Minimum Wages and Spatial Equilibrium: Theory and Evidence

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September 16, 2015

This paper may change in the near future.

Check **http://www.columbia.edu/~jm3364/Minimum_Wage_and_Space.pdf** for the latest version.

Abstract

Often, minimum wage laws are decided at the state or regional level, and even when not, federal level increases are only binding in certain states. This has been used in previous literature to evaluate the effects of minimum wages on earnings and employment levels. This paper introduces a spatial equilibrium model to think about the seemingly conflicting findings of this previous literature. It shows that the introduction of minimum wages can lead to an increase or a decrease in population depending on the local labor demand elasticity and on how unemployment benefits are financed. The paper provides empirical evidence consistent with the model. On average, increases in minimum wages lead to increases in average wages, decreases in employment and net population loss of low-skilled workers. The low-skilled local labor demand elasticity is estimated to be above 1, which in the model is a necessary condition for the migration responses found in the data.

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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 these 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), Hornbeck (2012), Hornbeck and Naidu (2012), Carrington (1996), 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 had not been shown before. More generally and relevant 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 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 combine all the changes in the effective minimum wage at the state level between 1985 and 2012.[2] Using all these events, I first show that prior to increases in minimum wages, wages of low-skilled workers tend to decrease while employment tends to increase. I interpret this as evidence that the timing of minimum wage changes is not entirely random – as implicitly assumed in previous papers. Second, I show that after the minimum wage changes, the negative trend in wages becomes positive, while the positive trend in employment disappears. This suggests that minimum wage laws have a positive impact on wages, as intended by the policy change, but also a negative impact on employment of low-skilled workers. This allows me to identify the local labor demand elasticity. My

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

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 workers should leave states that increase minimum wages. This prediction is supported by the data. A 1 percent reduction in the share of employed low-skilled workers reduces the share of low-skilled population by between .5 and .8 percent. These wage, employment and migration responses affect the low-skilled workers and not the high-skilled – which can be thought as a placebo test or control group.

This paper is related to some recent work. A handful of papers have studied migration responses to minimum wage laws. 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 the employment effect and the internal migration decisions. I view this as more direct evidence than the one reported in Cadena (2014).

There is also an active debate on the spillovers 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 were of about 11 percent. Around 20 percent of full time low-skilled workers of various ages are potentially affected by these policy changes. If those were the only workers affected and their wages changed by exactly 11 percent, the change in minimum wage laws would increase 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 than 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 the same workers in different regions may be more important than between workers of different types.

The immigration literature has also estimated local labor demand elasticities. If an (unexpected) inflow of low-skilled workers exogenously arrives to a particular local labor market, wages of competing workers are expected to decrease. Estimates of 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 zero (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 is in contradiction with the debate in the minimum wage literature. Most of the immigration literature, however, looks at longer time horizons – usually one decade – than what has been the focus of the minimum wage literature. When looking at shorter time horizons, I find in Monras (2015b), local labor demand elasticities that are in line with the one estimated in this paper.

Taken altogether, this paper argues that to properly understand the effect of minimum wages, it is crucial to think about what all the relevant group of workers affected by the policy change, whether this policy is implemented in years with particular economic conditions and to take into account that internal migration quickly reacts to changes in local labor market conditions.

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 K and labor 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 $Y_i = AF(K_i, L_i)$. Labor, instead, is fully mobile. Without loss of generality, we can normalize the total population to one: $P_1 + P_2 = 1$ (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 will 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 end in one of the two regions. I abstract from those in this paper. Fourth, I also abstract from other possible congestion forces, more 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 obscure them when 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. Firms maximize profits so:

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

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 (see for example Blanchard and Katz (1992)), but the main results of this paper do not depend on how I obtain this short-run local labor demand curve.

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 with certain probability (given by the unemployment rate) they will not have a job and will receive instead the (per worker) unemployment benefits (B), while with certain probability they will work at the market wage rate (w) and will have to pay taxes (τ). I also assume that the reservation wage is equal to zero.

