What is the Optimal Minimum Wage?

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Abstract

The extensive literature on minimum wages has found evidence for compression of relative wages and mixed results for employment. This literature has been plagued by a number of problems. The median-minimum wage-ratio has been used as the independent variable. First, the median is endogenous. Second, the minimum wage policies are also endogenous. Third, it is difficult to disentangle (i) compression of relative wages and (ii) truncation due to disemployment effects. Fourth, compression combined with an upward sloped labour supply curve implies both negative demand effects for the least skilled workers and positive supply effects for higher types. We offer solutions for all four problems, by using instruments for the mean and the minimum, by using data on personal characteristics, and by a careful specification of the heterogeneity in employment effects. We apply our method to US data starting from 1979, allowing for wide variation in minimum wages.

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1 Introduction

The extensive literature on the impact of minimum wages in the US typically reports strong compression of relative wages and a small employment effect. Many papers cannot rule out that an increase in the minimum wage will actually raise rather than reduce employment, see e.g. Card and Krueger (1994), Dube et al. (2010), Cengiz et al. (2019), Bailey et al. (2020) and Fishback and Seltzer (2020). Similar results have been reported for other countries, see Dolado et al. (1996) for Europe, Machin and Manning (1994) and Stewart (2012) for the UK, Ahlfeldt et al. (2018) for Germany and Engbom and Moser (2018) and Haanwinckel and Soares (2021) for Brazil.

Although this extensive literature has provided much insight, it has been plagued by a number of persistent problems, see e.g. Autor et al. (2016) and Neumark and Shirley (2021). First, minimum wage policies are endogenous, in particular at the state level. It isn't pure coincidence that California and Washington are among the states with both the highest median and the highest statutory minimum wage. Second, most research uses the Kaitz index (the ratio of the minimum to the median wage), as a measure of the bindingness of the minimum wage. However, the median is endogenous, due to either truncation of workers with low human capital or compression of relative wages. Moreover, there might be reverse causality: some outside force may drive up both the median and wage dispersion in a region, e.g. the IT revolution in San Francisco. The rise in the median will then lead to a fall in the Kaitz index, which induces the researcher to conclude that a less binding minimum wage leads to higher wage dispersion. Third, disentangling truncation and compression effects is almost impossible when using data on wages only without making strong functional form assumptions. Finally, there might be positive employment effects for low initial levels of the minimum, but nobody will believe that these effects remain positive indefinitely for higher levels of the minimum. Moreover, this effect is the unlikely to be the same for all levels human capital. Employment for the lowest percentiles of the human capital distribution might be reduced by an increase in the minimum, while higher percentiles still benefit. This paper addresses these problems.

A short review of the literature on minimum wages over the past 40 years is helpful for understanding our approach. Our review starts with Meyer and Wise (1983)'s analysis of the truncation effect of the minimum on the wage distribution, using data on wages only. They hypothesize that the minimum truncates an otherwise invariant wage distribution. The truncated lower tail can be split into three parts. For the first part of the truncated workers, the wage is raised to the statutory minimum, yielding a spike in the wage distribution. For the second part, there is non-compliance: workers get paid below the statutory minimum. The third part measures the disemployed effect. Meyer and Wise report a substantial loss of employment.

Subsequent research by Card and Krueger (1994), based on time series evidence and on a difference-in-difference approach between New Jersey and Pennsylvania found much smaller employment effects. This finding initiated a flow of papers explaining the combination of small or even negative truncation effects and strong wage compression.

A first strand of papers use monopsony models and models with search frictions, notably Bontemps et al. (2000), Machin et al. (2003), Flinn (2006) and Engbom and Moser (2018). These models can explain why an increase in the minimum wage might raise rather than reduce employment. Models with search frictions predict that job seekers underinvest in search when the Hosios condition is violated by job seekers capturing too smal a share of the match surplus. An outside legal intervention in wage setting can alleviate this hold up problem.

A second strand followed up on an idea first expressed by Rosen (1974) to apply hedonic pricing models for the analysis of minimum quality standards. In a Walrasian market, a minimum wage is akin to a minimum quality standard for human capital. Contributions in this strand are Teulings (1995, 2000) and Haanwinckel and Soares (2021). The idea is that small disemployment effects of minimum wages can go hand in hand with strong wage-compression effects by a chain of substitution effects, driving up the wages of those workers that are the closest substitutes for workers whose human capital falls below the implicit minimum quality standard imposed by the minimum wage and who therefore lose their job.

