}\\ &= (1-\rho)\left(\frac{u_1}{1-u_1}\right)^{1-\rho}\frac{1}{1-u_1}\frac{\partial\ln u_1}{\partial\ln\underline{w}_1}.\end{aligned}$$

Now we need to compute $\partial\ln u_1/\partial\ln\underline{w}_1$:

$$\begin{aligned}\frac{\partial\ln u_1}{\partial\ln\underline{w}_1} &= \frac{\partial\ln P_1 - L_1}{\partial\ln\underline{w}_1} - \frac{\partial\ln P_1}{\partial\ln\underline{w}_1}\\ &= \frac{1}{P_1 - L_1}\left[P_1\frac{\partial\ln P_1}{\partial\ln\underline{w}_1} - L_1\frac{\partial\ln L_1}{\partial\ln\underline{w}_1}\right] - \frac{\partial\ln P_1}{\partial\ln\underline{w}_1}\\ &= \frac{1-u_1}{u_1}\left[\frac{\partial\ln P_1}{\partial\ln\underline{w}_1} + \varepsilon_1\right].\end{aligned}$$

We can bring this expression to the one above:

$$\frac{\partial(u_1/(1-u_1))^{1-\rho}}{\partial\ln\underline{w}_1} = (1-\rho)\left(\frac{u_1}{1-u_1}\right)^{-\rho}\frac{1}{1-u_1}\left[\frac{\partial\ln P_1}{\partial\ln\underline{w}_1} + \varepsilon_1\right],$$

which can be reexpressed as

$$\frac{\partial(u_1/(1-u_1))^{1-\rho}}{\partial\ln\underline{w}_1} = \left(\frac{1-\rho}{(1-u_1)^{1-\rho}u_1^\rho}\right)\left[\frac{\partial\ln P_1}{\partial\ln\underline{w}_1} + \varepsilon_1\right].$$

We can bring this expression to the one above:

$$\rho - \varepsilon_1 + \frac{1}{\Omega_1}\tau_1^\rho\left(\frac{1-\rho}{(1-u_1)^{1-\rho}u_1^\rho}\right)\left[\frac{\partial \ln P_1}{\partial \ln \underline{w}_1} + \varepsilon_1\right] - \frac{\partial \ln P_1}{\partial \ln \underline{w}_1} = \frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}\frac{\partial \ln P_1}{\partial \ln \underline{w}_1},$$

which can be reexpressed as

$$\rho - \varepsilon_1 + \frac{(1-\rho)\tau_1^\rho}{u_1\tau_1^\rho + (1-\tau)^\rho(1-u_1)^{1-\rho}u_1^\rho}\left[\frac{\partial \ln P_1}{\partial \ln \underline{w}_1} + \varepsilon_1\right] - \frac{\partial \ln P_1}{\partial \ln \underline{w}_1} = \frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}.$$

We can now define $\bar{\tau}_1 = \tau_1^\rho/(u_1\tau_1^\rho + (1-\tau_1)^\rho(1-u_1)^{1-\rho}u_1^\rho)$ and note that $\bar{\tau}_1 < 1$.[39]

Thus, collecting terms we have

$$\frac{\partial \ln P_1}{\partial \ln \underline{w}_1} = \frac{\rho - \varepsilon_1(1-\bar{\tau}_1(1-\rho))}{\left(1-\bar{\tau}_1(1-\rho) + \frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}\right)}.$$

Finally, note that the denominator is always positive because $\bar{\tau}_1 < 1$.

Thus, $\partial \ln P_1/\partial \ln \underline{w}_1 < 0$ if and only if $\rho - \varepsilon_1(1+\bar{\tau}_1(1-\rho)) < 0$. And so $\partial \ln P_1/\partial \ln \underline{w}_1 < 0$ if and only if $\rho/(1+\bar{\tau}_1(1-\rho)) < \varepsilon_1$. And this equation finishes the proof. Note that the proof simplifies considerably when $\rho = 0$.