2.3 Equilibrium

Two conditions define the equilibrium in this model. First, firms chose 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.

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:

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

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 any 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. This menas 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 equation 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 analyse the case when unemployment benefits are locally or nationally funded.

2.6 Locally funded unemployment benefits

In this section I analyse the case when 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. 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).[3] 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 one.*

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 an 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 that does not affect the expected value of the region.

2.7 Centrally funded unemployment benefits

In this section, I analyze the case when unemployment benefits are funded by the central government that imposes a common tax (τ) in both regions, as is the case in many countries. In this case, the financing constraint is: $(P_1 - L_1)B_1 = \tau \underline{w}_1 L_1 + \tau w_2 P_2$.[4]

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

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

In this case, we need to change some of the derivations in the previous section. Using the indifference condition for the location choice, we obtain:

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

This equation simply says that a worker in region 1 is unemployed with certain probability and receives the unemployment benefits, while with certain probability she is employed and receives the minimum wage (minus the taxes paid on this wage), while if she were in region 2 she would work with certainty and receive the wage in region 2, minus the taxes used to finance the unemployment benefits in region 1. In equilibrium workers should be indifferent between these two possibilities.

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 ($B_1 < w_1^{FME}$).[5] 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 zero. 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, then the only thing that matters is the local labor demand elasticity. It is only when there are unemployment benefits that there is an extra effect coming from the taxes in region 2 used to pay unemployment benefits in region 1.

When unemployment benefits are not zero there is a net transfer of resources from region 2 to region 1. If this is sufficiently high, which depends and 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 labor demand elasticity happen only in disequilibrium. It is only when we move from the no minimum

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

wage free market equilibrium to the new minimum wage equilibrium that this can arise. In other words, with minimum wages already in place, in what direction people move only depends again on the local labor demand elasticity. 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. However, if region 1 already has binding minimum wages and raises them, 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 combine all the changes in the effective minimum wage that took place between 1985 and 2012 – i.e. combining both the state and federal level changes – to show results on average wages, employment and migration. There are 441 state-year pairs where a state suffers a binding change on its minimum wage, sometimes because the state decides to change the state minimum wage law, and sometimes because the federal increase is binding. I use all these events to build my identification strategy. I consider three periods before and three periods after, and drop the state-year pairs outside these 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).[6]

I use three main variables of interest: 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 or less. This

[6] 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.

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 is what 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 regressions allowing for the returns to skill to be specific to the low-skilled labor market. 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.[7] 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 one for low-skilled workers. The assumption behind this procedure is 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. I run this regressions 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 the Appendix A I provide more details on how I construct all these variables.

To measure employed workers, I simply compute the share of workers (aged 25 to 64) who are full time employed according to the CPS. There are various variables in the CPS that identify whether a worker is employed or not. These can be divided in two groups of variables. The first are variables that refer to the worker's activity in the previous year. The second one are variables that refer to the working activity of the worker during the preceding week. The first group of variables is only available on the March Files of the CPS. The other variables are available also for the other months.

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

It is obvious that this is not the only possible measure of employment. The main results explained so far do not depend on how I define full-time employment. It is worth noting, however, that there are important differences in how increases in minimum wages affect part-time adult low-skilled employment and how it affects part-time teen employment. I discuss these, and the various employment measures when discussing Table 5 in section 3.6. Appendix A provides a detailed decription of the exact variables from the CPS that I use.

