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Minimum Wages and Spatial Equilibrium: Theory and Evidence

Joan Monras

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CENTRO DE ESTUDIOS
MONETARIOS Y FINANCIEROS
Casado del Alisal 5, 28014 Madrid, Spain
www.cemfi.es

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Abstract

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 average wages and decreases in employment among the low-skilled. The labor demand elasticity is estimated to be above 1, in the model a necessary condition for the migration responses observed in the data. Low-skilled workers tend to leave the regions that increase minimum wages.

JEL Codes: J08, J23, J38, J61, R12.

Keywords: Minimum wages, spatial equilibrium, internal migration.

Joan Monras
CEMFI
monras@cemfi.es

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1 Introduction

After many years of research, there is still a heated debate on what the employment effects of minimum wages are (Allegretto et al., 2011; Card, 1992a,b; Card and Krueger, 1994, 2000; Dube and Zipperer, 2015; Dube et al., 2007, 2010; Neumark and Wascher, 2000; Neumark et al., 2014). 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 for example Rosen (1974), Roback (1982), Glaeser (2008), Blanchard and Katz (1992), Carrington (1996), Hornbeck (2012), Hornbeck and Naidu (2012), Monras (2015a)). What happens, then, when, in a multi-region 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 direct answer. 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 US is well explained by this model. To test the implications arising from the model I depart from existing literature on minimum wages and concentrate on prime age low-skilled workers, defined by workers with at most a high school diploma. I show that minimum wages are binding for around 20 percent of this group of workers.[2] As in previous literature, I then combine all the changes in the effective minimum wage at the state level between 1985 and 2012.[3] Using all 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

[1] All these papers use US data. Obviously, researchers have also evaluated the impact of minimum wages in other countries; see for example Machin and Manning (1994). The spatial comparisons are more difficult in other countries, however, since there is no variation across regions.

[2] 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 number of teen-age workers. I document all these points in detail below.

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

– as implicitly assumed in previous papers.[4] 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 (Forthcoming). Relative to them, in this paper I show that not only 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 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 -1.2. According to the model, this has a clear prediction for internal migration: low-skilled population leaves states that increase minimum wages. This prediction is supported by the data. A 1 percent reduction in the share of employed low-skilled population reduces the share of low-skilled *population* – irrespective of their employment status – by between .5 and .8 percent.[7] 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 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 other 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 internal migration decisions and the employment effect. I view this as more direct evidence

[4]This observation is crucial for explaining the small employment responses estimated in some of the previous research.

[5]This is also somewhat visible in Figure 3 of Allegretto et al. (2011) although less than in this paper because of the 2 year time gaps that they use. Concentrating on the entire pool of low-skilled workers strengthens this finding. I replicate some of their findings in Appendix 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 et al. (2014)). Meer and West (Forthcoming) would have detected it had they included leads to their econometric specification.

[7]To measure internal migration I use the share of low-skilled (working age) population. Note that the share of low-skilled population in a state can only change due to different cohort sizes over time, different education levels of different cohorts or migration – either of the high- or the low-skilled. I control for these potential differences across cohorts using state and year fixed effects and state specific linear time trends so that the variation left very likely reflects migration choices. It is worth emphasizing at this point that while the March-CPS data asks questions directly related to migration, it is unfortunate that this question is not asked every year. This limits its usefulness in this context given the frequency of the changes in state-level minimum wages.

than that reported in Cadena (2014).[8]

There is currently an active debate on the spillover effects of changes in minimum wages on various groups of workers. In line with the recent work by Autor et al. (2015), my results are consistent with small spillover effects. On average, effective minimum wage increases are of about 11 percent. Around 20 percent of full-time low-skilled workers of various ages are potentially affected by these policy changes. If these were the only workers affected and their wages changed by exactly 11 percent, the change in minimum wage laws would increase the average wages of all low-skilled workers by around 2.2 percent. This is very close to the 2.7 percent estimated in this paper. I also show that with March CPS data it is difficult to obtain precise estimates of whether teenage workers are affected differently from the overall low-skilled population. However, the point estimates of the teenage employment effects are similar and statistically indistinguishable from those of the overall low-skilled population. Relative to this debate, this paper suggests that spillovers between similar workers in different regions may be more important than between workers of different types.

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 variables strategies, usually estimate small wage decreases, often not distinguishable from 0 (see also Card (2001) and Card (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 why over longer time horizons the elasticities are lower is driven, among other reasons, by internal migration.[9] These findings are also consistent with the recent reassessment of the impact of the Mariel Boatlift immigrants (see the Appendix in Monras (2015b), Borjas (2015) and Borjas and Monras (2016)).

Taken altogether, 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 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.

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

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

2 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 $Y_i = AF(K_i, L_i)$.[10] 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 income. Expected income is simply the wage rate when there is no unemployment. If there is unemployment, then the expected income is the unemployment rate times the amount of unemployment benefits plus the employment rate times wages. 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 non-tradable 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 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 the aforementioned complications.

2.1 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. 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 for example Blanchard and Katz (1992)), but

[10] 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.

the main results of this paper do not depend on how I obtain this short-run local labor demand curve.[11]

2.2 Mobility decision

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

$$V_i = (u_i * B_i + (1 - u_i) * (1 - \tau_i) * w_i) \text{ for } i \in \{1, 2\} \tag{2}$$

This equation simply says that workers understand that 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 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 0.

2.3 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:

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

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. The fact that wages are decreasing in population implies that both regions have some workers.

2.4 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:

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

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:

[11] More generally, all that I need in the model is that the congestion forces are stronger than the agglomeration forces.

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

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.

2.5 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 0). 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 $w_1 = w_2$, which given the local labor demand (see Equation 1) implies that:

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

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:

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

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 $w_i^{FME} = AF_L(\bar{K}_i, L_i^{FME})$ 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.

2.6 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 that 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:

$$(u_1 * B_1 + (1 - u_1) * (1 - \tau_1) * \underline{w}_1) = w_2$$

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 the fact that $B_1 = \frac{L_1}{P_1 - L_1}\tau_1 \underline{w}_1$ to obtain:

$$\underline{w}_1 \frac{L_1}{P_1} = w_2 \tag{8}$$

This last equation implicitly defines the population in Region 1 (P_1).[12] 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 $\frac{\partial \ln L_i}{\partial \ln w_i} = -\varepsilon_i$. It is important to keep in mind that this elasticity may be different at different levels of land and population.