To prove proposition 2 we need to totally differentiate equation (9) and the budget constraint. To do so, we can rewrite equation (9) as

$$P_1\tilde{B}_1^\rho - L_1\tilde{B}_1^\rho = w_2^\rho P_1 - L_1\underline{w}_1^\rho,$$

where $\tilde{B}_1(1-\tau) = B_1$. Note that $\partial \ln \tilde{B}_1/\partial x = \partial \ln \tilde{B}_1/\partial x$ if τ is independent of x.

And we can rewrite the budget constraint as

$$P_1\tilde{B}_1 - L_1\tilde{B}_1 = \tilde{\tau}\underline{w}_1 L_1 + \tilde{\tau}w_2P_2,$$

where $\tilde{\tau} = \tau/(1-\tau)$.

Note that these are two equations that once differentiated will give us two unknowns: $\partial \ln P_1/\partial \ln \underline{w}_1$ and $\partial \ln B_1/\partial \ln \underline{w}_1$.

[39] To see this, we have that $\tau_1^\rho/(u_1\tau_1^\rho + (1-\tau_1)^\rho(1-u_1)^{1-\rho}u_1^\rho) < 1$ if and only if $\tau_1/(1-\tau_1) < u_1/(1-u_1)$. But from the government budget constraint we have that $u_1/(1-u_1) = \tau_1\underline{w}_1/B_1$. So $\tau_1/(1-\tau_1) < u_1/(1-u_1)$ if and only if $B_1 < (1-\tau_1)\underline{w}_1$, which is one of the assumptions since unemployment benefits cannot be higher than net wages.

From the first equation we have that

$$P_1\tilde{B}_1^\rho\left[\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}+\rho\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]-L_1\tilde{B}_1^\rho\left[\frac{\partial \ln L_1}{\partial \ln \underline{w}_1}+\rho\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]=$$
$$w_2^\rho P_1\left[\rho\frac{\partial \ln w_2}{\partial \ln \underline{w}_1}+\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\right]-L_1\underline{w}_1^\rho\left[\frac{\partial \ln L_1}{\partial \ln \underline{w}_1}+\rho\right],$$

which can be rewritten as

$$P_1\tilde{B}_1^\rho\left[\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}+\rho\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]-L_1\tilde{B}_1^\rho\left[-\varepsilon_1+\rho\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]=$$
$$w_2^\rho P_1\left[\frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}+\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\right]-L_1\underline{w}_1^\rho[-\varepsilon_1+\rho].$$

We can collect terms and obtain

$$\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[P_1\tilde{B}_1^\rho-w_2^\rho P_1\left(\frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}+1\right)\right]=$$
$$\varepsilon_1\left[-L_1\tilde{B}_1^\rho+L_1\underline{w}_1^\rho\right]+\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\left[-\rho P_1\tilde{B}_1^\rho+\rho L_1\tilde{B}_1^\rho\right]-L_1\underline{w}_1^\rho\rho.$$

Then we can simplify slightly

$$\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}P_1\left[\tilde{B}_1^\rho-w_2^\rho\frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}-w_2^\rho\right]=$$
$$\varepsilon_1 L_1\left[\underline{w}_1^\rho-\tilde{B}_1^\rho\right]+\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\rho\tilde{B}_1^\rho[L_1-P_1]-L_1\underline{w}_1^\rho\rho$$

and even further

$$\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[\tilde{B}_1^\rho-w_2^\rho\frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}-w_2^\rho\right]=$$
$$\varepsilon_1(1-u_1)\left[\underline{w}_1^\rho-\tilde{B}_1^\rho\right]-\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\rho\tilde{B}_1^\rho u_1-(1-u_1)\underline{w}_1^\rho\rho.$$

We can now turn to the budget constraint. We differentiate the budget constraint to obtain

$$P_1\tilde{B}_1\left[\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}+\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]-L_1\tilde{B}_1\left[\frac{\partial \ln L_1}{\partial \ln \underline{w}_1}+\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]=$$
$$\tilde{\tau}\underline{w}_1 L_1\left[1+\frac{\partial \ln L_1}{\partial \ln \underline{w}_1}\right]+\tilde{\tau}w_2P_2\left[\frac{\partial \ln w_2}{\partial \ln \underline{w}_1}+\frac{\partial \ln P_2}{\partial \ln \underline{w}_1}\right]$$

or

$$P_1\tilde{B}_1\left[\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}+\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]-L_1\tilde{B}_1\left[-\varepsilon_1+\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\right]=$$
$$\tilde{\tau}\underline{w}_1L_1[1-\varepsilon_1]+\tilde{\tau}w_2P_2\left[\frac{1}{\varepsilon_2}\frac{P_1}{1-P_1}\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}-\frac{P_1}{1-P_1}\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\right].$$