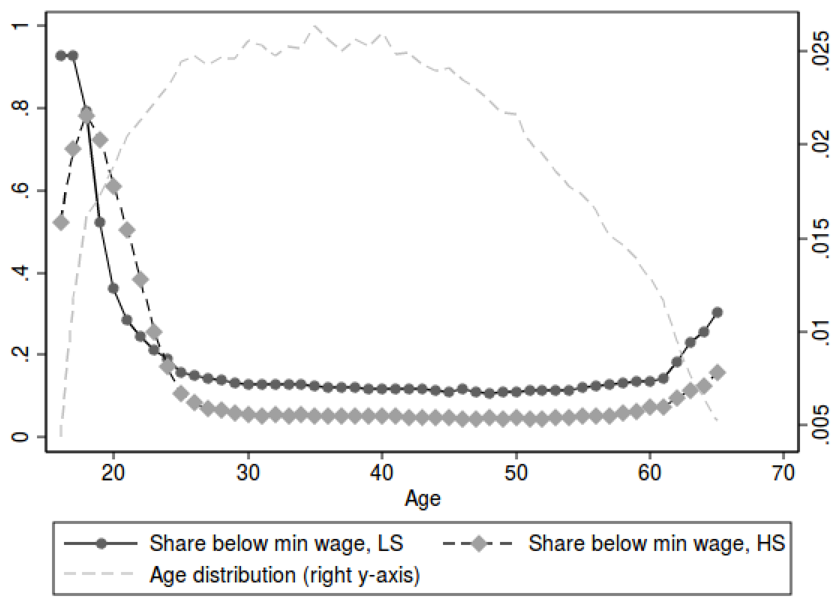
[7] Which are computed using the yearly income wage and the amount of weeks worked.

I distinguish high- and low-skilled workers using the high school diploma cut-off previously mentioned. I also use this cut-off to compute the share of working age population who is low-skilled, irrespective of their employment status. 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 about who should be taken into account as a potential minimum wage earner I plot in Figure 1 the share of workers who have weekly income 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 is much higher for workers below 24 years old, a non-negligible share of older low-skilled workers is also potentially affected. This figure also shows that the share of low-skilled workers below 24 years old is very small.

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.[8] 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.

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 dashed lines show the age distribution of the population.

Table 1 shows more concrete numbers than 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

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

full time, compared to around 52 percent among low-skilled who are older than 25 years old, and compared to almost 65 percent among the high-skilled. 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 around half of the US population that constitutes the potential labor market for low-skilled workers. Among those, around half work full time, while the other 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 than other low-skilled workers.

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. 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 state-year pairs, 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 which have changed the minimum wages a lot more often.

Over time, there is some variation in the number of states who are affected by a minimum wage change. Years when the federal level changes, like 1990, 1997 or 2009 are years where the vast majority of US states see changes in its effective minimum wage, 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.

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 its effective minimum wage in all these years.

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 in fact 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 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:

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

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.[9]

In this case, the dummies "event k" will be 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), 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 having had already 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.