Proposition 1. *When unemployment benefits are financed locally, whether Region 1 gains or loses population depends on whether the local labor demand elasticity (ε_1) is greater or smaller than 1.*

Proof. We only need to totally differentiate Equation 8 to obtain:

$$1 - \varepsilon_1 - \frac{\partial \ln P_1}{\partial \ln \underline{w}_1} = \frac{\partial \ln w_2}{\partial \ln \underline{w}_1} = \frac{\partial \ln w_2}{\partial \ln L_2}\frac{\partial \ln(1-P_1)}{\partial \ln \underline{w}_1} = \frac{1}{\varepsilon_2}\frac{P_1}{1-P_1}\frac{\partial \ln P_1}{\partial \ln \underline{w}_1}$$

Thus,

$$\frac{\partial \ln P_1}{\partial \ln \underline{w}_1} = \frac{1-\varepsilon_1}{(1 + \frac{1}{\varepsilon_2}\frac{P_1}{1-P_1})}$$

And this equation finishes the proof.

□

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 inelastic ($\varepsilon_1 < 1$), 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 elastic ($\varepsilon_1 > 1$), 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. Under locally funded unemployment benefits, taxes are simply a transfer from employed to non-employed workers within the region. Given the assumed indirect utility function, this cannot affect the expected value of the region.[13]

[12] Employment is directly determined by the binding minimum wage.

[13] If workers were averse to being unemployed, these results would change somewhat. In fact, even small employment losses could, in that case, make the region that introduces minimum wages less attractive.

2.7 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.[14] Using the indifference condition for the location choice, we obtain:

$$(\frac{P_1 - L_1}{P_1} * B_1 + \frac{L_1}{P_1} * (1-\tau) * \underline{w}_1) = (1-\tau) * w_2 \tag{9}$$

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. The second group are 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 ($B_1 < w_1^{FME}$).[15] Overall, it is not clear whether Region 1 becomes more or less attractive. It basically depends on two things. First, it depends on the level of minimum wages that the government introduces. This generates some unemployment. As before, this is particularly worrisome if the local labor demand is very elastic. The second important thing is the level of unemployment benefits that the government decides to pay, since they are partially financed by wages in Region 2.

Equation 9 can be re-written as:

$$\frac{L_1}{P_1}\underline{w}_1 + \frac{\tau w_2 P_2}{P_1} = (1-\tau) * w_2 \tag{10}$$

In order to see the importance of the unemployment benefits, it is useful to first think what would happen if they were 0. In this case, Equation 10 simplifies to $\underline{w}_1 \frac{L_1}{P_1} = w_2$, which is the exact same Equation 8 as before. 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 0, 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. A simplification of Equation 10 makes this more explicit:

$$L_1 * \underline{w}_1 = (P_1 - \tau) * w_2 \tag{11}$$

This expression highlights that movements from Region 2 toward Region 1 independent of the local

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

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

labor demand elasticity happen only in disequilibrium. It is only when we move from the no minimum wage free market equilibrium to the new minimum wage equilibrium that this can arise. To summarize:

Proposition 2. *When unemployment benefits are financed nationally, whether Region 1 gains or loses population following the introduction of minimum wages depends on how high minimum wages and unemployment benefits are set. If Region 1 already has a binding minimum wage and raises it, then whether it gains or loses population depends exclusively on the local labor demand elasticity.*

Proof. The first part of the proposition has already been discussed in the paragraphs leading to the proposition.

For the second part, we need to totally differentiate 11 to obtain:

$$1 - \varepsilon_1 = \frac{\partial \ln w_2}{\partial \ln \underline{w}_1} + \frac{\partial \ln (P_1 - \tau)}{\partial \ln \underline{w}_1}$$

This can be re-expressed as:

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

And we know that $P_1 > \tau$ whenever the economy is in spatial equilibrium.

□

3 Empirical evidence

In this section, I use all the changes in the effective minimum wage that took place between 1985 and 2012 – i.e. 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 these events to build my identification strategy. I consider three periods before and three 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.

3.1 Data description, summary statistics, and empirical definition of the low-skilled labor market

This paper is mainly based on the widely used and openly available March files of the Current Population Survey, available on Ruggles et al. (2008). I combine these March CPS data with data compiled by Autor et al. (2015) on the minimum wage law changes (Table 1 in their Appendix).[16]

I study the evolution of three outcome variables: average wages, shares of employed workers, and shares of low-skilled population. I define low-skilled workers as workers who have a high school diploma

[16] 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.

or less. 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.

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

$$\ln w_i = \alpha + \beta X_i + \varepsilon_i \tag{12}$$

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 12 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 value 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.[17] I run this regression using all full-time employed workers who have a non-zero 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 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 to 64) who are employed full-time according to the CPS. There are various variables in the CPS that identify whether a worker is employed or not. These can be divided into two groups of variables. The first are variables that refer to a worker's activity in the previous year. The second are variables that refer to the working activity of a worker during the preceding week of the survey month. The first group of variables is only available on the March Files of the CPS. The other variables are also available for the other months.

The main employment variable that I use is the share of workers (of a particular skill group) that are working full-time. Full-time workers are defined as those who are working in March and in the previous year were employed full-time during the entire year (i.e. for at least 40 weeks and usually for 40 hours per week). The main results of the paper use this measure. It has the virtue of considering workers that are currently working and have done so for quite some time and in a consistent manner. These should be workers that are more attached to and more integrated into the labor market. I devote part of Section 3.6 to show results using alternative measures and subgroups of workers.

I distinguish high- and low-skilled workers using the high school diploma cut-off previously mentioned.

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

I also use this cut-off to compute the share of working age population who are low-skilled, irrespective of their employment status. This is my main migration variable. The March-CPS also allows to identify the home location of each individual in the preceding year. This, in theory, would allow to better identify migration choices. However, I prefer to use the share of low-skilled population because location information in the preceding year is not available for every CPS year. Given the frequency of the minimum wage changes, using the direct migration information would restrict the span of the study. The share of low-skilled population can also change with changes in the cohort size and educational attainment. As long as these cohort changes evolve smoothly in each state over time, the state and year fixed effects and the state-specific year trends that I use in the regression framework should control for it.

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 weekly incomes below the income that a minimum wage worker would earn when working 40 hours per week at the following year's minimum wage. I compute this for every age group.