Again, we can now collect terms:

$$\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\left[P_1\tilde{B}_1-L_1\tilde{B}_1\right]=\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[-P_1\tilde{B}_1+\tilde{\tau}w_2P_2\left(\frac{1}{\varepsilon_2}\frac{P_1}{1-P_1}-\frac{P_1}{1-P_1}\right)\right]$$
$$+\varepsilon_1\left[-L_1\tilde{B}_1-\tilde{\tau}\underline{w}_1L_1\right]+\tilde{\tau}\underline{w}_1L_1.$$

And then we can simplify to

$$\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\tilde{B}_1[P_1-L_1]=\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}P_1\left[-\tilde{B}_1+\tilde{\tau}w_2P_2\left(\frac{1-\varepsilon_2}{\varepsilon_2(1-P_1)}\right)\right]$$
$$-\varepsilon_1L_1\left[\tilde{B}_1+\tilde{\tau}\underline{w}_1\right]+\tilde{\tau}\underline{w}_1L_1$$

or even to

$$\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\tilde{B}_1u_1=\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[-\tilde{B}_1+\tilde{\tau}w_2P_2\left(\frac{1-\varepsilon_2}{\varepsilon_2(1-P_1)}\right)\right]$$
$$-\varepsilon_1(1-u_1)\left[\tilde{B}_1+\tilde{\tau}\underline{w}_1\right]+\tilde{\tau}\underline{w}_1(1-u_1).$$

To make it easier for the other equation, we can write

$$\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\tilde{B}_1^{\rho}u_1=\tilde{B}_1^{\rho-1}\Bigg(\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[-\tilde{B}_1+\tilde{\tau}w_2P_2\left(\frac{1-\varepsilon_2}{\varepsilon_2(1-P_1)}\right)\right]$$
$$-\varepsilon_1(1-u_1)\left[\tilde{B}_1+\tilde{\tau}\underline{w}_1\right]+\tilde{\tau}\underline{w}_1(1-u_1)\Bigg)$$

and even

$$\frac{\partial \ln B_1}{\partial \ln \underline{w}_1}\tilde{B}_1^{\rho}u_1=\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[-\tilde{B}_1^{\rho}+\tilde{\tau}w_2\tilde{B}_1^{\rho-1}P_2\left(\frac{1-\varepsilon_2}{\varepsilon_2(1-P_1)}\right)\right]$$
$$-\varepsilon_1(1-u_1)\left[\tilde{B}_1^{\rho}+\tilde{\tau}\tilde{B}_1^{\rho-1}\underline{w}_1\right]+\tilde{\tau}\tilde{B}_1^{\rho-1}\underline{w}_1(1-u_1).$$

We can now put the two differentiated linear equations together, and we obtain

$$\begin{aligned}\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[\tilde{B}_1^\rho - w_2^\rho \frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1} - w_2^\rho\right] &= \varepsilon_1(1-u_1)\left[\underline{w}_1^\rho - \tilde{B}_1^\rho\right] \\ &\quad - \rho\left(\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}\left[-\tilde{B}_1^\rho + \tilde{\tau} w_2 \tilde{B}_1^{\rho-1} P_2\left(\frac{1-\varepsilon_2}{\varepsilon_2(1-P_1)}\right)\right]\right. \\ &\quad \left. - \varepsilon_1(1-u_1)\left[\tilde{B}_1^\rho + \tilde{\tau}\tilde{B}_1^{\rho-1}\underline{w}_1\right] + \tilde{\tau}\tilde{B}_1^{\rho-1}\underline{w}_1(1-u_1)\right) \\ &\quad - (1-u_1)\underline{w}_1^\rho \rho,\end{aligned} \tag{C1}$$

which can be simplified to

$$\frac{\partial \ln P_1}{\partial \ln \underline{w}_1} = \frac{(1-u_1)\left[\underline{w}_1(1-\varepsilon_1)\tilde{\tau}\rho\tilde{B}_1^{\rho-1} + \underline{w}_1^\rho(\rho-\epsilon_1) + \tilde{B}_1^\rho(1-\rho)\right]}{w_2^\rho\left(1+\frac{\rho}{\varepsilon_2}\frac{P_1}{1-P_1}\right) - (1-\rho)\tilde{B}_1^\rho - \rho\tilde{\tau} w_2 \tilde{B}_1^{\rho-1}\left(\frac{1-\varepsilon_2}{\varepsilon_2}\right)}.$$