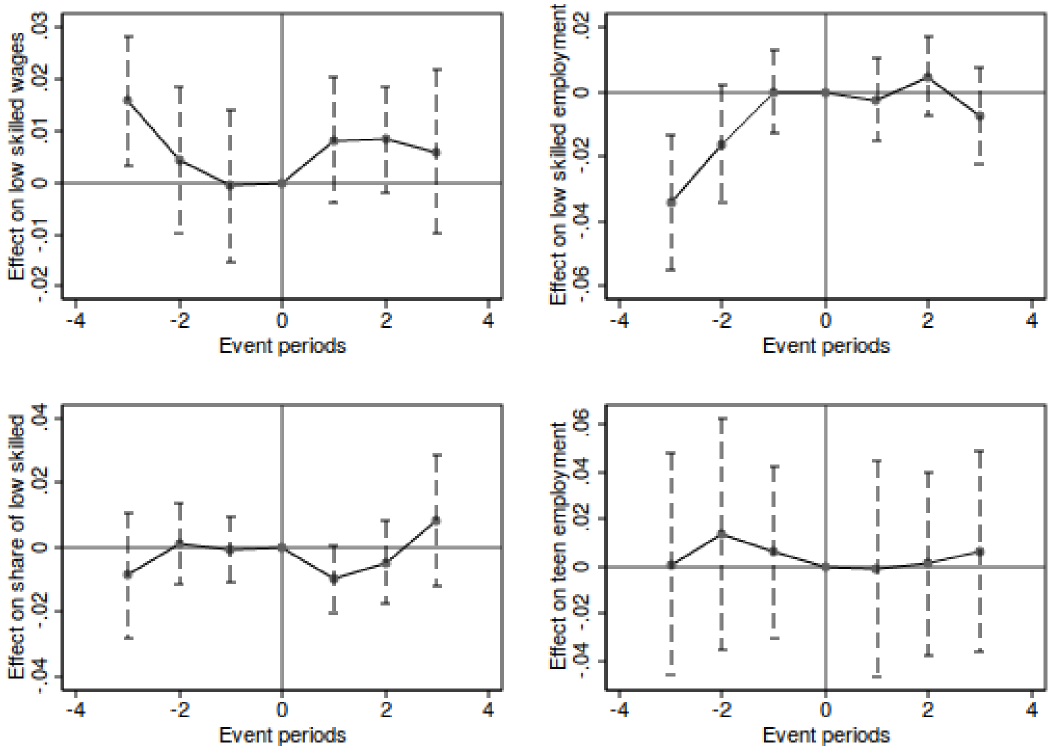
The estimates of these event period dummies are shown in Figure 2 for four outcome variables: average low-skilled (composition adjusted) wages, share of full time employment among low-skilled workers, share of low-skilled population and share of full time employment among teenage workers. The first graph shows the evolution of low-skilled wages around changes in minimum wage laws. Two things stand out. First, prior to the policy change average wages seem to be declining. Second, this trend seems to change in the year when minimum wage increases and particularly during the following year. I interpret this as evidence that the change in the policy did affect wages of low-skilled workers. It is also evidence that the policies tend to be implemented in periods of declining low-skilled wages.

Similar considerations apply when analysing what happens with the share of low-skilled 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. This can be interpreted as evidence that minimum wage changes tend to happen during periods when low-skilled wages decline, and low-skilled employment is strong. If policy makers anticipate that augmenting minimum wages will curve 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 workers

[9] Given the frequency of the minimum wage changes, I am somewhat constrained on 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



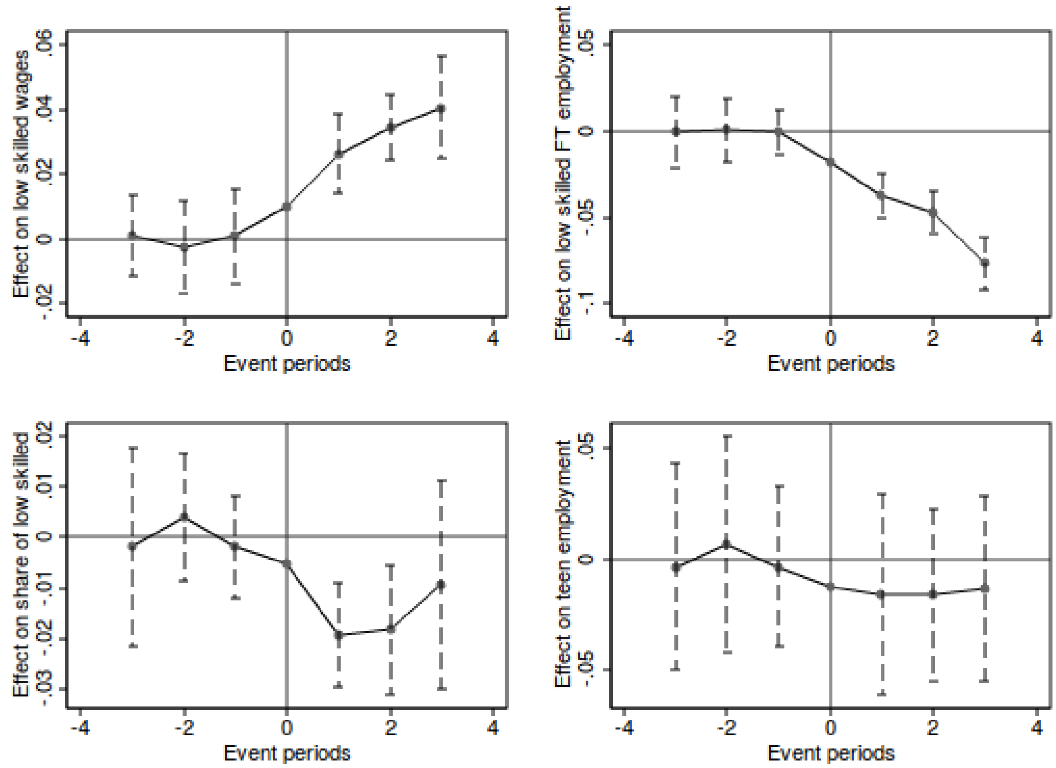
Notes: The four graphs show the estimate "event" dummies from regression 15 for four different outcome variables: Average (composition adjusted) low-skilled wages, full time low-skilled employment shares, share of low-skilled population and teen employment. The dotted vertical lines are 95 percent confidence intervals of robust standard errors clustered at the state level.