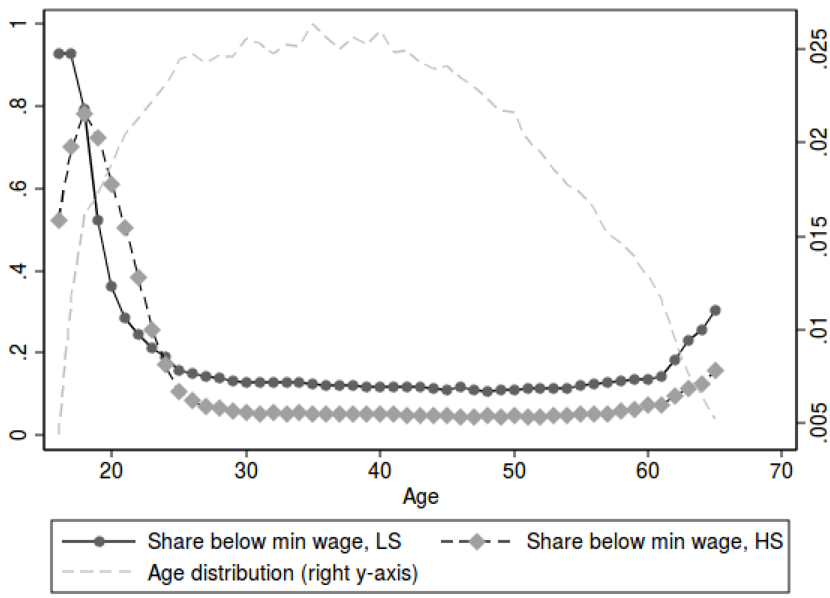
The graph in Figure 1 shows that while it is true that the share of workers potentially affected by minimum wage changes are much higher for workers below 24 years old, a non-negligible share of older low-skilled workers are also potentially affected. This figure also shows that the number of low-skilled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

On average, close to 20 percent of low-skilled workers are potentially affected by minimum wage changes. This share is significantly lower 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.

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 25 percent of teens are working full-time, compared to around 52 percent of low-skilled workers who are older than 25 years old, and compared to almost 65 percent 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 around 50 percent. Thus, we have it that 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, almost 20 percent are close to or below the income that a worker working 40 hours a week and earning the minimum wage would earn. Among the teens, this share of potentially affected workers is much higher, around 70 percent, but they only represent slightly less than 13 percent of the population and they are half as likely to be working full-time as other low-skilled workers.

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

Figure 1: Descriptive statistics about how binding minimum wages are



Notes: The first 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-colored, dashed lines show the age distribution of the population.

Table 1: Summary statistics

Variable	**Mean**	**Std. Dev.**
Share of low skilled who are employed, Full-time	0.524	0.053
Share of low skilled who are employed, Part-time	0.153	0.036
Share of low skilled who are employed, Full time equiv.	0.601	0.052
Share of low skilled who are employed, alternative measure	0.462	0.051
Share of teens who are employed	0.258	0.064
Share of high-skilled who are employed	0.642	0.043
Share low skilled population	0.471	0.091
Share of of population who are teens	0.129	0.015
Percentage change in Min. Wage	0.112	0.056
Share year-states with a minimum wage change	0.353	0.478
N	1249	

Notes: 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. Workers are considered to be employed if they are working full-time.

3.2 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.

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

Notes: 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 these years.

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 these events was of around 11 percent, 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 percent. Thus, these are policy changes that are relatively 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.

3.3 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 these events in one graph per outcome variable. To do so, I use the following regression:

$$y_{st} = \alpha + \sum_{k=-3, k\neq 0}^{k=3} \delta_k * \text{event}_{k,st} + \delta_t + \delta_s + \varepsilon_{st} \qquad (13)$$

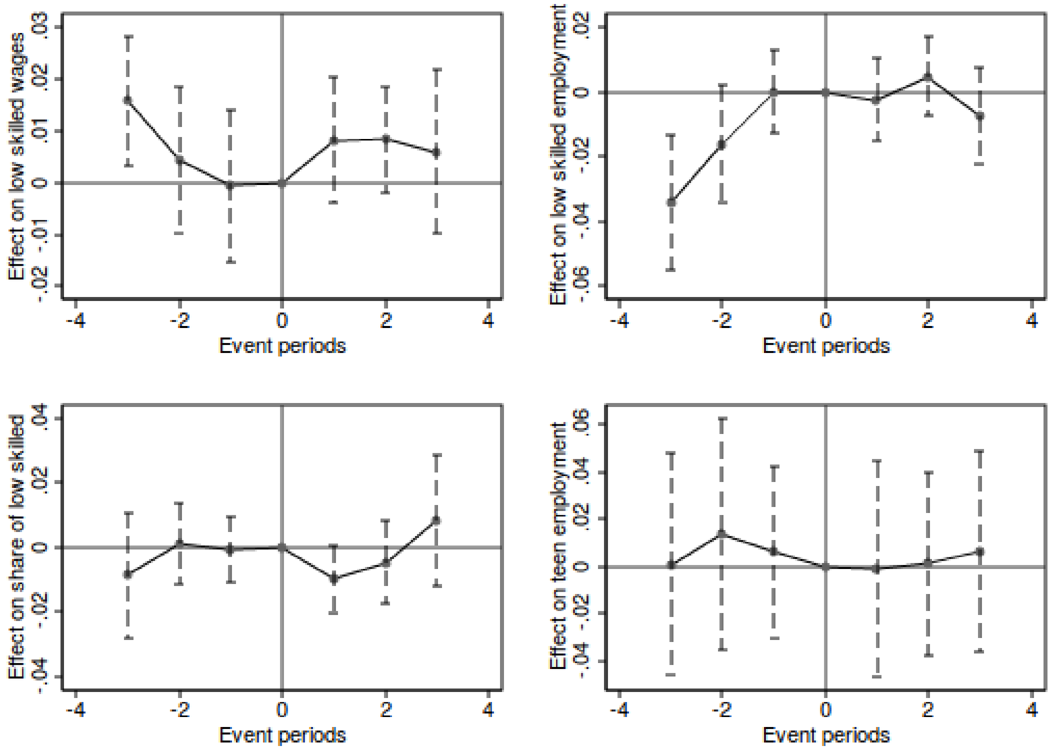
where y_{st} is the (log of the) outcome of interest, $\text{event}_{k,st}$ is a dummy that takes value 1 if in state s and at time $t-k$ there was a change in the effective minimum wage. δ_t and δ_s denote year- and state-fixed effects. ε_{st} is the error term. I only consider three periods before the year when the minimum wage changes and three periods after it.[19] It is worth noting that by using pre-event and post-event 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 these events. Later, in Section 3.6, I introduce some functional form assumptions to leverage the different intensities in the change of the minimum wage across all these different events.

The dummies “event 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 the events, controlling for common shocks and state-wide 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 in 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 either represent a true year after the change in minimum wages or one year after a series of consecutive changes in minimum wages. Similarly, the 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, like 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.

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

Figure 2: Wages, employment, and migration responses to minimum wage increases



Notes: The four graphs show the estimate "event" dummies from Regression 15 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 are 95 percent confidence intervals of robust standard errors clustered at the state level.