We note that the denominator is positive as long as $\tilde{B}_1$ is not too high. If $\tilde{B}_1$ is relatively high (relative to the population in region 2), then region 1 can become more attractive irrespective of the local labor demand because a large fraction of wages in region 2 are used to pay unemployment benefits in region 1.

If $\rho = 1$, this simplifies to

$$\frac{\partial \ln P_1}{\partial \ln \underline{w}_1} = \frac{(1-u_1)\underline{w}_1(1-\varepsilon_1)(1+\tilde{\tau})}{w_2\left(1+\frac{1}{\varepsilon_2}\frac{P_1}{1-P_1}\right) - \tilde{\tau} w_2\left(\frac{1-\varepsilon_2}{\varepsilon_2}\right)}.$$

In this case, $\partial \ln P_1/\partial \ln \underline{w}_1 < 0$ if and only if $\varepsilon_1 > 1$.

If $\rho < 1$, then $\partial \ln P_1/\partial \ln \underline{w}_1 < 0$ if and only if $\underline{w}_1(1-\varepsilon_1)(1+\tilde{\tau}\rho\tilde{B}_1^{\rho-1}) + \tilde{B}_1^\rho(1-\rho) < 0$, which we can express as $1 + [(\tilde{B}_1^\rho(1-\rho)(1-\tau))/(1-\tau+\tau\rho\tilde{B}_1^{\rho-1})] < \varepsilon_1$. This means that even region 1 can lose population even if employment effects are not very strong.

Appendix D

Extension of Results

D1. Reasons for Internal Migration

The results in this paper rely on the idea that one of the most important drivers of internal migration is employment. To investigate whether this is plausible I use information available in the CPS files on the reasons that individuals who moved gave for moving. To build this table I use the sample of workers in the CPS survey years from 1985 to 2012 (excluding 1995) aged 25–60 who changed residence to a state different from the one in which they were living.

Table D1 shows that among those who migrated to a different state, almost 50% moved for a reason related to the labor market, making it the most important reason for moving.

The second largest motive for migration is "family related reasons," followed by "housing reasons." Within these categories, it is unclear whether some subcategories are also related to the labor market. For instance, someone who moves because the wife or husband changes jobs would probably be classified as moving because of "other family reason," which is used by 15% of respondents. Yet in a way the moving decision is also related to the labor market.

Moreover, given that an important component of the internal migration response may also be related to reductions in movement toward states that increase minimum wages, this would also be moving decisions that are related to the labor market that are not necessarily captured in this table, as there may be workers who stay where they live when they would have otherwise moved.

Taken together, this table suggests that moving decisions are intimately linked to job prospects.

Table D1
Reasons to Move

Reason to Move	Distribution
Job-related reasons:	
New job or job transfer	.324
To look for work or lost job	.061
Other job-related reason	.050
Family-related reasons:	
Change in marital status	.053
To establish own household	.038
Other family reason	.149
For easier commute	.023
Retired	.009
Housing-related reasons:	
Wanted to own home, not rent	.029
Wanted new or better housing	.052
Wanted better neighborhood	.020
For cheaper housing	.029
Other housing reason	.048
Other reasons:	
Attend/leave college	.038
Change of climate	.019
Health reasons	.015
Other reasons	.041
Natural disaster	.003
Foreclosure or eviction	.001

NOTE.—This table shows the distribution of reasons given for moving across states among individuals aged 25–60.