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. 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 teen employment to obtain strong conclusions.

In all, Figure 2 suggests that controlling for pre-event trends is extremely important. I argue in this paper that we can evaluate the effect of the policy by looking at the change in the trend. This is done in Figure 3. This Figure is the same as Figure 2 but where I fit (and remove) a linear trend in the 3 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 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

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



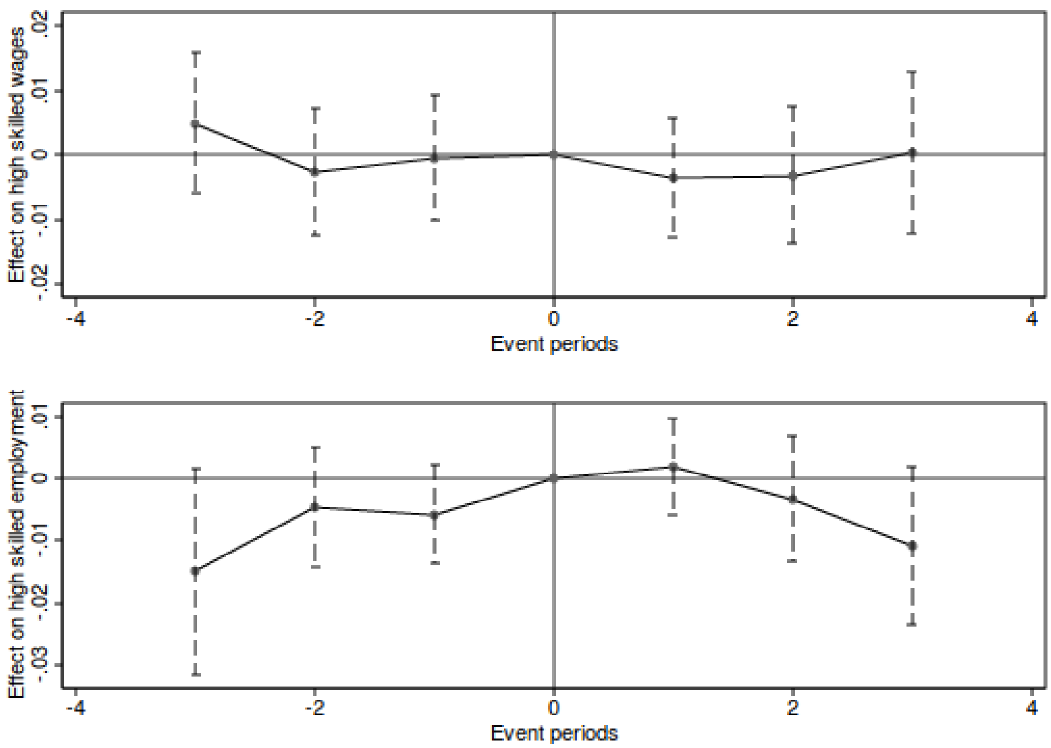
Notes: The four graphs show the estimate "event" dummies from regression 15 for four different outcome variables: Average (composition adjusted) low-skilled wages, full time low-skilled employment shares, share of low-skilled population and teen employment. In these graphs, the three pre-event periods 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.