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 employment among low-skilled workers, share of low-skilled population, and share of full-time employment among teenage workers. The first graph shows the evolution of low-skilled 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 employed. 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 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 state minimum wage changes tend to happen during periods when low-skilled wages decline and low-skilled employment is strong. If policy makers anticipate that augmenting 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.

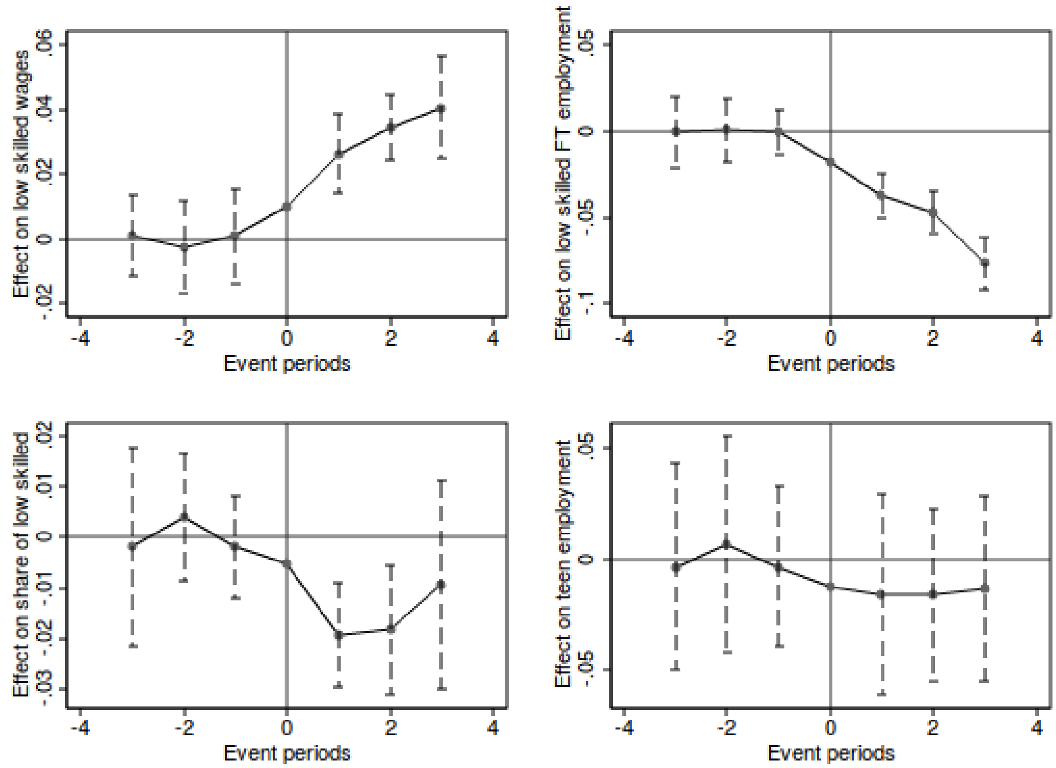
The third graph shows what happens to migration. In it we see how the share of low-skilled working age *population* does not seem to have a particular trend before the change in minimum wages and how it drops right after. This suggests that there is a migration reaction, presumably to the employment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

In all, Figure 2 suggests that controlling for pre-*event* 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 highlight the results under the aforementioned identification assumption. More explicitly, in order to build Figure 3, I fit (and remove) a linear trend in the three periods preceding the policy change.

The results shown in Figure 3 are clear and strong. Once I allow for a linear trend preceding the policy change (so that the average is around 0 in the three periods before the event), it is easy to observe that: 1) average low-skilled (composition-adjusted) wages increase. This is strong 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). 2) The (log) share of full-time employed low-skilled workers decreases. In fact, Figure 3 suggests that the decline in low-skilled employment is *larger* than the increase in average wages. This is evidence that suggests that the local labor demand elasticity is above 1. As I argued in the model, a local labor demand elasticity above 1 has a clear prediction for internal migration: 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 there is a lot of imprecision when limiting our attention to teenage workers.

Figure 4 shows that this evolution of wages and employment is exclusive to low-skilled workers. If I repeat the exact same graphs but using high- instead of low-skilled workers, we see that there are no trends prior to the policy change and, more importantly, that there are no changes to this following the policy change.

Figure 3: Wages, employment, and migration responses to minimum wage increases, de-trended



Notes: The four graphs show the estimate "event" dummies from Regression 15 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. In these graphs, the three pre-event periods are fitted to a linear trend that is removed from the graph. The dotted vertical lines are 95 percent confidence intervals of robust standard errors clustered at the state level.

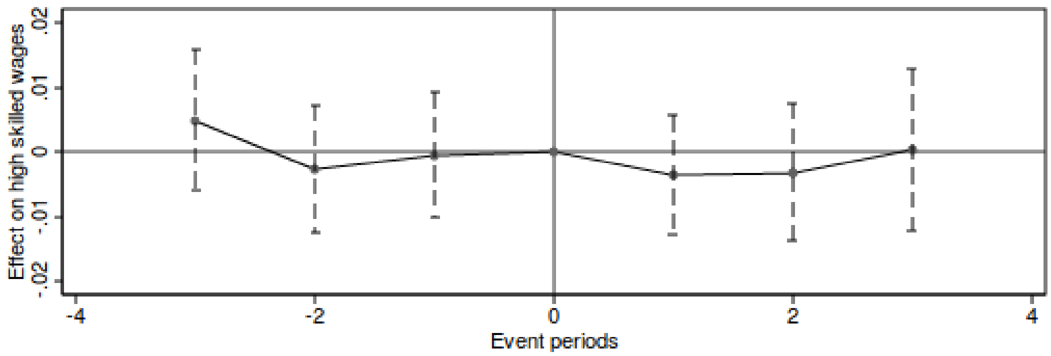
3.4 Estimates, elasticities, and discussion of the findings