D2. Internal Migration Propensities

In this section I report that younger workers usually migrate more often than older ones. This can be seen in figure D1, where I plot the 5-year internal migration rate using census data for each age cohort. The figure shows that around 17%–18% of individuals who are 28 years old have lived in a state different from the one in which they currently live. This has remained stable in the United States throughout the 1980s, 1990s, and 2000s, that is, the period of my study.

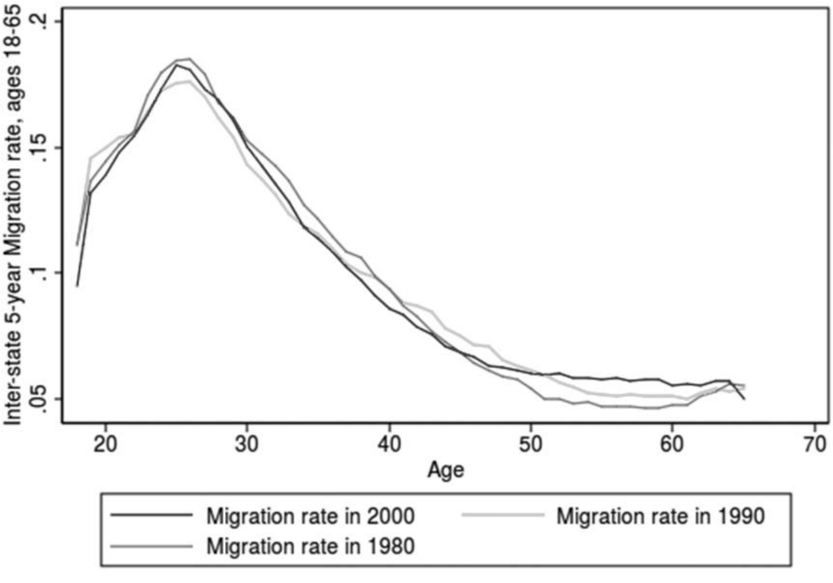

FIG. D1.—Internal migration by age cohort. This figure reports the share of population of a given age cohort that was living in a different state 5 years prior to the corresponding census.

D3. Robustness of the Results to Using Nonconsecutive Year Changes Exclusively

In what follows I show the equivalent to figure 3 and table 3 but excluding minimum wage changes that occur in consecutive years. As explained in the main text, year 0 of the event-type graphs is special in that it captures years that have experienced changes in minimum wages. This sometimes occurs in two consecutive years, and in these cases both consecutive years are used for the estimation of the effect on year 0.

To make sure that this methodology is not dependent on these events when there are consecutive changes in minimum wages, I repeat figure 3 and table 3 excluding all of the events that come from changes of the minimum wage that occur in these consecutive years. The results are shown in figure D2 and table D2.

As can be seen in both figure D2 and table D2, results are very similar to the original strategy.

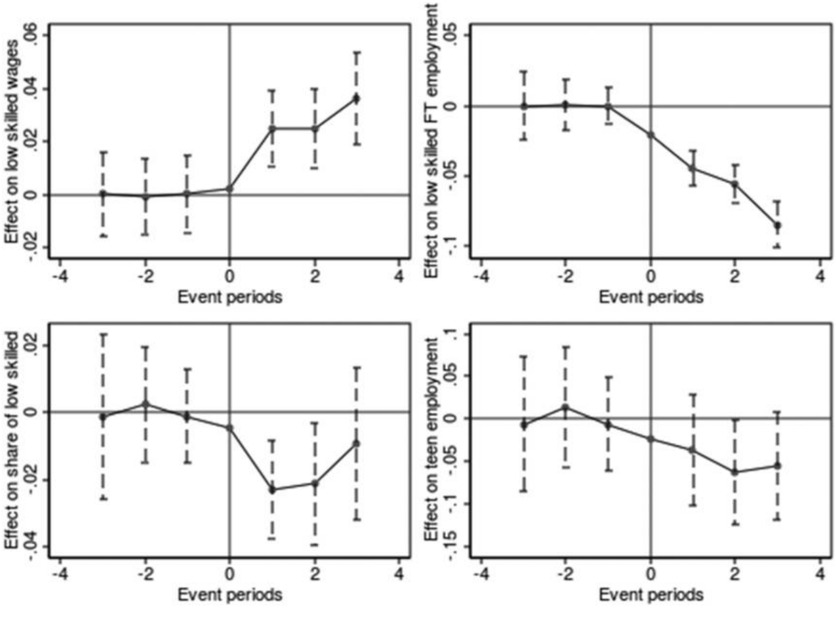

FIG. D2.—Wages, employment, and migration responses to minimum wage increases, nonconsecutive years. The four graphs show the estimate "event" dummies from regression 11 for four different outcome variables: average (composition-adjusted) low-skilled wages, full-time low-skilled employment shares, share of low-skilled population, and teenage employment. The dotted vertical lines show 95% confidence intervals of robust standard errors clustered at the state level.