below one. As I argued in the model, a local labor demand elasticity below one has a clear prediction for internal migration: the share of low-skilled workers should 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, there are no changes in these trends following the policy change.

In the appendix **??** I show alternative measures of looking at low-skilled employment. I show that I obtain very similar results and patterns if instead of using the share of low-skilled workers who are full time employed, I use the share of low-skilled who are full time equivalents (counting part time employed workers as half of the full time ones), if I use the number of weeks worked during the year, the usual hours worked per week or even when I look at the employment benefits paid by the state – using a different data set. I concentrate on full time employment because most of the change occurs through this margin, as can be seen when observing the magnitudes of the change in usual hours worked and weeks worked.

Figure 4: Wages, employment, and migration responses to minimum wage increases, detrended



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.

3.4 Estimates, elasticities and discussion of the findings

The previous graphs set the ground for my identification strategy. To quantify the effects displayed in them, I use the following regression:

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

where the "Post treatement" is simply a dummy variable taking value one the three years after the change in minimum wages, and taking value zero 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, during the period 0 is when the policy changes, so there are parts of the year with the policy change in place and parts without it. Also there are some events coded as zero that are the second year of consecutive changes in minimum wages. The variable "Pre-event trend" is a linear trend during the 3 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 could be a result of the policy or simply a change in the trend that is unrelated to the event. I report estimates under these two alternative assumptions. 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 order to make my identification strategy more transparent, I also report results on the simpler regression:

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

which is essentially the same as equation 14 but without allowing for specific trend changes.

The results are shown in Table 3. In it I show 4 different estimates, that are labelled as Model 1, Model 2, Model 3 and Model 4. Model 1 shows the estimates of running the simpler regression 15. As we can anticipate by looking at Figure 2, the estimates from this model are always 0. These estimates are essentially comparing the first 3 pre-event periods with the following one. Given the pre-trends shown in Figure 2 we can anticipate slightly positive estimates on wages, on employment and slightly negative estimates on 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 zero 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 workers 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, a 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 -.81, as shown also 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 below one, which, according to the model, should imply that the share of low-skilled population should decrease. In the 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[10] 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

[10] 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.

this case the standard errors are almost 5 times larger, showing the fact that I am using only 13 percent as much micro level information (see Table 1).

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.

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 the 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 rather than already in period 0). The estimate of the implied local labor demand elasticity is again below 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 estimates are very similar to Model 3.

Finally, I include a fifth model that includes state-specific time trends to equation 14. I report in this column the same coefficient as in Model 4. All the results are unchanged. This is true no matter what model I decide to use.[11] This means that the results in this paper do no depend on controlling for state specific linear trends or not. This is important given the recent debates over this issue reported in Dube et al. (2010), Allegretto et al. (2011) and responded by Neumark et al. (2014).[12]

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

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

[12] When I replicate Dube et al. (2010) and Neumark et al. (2014) I obtain very similar results even when using yearly data. It is more difficult though to control for pre-event trends using their estimation strategy.

(2015b) using migration shocks.

In Table 4 I show the wage and employment estimates for the high-skilled. Consistent with Figure 4, all the estimates in this table are small and never statistically distinguishable from 0. This can be thought as a control group, or as a placebo exercise for the results on the low-skilled.

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 plus Period 0	Change trend plus Period 0	Model 4 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 received the first immigrants. These first immigrants shaped the subsequent migration flows, so that an important reason why new migrants move into high immigration regions is not because those are more attractive but simply because they have better connections there.