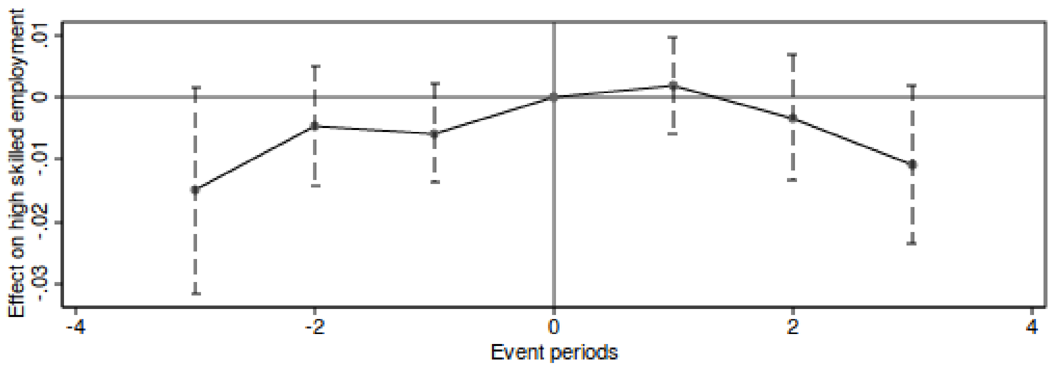
The previous graphs are meant to explain my identification strategy and show why I obtain the results that I do in the regressions. To quantify the effects displayed in the graphs, I use the following regression:

$$\begin{aligned} y_{st} = {} & \alpha + \beta_1 \text{Post treatment}_{st} + \beta_2 \text{Period Zero}_{st} + \beta_3 \text{Pre-event trend}_{st} \\ & + \beta_4 \text{Post-event trend}_{st} + \delta_t + \delta_s + \delta_s * t + \varepsilon_{st} \end{aligned} \tag{14}$$

where the "Post treatement" is simply a dummy variable taking value 1 for the three years after the change in minimum wages, and taking value 0 for the three years before the change – including the year the change takes place. The variable "Period Zero" is simply a dummy variable taking value 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 0 that are the second year of consecutive changes in minimum wages. The variable "Pre-event trend" is a linear trend during the three periods before the policy change takes places. This should control for the linear pre-event trend observed in Figure 2. The variable "post-event trend" allows for a change in the trend after the policy change takes place. This

Figure 4: Wages, employment, and migration responses to minimum wage increases, de-trended





Notes: The two graphs show the estimate "event" dummies from Regression 15 for two different outcome variables: average (composition-adjusted) high-skilled wages and high-skilled full-time employment shares. The dotted vertical lines are 95 percent confidence intervals of robust standard errors clustered at the state level.

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 ($\delta_s * t$). This should account for different linear evolutions of the outcome variables that are systematically different across states.

In order to make my identification strategy more transparent, I also report results on the simpler regression:

$$y_{st} = \alpha + \beta_1 \text{Post treatment}_{st} + \delta_t + \delta_s + \varepsilon_{st} \tag{15}$$

which is essentially the same as Equation 14 but without allowing for specific changes to trends around the events. Note that this is a simple event type strategy. In order to obtain unbiased estimates of the effect of the policy change (β_1 in equation 15) 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 five different estimates, which are labelled as "Model 1", "Model 2", "Model 3", "Model 4", and "Model 5". Model 1 shows the estimates of running the simpler regression in equation 15. As we can anticipate by looking at Figure 2, the estimates from this model are always around 0. These estimates are essentially comparing the first three pre-event periods with the four periods following the policy change. Given the pre-trends shown in Figure 2, we can anticipate slightly positive estimates of wages and of 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 14. I report the estimate $\beta_1 - \beta_3$. This assumes that there is a pre-event trend that changes after the policy change. These estimates are the estimates in Figure 3 but where the period 0 is not assumed to have a differential role, and where the possible change in trend in the "post" period 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 percent (see Table 1) translates into a 2.7 percent increase in average wages. Given that the share of low-skilled population potentially affected by the minimum wage is around 20 percent (see Figure 1), an estimate of around 2.7 percent implies that there are no big spillovers across the entire wage distribution. Suppose that this 20 percent is the only group affected be the policy change and their wages increase by exactly 11 percent. Then, 20 percent of the workers have an increase in wages of 11 percent, which means that the average increase for all low-skilled workers is around 2.2 percent (not far from the estimated 2.7 percent). These small spillover effects on wages of workers not directly affected by minimum wages are in line with what is documented in Autor et al. (2015).

This increase in average wages translates into a decrease in the share of low-skilled workers who are full-time employed of around 3.3 percent. This implies a local labor demand elasticity of around -1.2, as also shown in the table, and an elasticity of employment to minimum wage changes of around -.27 (in line with part of the literature). The estimate of the local labor demand elasticity is above 1, which, according to the model, implies that the share of low-skilled population will decrease. In Model 2 of Table 3, I estimate that the decrease in the share of low-skilled population is around 2.8 percent, which implies a sensitivity of internal migration[20] to employment changes of around .83. All these estimates are significantly different from 0 at the 5 percent confidence level (also shown in the table). Instead, the -1.8 percent estimate for the change in the share of teenage workers that are full-time employed is not distinguishable from 0 (or from the estimate on low-skilled employment). Note that in this case the standard errors are almost five times larger, showing the fact that I am using only 13 percent as much micro-level information (see Table 1).

The third model also uses Equation 14 and I report the estimate $\beta_1 - \beta_3 + \beta_2$. This assumes that the policy change has an immediate effect in period 0, and adds to it the longer-run effect in the periods that follow, taking into account the trend previous to the policy change. This, as one can anticipate from Figure 3, results in larger estimates for wages and employment, and almost unchanged estimates on migration (as can be seen in the graph, migration seems to respond more in period 1 than in period 0). The estimate of the implied local labor demand elasticity is again above 1 and consistent with the estimate on internal migration predicted by the model. For the fourth model I report the estimate $\beta_1 - \beta_3 + \beta_2 + \beta_4$. This means that I include the post-trend as an effect of the policy change. The

[20]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.

Table 3: Effect of minimum wages changes on low-skilled wages, employment and migration

	Model 1	Model 2	Model 3	Model 4	Model 5
	FE	Pre-trend	Pre-trend plus Period 0	Change trend plus Period 0	Model 4 State trends
Effect on low-skilled wages	.006	.027	.037	.036	.040
s.e.	(.004)	(.013)	(.022)	(.021)	(.019)
p-value	[.163]	[.041]	[.099]	[.093]	[.038]
Effect on share of low-skilled employed, Full-time	.003	-.033	-.051	-.052	-.045
s.e.	(.004)	(.013)	(.018)	(.018)	(.019)
p-value	[.412]	[.008]	[.006]	[.005]	[.016]
Effect on share of low-skilled population	-.004	-.028	-.032	-.024	-.021
s.e.	(.005)	(.012)	(.016)	(.016)	(.016)
p-value	[.514]	[.018]	[.048]	[.134]	[.208]
Effect on share of teens employed, Full-time	.000	-.018	-.029	-.025	-.005
s.e.	(.018)	(.038)	(.058)	(.055)	(.054)
p-value	[.985]	[.642]	[.624]	[.650]	[.931]
Implied local labor demand elasticity		-1.235	-1.396	-1.471	-1.138
Implied migration sensitivity		.827	.629	.449	.456

Notes: This table reports 5 models. The first one controls for year and state fixed effects and compares three years before and three years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a discontinuity at period 0. Model 4 adds to model 3 a possible change in post-trend around the policy change. Model 5 is the same as Model 4 but controlling for state specific linear trends. Robust standard errors clusterred at the state level are reported. More details can be found in the text.

estimates are very similar to Model 3.