Table D2
Effect of Minimum Wage Changes on Low-Skilled Wages, Employment, and Migration

	Model 1: Fixed Effects	Model 2: Pretrend	Model 3: Change Trend	Model 4: State Trends
Effect on low-skilled wages	.007	.026	.024	.021
Standard error	(.004)	(.014)	(.012)	(.011)
p-value	[.068]	[.053]	[.048]	[.051]
Effect on share of low-skilled employed, full time	.003	−.043	−.051	−.044
Standard error	(.005)	(.013)	(.012)	(.013)
p-value	[.559]	[.001]	[.000]	[.001]
Effect on share of low-skilled population	−.005	−.034	−.023	−.014
Standard error	(.006)	(.016)	(.016)	(.014)
p-value	[.391]	[.032]	[.135]	[.286]

Table D2 (*Continued*)

	Model 1: Fixed Effects	Model 2: Pretrend	Model 3: Change Trend	Model 4: State Trends
Effect on share of teens employed, full time	−.013	−.033	−.036	−.022
Standard error	(.017)	(.038)	(.035)	(.034)
p-value	[.424]	[.381]	[.300]	[.512]
Implied local labor demand elasticity		−1.637	−2.117	−2.049
Implied migration sensitivity		.780	.461	.330

NOTE.—This table reports four models. The first controls for year and state fixed effects and compares 3 years before and 3 years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a possible change in postevent trend around the policy change. Model 4 is the same as model 3 but controls for state-specific linear trends. Robust standard errors clustered at the state level are reported. More details can be found in the text.

D4. Internal Mobility of High-Skilled Population

This subsection provides the visual evidence of the response of the in- and out-migration rates of high-skilled workers that are the basis for the results reported in table 5.

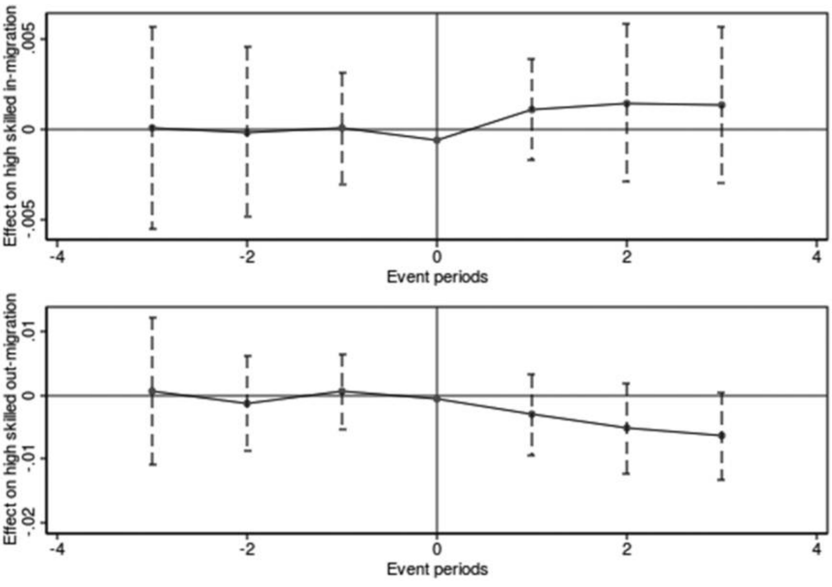

FIG. D3.—Migration responses to minimum wage increases. The two graphs show the estimate "event" dummies from regression (11) for two different outcome variables: high-skilled in-migration rate and high-skilled out-migration rate. The dotted vertical lines show 95% confidence intervals of robust standard errors clustered at the state level.

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