Most of the literature on immigration that compares high and low immigration regions finds small wage effects (**?** is an early example).[13] If the economy is well described by a perfectly competitive model of the labor market, this suggests that, given this evidence, the local labor demand elasticity is very elastic, so that large inflows of workers have small effects on wages.

If this is the world where we live, increases in minimum wages should have 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 in Card (1992a,b), Allegretto et al. (2011); Dube et al. (2007, 2010).[14] This would imply that the local

[13] See also Card (2001) for another seminal contribution in this literature and see Card (2009) for a recent literature review.
[14] These are contested findings, see Neumark et al. (2014) for a longer discussion.

labor demand elasticity is inelastic, i.e. the employment effects are smaller than the wage effects. But if this is the case, the model presented before suggests that internal migration is particularly important since more people would be attracted towards the region that introduces the minimum wage. Can we reconcile this empirical evidence?

In some previous research, I document that whether wages respond to immigrant inflows depends crucially on whether migrants migrate because of push factors or not, and on the time horizon that we use to evaluate the wage effects (Monras, 2015b).[15] 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, I show in this that the migration responses are in line with the importance of the employment effect that model predicts.

3.6 Robustness and heterogenenity

3.6.1 Heterogeneity on 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 to see 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. I also provide evidence that unemployment benefits paid by the states increased after minimum wage increases. All these results are shown in Table 5. The identification strategy and the display of the results is identical to what I discussed in section 3.4. The message is clear. Given the overall identification strategy previously discussed, and independently of how I measure it, minimum wages lead to decreases in adult low-skill full-time employment and increases in adult part-time employment. Among teens 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 the high skilled.

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.[16] 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 zero, with implicit demand elasticities close but in general above one.

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

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

[16] 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.

force in the midst of the previous year or who have jobs that last for less than 40 weeks during the year. It is also workers who, even if they worked for more than 40 weeks, their usual hours worked per week was below 40. The results for this subgroup are clear. When minimum wages increase there are more part-time workers above 25 years old (than what the linear pre-trend would have predicted). Table 5 shows that the share of part-time workers increases by around 7 to 10 percent.[17]

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.

The fifth row counts as an employed worker the workers that are working, irrespective of whether they are 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)

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

almost exactly cancels out. The point estimates are slightly negative (2.7 x 52 is larger than 7 x 15). If instead, I consider part-time workers as half of a worker, I obtain decreases in the share of full time equivalent workers that are statistically different from zero. The magnitudes of these decreases are of around 2 - 3 percent (from an average of 60 percent).[18]

The estimates on full-time equivalent workers would imply local labor demand elasticities that are slightly below one. I do not consider this to be too problematic for the model. The model assumed risk neutral agents. With risk averse agents, the threshold for internal migration to move away from locations that increase minimum wages could be higher 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, in fact, when I do not restrict my attention to teen full-time employment (which is quite low) but I also look at part-time employment (which is much higher), I not only increase the precision of my estimates (which can often be distinguished from 0) but also become slightly more negative. There is some disagreement between these estimates and estimates from other CPS files (as I show in Appendix **??**), which makes me less sure about these results. This discrepancy also explains part of the positive results on teen employment obtained in previous literature.

Rows 10 and 11 consider the share of workers, among the low-skilled and the teenagers, who are not working. Increases in minimum wages seem to increase slightly teen 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 of 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 the adult low-skilled workers seems to increase. Third, teen 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 Federal changes versus states changes in minimum wages

This section reports results distinguishing the federal changes in minimum wages and the state level changes. 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 event that I used before to estimate the average wage, employment and migration responses.

Table 6 uses only changes in the federal level minimum wage, while table 7 uses only state-level changes. The results are similar, though the precision of the estimates decreases. In both cases I obtain positive estimates for the effect of minimum wage increases on average low-skilled wages, but it seems that federal changes are more effective than state-level changes. The employment response is very similar

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

across the two tables. The migration response, instead, seems to be stronger when analysing state-level changes.