Finally, I estimate a fifth model that includes state-specific linear year trends in Equation 14 – 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 4. All the results are unchanged relative to column 4. This is also true if I report the coefficients reported in the other columns.[21] This means that the results in this paper do not depend on either controlling for state-specific linear year trends or not, 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 et al. (2010), Allegretto et al. (2011) and responded to by Neumark et al. (2014). It is also worth mentioning that, with the March-CPS data that I use in this paper I can replicate the discussion Dube et al. (2010) and Neumark et al. (2014) and I obtain very similar results.[22]

Overall, Table 3 shows strong evidence consistent with the model and with the intended 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 between -1.14 and -1.47, consistent with the estimates reported in Monras (2015b) using migration shocks.

Table 4 serves as a placebo test. In this table I show the wage and employment estimates for the *high-skilled* workers. Consistent with Figure 4, all the estimates in this table are small and never statistically distinguishable from 0. 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 US.

[21] The results on migration are in fact statistically different from 0 when not including the post-event slightly upward trend that can be seen in Figure 3.

[22] Results are reported and briefly discussed in Appendix B.

Table 4: Effect of minimum wages changes on high-skilled wages, employment and migration

	Model 1	Model 2	Model 3	Model 4	Model 5
	FE	Pre-trend	Pre-trend	Change trend	Model 4
			plus Period 0	plus Period 0	State trends
Effect on high-skilled wages	-.003	.001	.005	.007	.007
s.e.	(.004)	(.009)	(.015)	(.016)	(.017)
p-value	[.515]	[.917]	[.746]	[.668]	[.694]
Effect on share of high-skilled employed	.000	.004	.004	-.002	-.001
s.e.	(.003)	(.009)	(.013)	(.014)	(.014)
p-value	[.958]	[.673]	[.783]	[.859]	[.942]

Notes: This table reports 5 models. The first one controls for year and state fixed effects and compares three years before and three years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a discontinuity at period 0. Model 4 adds to model 3 a possible change in post-trend around the policy change. Model 5 is the same as Model 4 but controlling for state specific linear trends. Robust standard errors clusterred at the state level are reported. More details can be found in the text.

3.5 Previous estimates of the local labor demand elasticity

In this section I compare my estimates of the local labor demand elasticity with previous estimates in the literature. 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. In order to avoid the endogenous location of migrants given the local labor market conditions, Altonji and Card (1991) developed what has been called the immigration network instrument. The idea is that some regions receive the first immigrants. These first immigrants shape the subsequent migration flows, so that an important reason why new migrants move into high-immigration regions is not because these are more attractive but simply because immigrants have better connections in them.

Part of the literature on immigration that compares high- and low-immigration regions finds small wage effects (Card (1990) is an early example).[23] If the economy is well described by a perfectly competitive model of the labor market, 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) and Card and Krueger (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,b), Allegretto et al. (2011); Dube et al. (2007, 2010).[24] This would imply that the local labor demand is inelastic, i.e. 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 towards 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

[23] See also Card (2001) for another seminal contribution to this literature and see Card (2009) for a recent literature review.
[24] These are contested findings; see Neumark et al. (2014) for a longer discussion.

crucially on whether or not migrants migrate because of push factors, and on the time horizon that we use to evaluate the wage effects (Monras, 2015b).[25] 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 -.75 (i.e. labor demand elasticity equal to 1/.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 (2015) and Borjas and Monras (2016) also report estimates of the effects of the Mariel Boatlift migrants that are in line with both the estimates in this paper and in Monras (2015b).

3.6 Robustness and heterogenenity

3.6.1 Heterogeneity in low-skilled employment

As mentioned before, there are different ways to compute employment levels using CPS data. There are also alternative data sets at our disposal for seeing whether minimum wage increases lead to employment effects or not. In this section I explore the response in employment of various subgroups of low-skilled workers to a minimum wage increase. I also provide evidence that the unemployment benefits paid by the states increase after minimum wage increases. All these results are shown in Table 5. The identification strategy and the display of the results is identical to that discussed in Section 3.4. The message is clear. Given the overall identification strategy previously discussed, and independent of how I measure it, 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 5 simply replicate the first two rows of Table 3 and should be useful as a reference point. An alternative measure to the full-time employment shown in Table 3, which is shown in the third row, is to simply consider that a worker is full-time employed if she worked more than 40 hours during the week prior to the CPS interview.[26] This measure, while direct, has the caveat that there may be workers who normally work part-time who just happened to be working more than 40 hours in March. There may also be workers who work more than 40 hours a week, but only during part of the year. When using this alternative measure of low-skilled full-time employment, the results are almost identical to the results previously discussed. Employment effects are negative and statistically different from 0, with implicit demand elasticities close to but in general above 1.

The fourth row considers workers who did not work full-time in the preceding year but who were employed in March. I define these as part-time workers. These are workers that either entered the labor force in the midst of the previous year or who have jobs that last for less than 40 weeks during the year. They also include workers who, even if they worked for more than 40 weeks, usually worked less than 40 hours per week. The results for this subgroup are clear. When minimum wages increase, there are more

[25] Given the rapid internal relocation responses, studies that use Census data, and thus ten year windows, are likely to miss most of the story.

[26] The measure that I previously used also takes into account whether workers were working more than 40 weeks per year in the preceding year, which gives a sense of their attachment to the labor market.