Table 6: The effect of changes in the federal minimum wage

	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 low-skilled wages	-.004	.025	.048	.046	.044
s.e.	(.008)	(.021)	(.033)	(.033)	(.032)
p-value	[.619]	[.235]	[.152]	[.167]	[.170]
Effect on share of low-skilled employed, Full-time	-.013	-.093	-.126	-.114	-.068
s.e.	(.009)	(.025)	(.036)	(.033)	(.041)
p-value	[.132]	[.000]	[.001]	[.000]	[.098]
Effect on share of low-skilled population	-.008	.000	.005	-.001	.006
s.e.	(.015)	(.031)	(.040)	(.040)	(.030)
p-value	[.593]	[.992]	[.902]	[.987]	[.841]

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.

These findings seem to suggest that migration may be more important when fewer states are affected by minimum wage changes. In these cases, migration reacts quite strongly which may in turn help to understand why the estimated effects on wages are lower, since there may be some selection on who migrates.

Table 7: The effect of changes in the state minimum wage

	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 low-skilled wages	.006	.005	.003	.006	.002
s.e.	(.006)	(.019)	(.029)	(.028)	(.031)
p-value	[.288]	[.797]	[.908]	[.836]	[.940]
Effect on share of low-skilled employed, Full-time	.010	-.026	-.043	-.040	-.042
s.e.	(.006)	(.021)	(.036)	(.038)	(.032)
p-value	[.096]	[.203]	[.235]	[.285]	[.193]
Effect on share of low-skilled population	-.002	-.055	-.078	-.065	-.052
s.e.	(.006)	(.022)	(.031)	(.029)	(.030)
p-value	[.752]	[.011]	[.012]	[.024]	[.082]

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.

Again, these results highlight the importance of thinking about the trends leading to the event. They also highlight the potentially large effects that minimum wages seem to have on employment, and how thinking about internal migration may be quite important.

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 the local labor demand elasticity and it helps in thinking about net labor flows between local labor markets. This is particularly relevant since many papers compare different local labor markets to infer the effect of a wide range of policy changes, without taking into account the responses of internal migration.

When using the model to think about minimum wages two things are important. 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. Second, in a world where there are already minimum wages in place, or where 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 than one, migration away from the region that increases its minimum wage, irrespective of how unemployment benefits are financed.

The second contribution of the paper is to provide empirical evidence which is in line with the model. In particular, using an event type study design, I compute large internal migration responses away from states that increase minimum wages and an estimated local labor demand elasticity of around -1.2.

This research suggests that policy makers deciding about increases in minimum wages should probably coordinate across states or regions. Otherwise they may be generating spillover effects on other regions, that come through internal migration.[19] Something that I have not investigated in this paper – for lack of more individual level detailed annual data –, is whether this migration generated by minimum wage increases is selected in some ways. This is likely to be the case, which would add another dimension to the possible consequences of this policy.

[19] Note that similar arguments apply if there is mobility across sectors and minimum wage laws that affect only certain sectors.

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A Data

In what follows I describe all the variable 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 to define those that are high-school graduates and high-school drop-outs as those that are low-skilled.

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

The employment status is computed using the variables EMPSTAT, WKSWORK1, UHRSWORK, HRSWORK. The main definition of full-time employed workers are workers whose EMPSTAT is equal to 10, 11 or 12 with a positive amount of weeks worked, a positive wage, who are not self-employed and worked full-time. Full-time work is define by workers who worked more than 40 weeks in the previous year (WKSWORK1) and who usually worked more than 40 hours (UHRSWORK). The alternative measure of full-time employment uses the variable HRSWORK. Full-time workers are workers working 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, the number of observation per cell is used with the stata command analytic weights.

Data on minimum wages is taken directly from Autor et al. (2015). Before using these data an RA had coded the minimum wage changes independently and we obtained 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 used other variables and the findings are in line with what reported here. I obtained 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.