Table 5: Effect of minimum wages changes on employment, various measures

	Model 1 FE	Model 2 Pre-trend	Model 3 Pre-trend plus Period 0	Model 4 Change trend plus Period 0	Model 5 Model 4 State trends
Effect on low-skilled wages	.006	.027	.037	.036	.040
s.e.	(.004)	(.013)	(.022)	(.021)	(.019)
p-value	[.163]	[.041]	[.099]	[.093]	[.038]
Effect on share of low-skilled employed, Full-time	.003	-.033	-.051	-.052	-.045
s.e.	(.004)	(.013)	(.018)	(.018)	(.019)
p-value	[.412]	[.008]	[.006]	[.005]	[.016]
Effect on share of low-skilled employed, alternative	.007	-.024	-.044	-.052	-.051
s.e.	(.006)	(.012)	(.020)	(.021)	(.021)
p-value	[.246]	[.052]	[.025]	[.012]	[.014]
Effect on share of low-skilled employed, Part-time	.020	.073	.102	.100	.085
s.e.	(.010)	(.036)	(.055)	(.054)	(.054)
p-value	[.052]	[.039]	[.063]	[.063]	[.116]
Effect on share of low-skilled employed, Full and part-time	.007	-.010	-.017	-.018	-.017
s.e.	(.004)	(.010)	(.014)	(.014)	(.014)
p-value	[.057]	[.343]	[.236]	[.180]	[.207]
Effect on share of low-skilled employed, Full-time equivalent	.006	-.020	-.032	-.033	-.029
s.e.	(.004)	(.010)	(.015)	(.014)	(.015)
p-value	[.140]	[.056]	[.032]	[.022]	[.043]
Effect on share of teens employed, Full-time	.000	-.018	-.029	-.025	-.005
s.e.	(.018)	(.038)	(.058)	(.055)	(.054)
p-value	[.985]	[.642]	[.624]	[.650]	[.931]
Effect on share of teen employed, Part-time	-.012	-.107	-.158	-.154	-.152
s.e.	(.012)	(.040)	(.055)	(.052)	(.053)
p-value	[.310]	[.008]	[.004]	[.003]	[.004]
Effect on share of teens employed, Full and part-time	-.005	-.052	-.079	-.075	-.063
s.e.	(.012)	(.030)	(.043)	(.039)	(.040)
p-value	[.679]	[.086]	[.065]	[.056]	[.115]
Effect on share of teen employed, Full-time equivalent	-.003	-.039	-.059	-.056	-.041
s.e.	(.013)	(.032)	(.046)	(.043)	(.042)
p-value	[.820]	[.220]	[.195]	[.190]	[.337]
Effect on share not employed among low-skilled	-.013	.017	.030	.031	.026
s.e.	(.008)	(.021)	(.031)	(.031)	(.031)
p-value	[.092]	[.408]	[.341]	[.320]	[.395]
Effect on share not employed among teens	-.006	.044	.068	.063	.050
s.e.	(.010)	(.023)	(.035)	(.034)	(.033)
p-value	[.570]	[.057]	[.054]	[.063]	[.126]
Effect on unemployment benefits, state account	-.018	.145	.272	.289	.282
s.e.	(.019)	(.063)	(.095)	(.089)	(.085)
p-value	[.341]	[.021]	[.004]	[.001]	[.001]

Notes: This table reports 5 models. The first one controls for year and state fixed effects and compares three years before and three years after the policy change. Model 2 allows for a particular trend before the policy change. Model 3 adds to model 2 a discontinuity at period 0. Model 4 adds to model 3 a possible change in post-trend around the policy change. Model 5 is the same as Model 4 but controlling for state specific linear trends. Robust standard errors clusterred at the state level are reported. More details can be found in the text.

part-time workers above 25 years old (than the linear pre-trend would have predicted). Table 5 shows that the share of part-time workers increases by around 7 to 10 percent.[27]

The fifth 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 2.7 - 3.6 percent (of an average of around 52 percent of the population) and an increase in the share of workers who are employed part-time of around 7 - 10 percent (of an average of 15 percent of the population) almost exactly cancels out. The point estimates are slightly negative (2.7 x 52 is larger than 7 x 15). If instead, I consider a part-time worker as half of a worker, I obtain decreases in the share of full-time equivalent workers that are statistically different from 0. The magnitudes of these decreases are of around

[27] On average, 15 per cent of the population are employed part-time; see Table 1.

2 - 3 percent (from an average of 60 percent).[28]

The estimates on full-time equivalent workers would imply local labor demand elasticities that are slightly below 1. I do not consider this to be too problematic for the model. The model assumes risk-neutral agents. With risk-averse agents, the threshold for internal migration away from locations that increase minimum wages could be lower than 1, and would be related to the degree of risk aversion.

Rows 6 to 9 repeat the same exercise but considering 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 0) and these also become slightly more negative.

Rows 10 and 11 consider the share of workers, among the low-skilled and the teenagers respectively, who are not working. Increases in minimum wages seem to slightly increase teenage non-employment, while adult low-skilled non-employment 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 to 30 percent larger than what states were paying before the increase in minimum wage) than the employment or wage effects.

Taken altogether, Table 5 provides evidence that, first, full-time employment decreases – no matter how I define it. Second, part-time employment among adult low-skilled workers seems to increase. Third, teenage employment seems to decrease, though sometimes the estimates are imprecise. All this leads to increases in unemployment benefits paid by the states.

3.6.2 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 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 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.

In order to investigate all this, I enlarge my estimation equation in the following way:

$$y_{st} = \alpha + \beta_1 \text{Post treatment x intensity}_{st} + \beta_2 \text{Pre-event trend x intensity}_{st} + \delta_t + \delta_s + \varepsilon_{st} \qquad (16)$$

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

[28]Obviously from the estimates on full- and part-time employment one can construct estimates that combine these two groups in a linear way very easily.

interaction of the "Post treatment" 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. In order to account for potential pre-trends 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.[29]

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. In order to leverage this variation I use the following equation:

$$\begin{aligned} y_{st} = \alpha &+ \beta_1 \text{Post treatment x intensity x share below min. wage}_{st} \\ &+ \beta_2 \text{Pre-event trend x intensity x share below min. wage}_{st} + \delta_t + \delta_s + \varepsilon_{st} \end{aligned} \tag{17}$$

where all 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 16 and 17 with a dummy-taking value 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 6: Effect of minimum wage changes on average low-skilled wages

VARIABLES	Average low-skilled wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Post treatment x intensity	0.120**		0.141**		0.132*	
	(0.0526)		(0.0601)		(0.0738)	
Post treatment x intensity x share		0.830**		0.891**		0.915*
		(0.317)		(0.389)		(0.495)
Pre event trend x intensity			-0.0366		-0.0386	
			(0.0220)		(0.0276)	
Pre event trend x intensity x share below min. wage				-0.0890		-0.141
				(0.164)		(0.196)
Pre event trend x intensity x federal change					0.00878	
					(0.0428)	
Post event x intensity x federal change					0.0243	
					(0.0743)	
Pre event trend x intensity x share below min. wage x federal change						0.338
						(0.299)
Post event x intensity x share below min. wage x federal change						-0.0532
						(0.519)
R-squared	0.331	0.330	0.336	0.331	0.337	0.335
Year FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes

Notes: This table shows estimates of Equations 16 and 17, using average low-skilled wages as a dependent variable. Standard errors are clustered at the state level. 1, 2, and 3 stars mean significance levels of .1, .05, and .01 respectively.

[29] I obtain similar results if I use Models 3 to 5.

Table 6 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 16 and 17, i.e. 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 pre-event 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 negative linear trend before the policy change, as reflected in the small and insignificant coefficients on “Pre event trend x intensity” and “Pre event trend x intensity x share below min. 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. The fact that the interaction of both the post-treatment dummy and the linear pre-event trend are small and indistinguishable from 0 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 7 reports the results for low-skilled employment. As before, columns 1 and 2 report simple difference-in-difference 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 non-distinguishable from 0. 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 pre-event trend interacted with the two continuous measures of the treatment. As before, these pre-event 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 pre-event 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 8 the responses of internal migration. Again, columns 1 and 2 investigate these responses without taking into account the possibility of there being specific pre-event trends. In line with what is suggested in Figure 3, the trends in the evolution of the share of low-skilled population leading to the policy change are not pronounced. 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.

4 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

Table 7: Effect of minimum wage changes on employment

VARIABLES	Share of employed low-skilled workers					
	(1)	(2)	(3)	(4)	(5)	(6)
Post treatment x intensity	-0.00359		-0.0253		-0.0109	
	(0.0324)		(0.0333)		(0.0350)	
Post treatment x intensity x share		0.129		-0.149		-0.0103
		(0.227)		(0.254)		(0.260)
Pre event trend x intensity			0.0387**		0.0301*	
			(0.0171)		(0.0178)	
Pre event trend x intensity x share below min. wage				0.406***		0.306**
				(0.124)		(0.120)
Pre event trend x intensity x federal change					0.0514**	
					(0.0253)	
Post event x intensity x federal change					-0.0344	
					(0.0863)	
Pre event trend x intensity x share below min. wage x federal change						0.685***
						(0.207)
Post event x intensity x share below min. wage x federal change						-0.361
						(0.595)
R-squared	0.739	0.739	0.741	0.744	0.743	0.749
Year FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes

Notes: This table shows estimates of Equations 16 and 17, using the share of employed low-skilled workers as a dependent variable. Standard errors are clustered at the state level. 1, 2, and 3 stars mean significance levels of .1, .05, and .01 respectively.

Table 8: Effect of minimum wage changes on internal migration

VARIABLES	Share of low skilled population					
	(1)	(2)	(3)	(4)	(5)	(6)
Post treatment x intensity	-0.100**		-0.121**		-0.118***	
	(0.0431)		(0.0492)		(0.0358)	
Post treatment x intensity x share		-0.599**		-0.742**		-0.724***
		(0.294)		(0.338)		(0.255)
Pre event trend x intensity			0.0372*		0.0438*	
			(0.0209)		(0.0258)	
Pre event trend x intensity x share below min. wage				0.210		0.255
				(0.133)		(0.166)
Pre event trend x intensity x federal change					-0.0350	
					(0.0405)	
Post event x intensity x federal change					-0.0149	
					(0.0965)	
Pre event trend x intensity x share below min. wage x federal change						-0.276
						(0.302)
Post event x intensity x share below min. wage x federal change						-0.0633
						(0.702)
R-squared	0.939	0.939	0.939	0.939	0.940	0.939
Year FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes

Notes: This table shows estimates of Equations 16 and 17, using the share of low-skilled population as a dependent variable. Standard errors are clustered at the state level. 1, 2, and 3 stars mean significance levels of .1, .05, and .01 respectively.

is particularly relevant since many papers compare different local 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 that should benefit from the policy change.

The second contribution of the paper is to provide empirical evidence which 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 -1.2. 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.

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A Data

In what follows I describe all the variables from the March CPS Files that I use in this paper. The source for these data is Ruggles et al. (2008). I also provide details on the other data set that I use.

A.1 March CPS

High- and low-skilled workers are defined using the variable EDUC, with those that are high-school graduates and high-school drop-outs defined as low-skilled.

The weekly wage is computed using the variables INCWAGE and WKSWORK1.

The employment status is computed using the variables EMPSTAT, WKSWORK1, UHRSWORK, and HRSWORK. The main definition of full-time employed workers are those whose EMPSTAT is equal to 10, 11, or 12, with a positive amount of weeks worked and a positive wage, and who are not self-employed. Full-time work is defined as that done by workers who worked more than 40 weeks in the previous year (WKSWORK1) and who usually worked more than 40 hours per week (UHRSWORK). The alternative measure of full-time employment uses the variable HRSWORK. By this measure, full-time workers are those who worked more than 40 hours in the preceding week.

For the share of full-time equivalents, I multiply the part-time employed workers by one half and I add them to the full-time employed.

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.

Data on minimum wages are taken directly from Autor et al. (2015). Before our use of these data, an RA coded the minimum wage changes independently; we obtain almost the exact same data set.

A.2 Unemployment benefits data

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 reported here. I obtain these data from:

http://www.oui.doleta.gov/unemploy/hb394.asp.

The definitions of the variables are in:

http://www.oui.doleta.gov/unemploy/hb394/gloss.asp.

B Replication of Allegretto et al. (2011) employment results

Table 9 replicates the employment results in Table 4 of Allegretto et al. (2011). In particular I run the regression:

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

where s indicate states and t years. When not using state-specific year trends I obtain a significant employment elasticity to minimum wage of -.3 for teen employment, and 0 for older low-skilled workers. This -.3 estimate for teens disappears when I include state-specific year trends. This is shown in columns (1) to (4) of Table 9. Columns (3) - (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 et al. (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 pre-event trends do not change with the inclusion or exclusion of state-specific linear year trends, as has been explained in the main text.

Table 9: Employment effects of minimum wage changes using state panel regressions

VARIABLES	(1) Share Emp. teens OLS	(2) Share Emp. teens OLS	(3) Share Emp. All OLS	(4) Share Emp. All OLS	(5) Share Emp. teens OLS	(6) Share Emp. teens OLS	(7) Share Emp. All OLS	(8) Share Emp. All OLS
(ln) Effective Minimum Wage	-0.281***	-0.0256	-0.0104	0.0305	-0.295***	-0.0368	-0.0724	-0.0446
	(0.0827)	(0.115)	(0.0457)	(0.0416)	(0.104)	(0.112)	(0.0455)	(0.0358)
Pre-event trend					0.0143	0.000729	0.0143***	0.0118***
					(0.0105)	(0.00728)	(0.00421)	(0.00340)
Post-event trend					-0.00345	0.00393	-0.00253	-0.00225
					(0.00686)	(0.00668)	(0.00219)	(0.00254)
Observations	1,428	1,428	1,428	1,428	1,249	1,249	1,249	1,249
R-squared	0.669	0.730	0.745	0.821	0.674	0.732	0.744	0.819
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes	yes	yes
State trends	no	yes	no	yes	no	yes	no	yes

Notes: This table replicates Table 4 in Allegretto et al. (2011) and the discussion in Neumark et al. (2014) using employment from the March CPS data.