Motivated by this research, DiNardo et al. (1996), Lee (1999), and Teulings (2003) seek to explain the negative effect of the minimum on wage dispersion not from truncation of workers with low human capital, as in Meyer and Wise (1983), but from compression of relative wages. In particular Lee (1999) and Teulings (2003) found that a minimum wage generates strong compression of wage-differentials above the minimum. Lee (1999)'s paper was probably the first to use inter-state minimum wage differentials as a source of variation, allowing to control for time and region fixed effects. However, similar to Meyer and Wise (1983), he uses data on wages only. Hence, Lee has essentially to assume that the fall in wage dispersion is due to compression and not truncation. He concludes that the full increase in wage inequality during the eighties can be attributed to the freeze of the nominal minimum wage during the Reagan presidency. However, the problem in his analysis is that minimum wages were found to compress wages differentials not only in the lower, but also in the upper half of the distribution, which is implausible. Teulings (2003) also found strong compression, but mainly for the lower half of the distribution. He uses also data on workers' human capital, allowing separate inference on truncation (i.e. changing the distribution of human capital) versus compression (changing the wage distribution for a constant distribution of human capital).

Both Lee (1999) and Teulings (2003) used the Kaitz index as their independent variable. Autor et al. (2016) have argued that this procedure is suspect when e.g. 50-10% log wage differential serves as the endogenous variable. The median enters both the explanatory and endogenous variable. Hence, measurement error in the median introduces an artificial correlation, biasing the estimation results. Moreover, cities tend to have both a higher median and a larger wage dispersion than rural areas. Again, this creates an artificial correlation biasing the estimation results. Correcting for these biases, Autor et al. (2016) did not find significant evidence for compression effects above the spike, thereby confirming the initial assumption of Meyer and Wise (1983). Though one might dispute the validity of their instruments, their analysis shows convincingly the problem of using the Kaitz index as the explanatory variable.

Neumark and Shirley (2021) question the general view that the disemployment effect are small or even negative. They argue that there is clear evidence for negative employment effects for subgroups of low human capital workers. Their argument suggests that there is strong heterogeneity in the impact of minimum wages on employment, not only by the level of the minimum wage, but also between subgroups of workers.

Cengiz et al. (2019) try to correct the Meyer and Wise (1983) model for the compression effects above the minimum reported by Lee (1999) and Teulings (2003). Using data on wages only, they start from Meyer and Wise (1983) estimate of the disemployment effect. From this estimate they subtract the added probability mass for wage levels slightly above the minimum, arguing that these workers earned less than minimum wage before its increase and should therefore not be included in Meyer and Wise (1983) estimate of the disemployment effect. They found the disemployment effect to be small. We argue in this paper that it is impossible to calculate the magnitude of this effect from wage data only without making strong functional form assumptions.

From this short history of the extensive research on minimum wages, the main elements of our design are easy to understand. We tackle the problem of the endogeneity of the median by using the spike in the wage distribution rather than the Kaitz index as our explanatory variable. We interpret the spike as the objective of the policy maker and the nominal minimum wage as the instrument for implementing this objective. The spike will be determined by the real minimum wage. Hence, it depends both on the nominal minimum wage and on counterfactual evolution of nominal wages in general. We use a Bartik instrument for agglomeration externalities derived from a companion paper, Chen and Teulings (2021), to instrument for the counterfactual wage. Moreover we address the systematic differences in the wage distribution between cities and the countryside by treating 34 SMSA's as separate regions. We disentangle the truncation and the compression effect by aggregating a vector personal characteristics into single index for workers' human capital, following Teulings (2003), which we use for the analysis of both relative wages and employment. We solve the problem of heterogeneity in employment effects by analysing the effect on employment for each percentile of the human capital distribution and by allowing this effect to be non-linear in the spike. Our specification does not make a priori choices regarding the sign of employment effects for each quantile of the distribution. Moreover, it allows for a sign reversal when the spike exceeds some critical threshold. We use data starting from 1979, when the spike accounted for 5% of total employment for the country as a whole and even 10% in some low wage regions, to allow for sufficient variation in the spike for reliably establishing this turning point. These non-linearities allows us to quantify trade-offs legislators face when setting the minimum wage.

We find strong evidence both for the compression of wage differentials above the spike and for heterogeneous employment effects. The return to human capital for the median worker is 11% lower when the spike is 5% compare to the absence of a spike; it is even 30% lower for a worker earning a wage just above the minimum. For the lowest quantiles of the human capital distribution we confirm the conclusion of Neumark and Shirley (2021) of negative employment effects for the lowest percentiles of the human capital distribution. However, starting from the 7^{th} percentile, the sum of the employment effects for all lower percentiles of a small minimum wage is positive. Total employment in the lower tail of the distribution is maximized by a spike of 9%, leading to positive employment effects up to the 16^{th} percentile of the human capital distribution. The additional employment of this spike relative to a situation without a minimum wage is 2.2%

of total employment. Conditional on the specification of the model, these effects are precisely measured. We argue that this strong positive employment effect demonstrates the relevance of monopsony models above the hedonic pricing models.

We provide counterfactual simulations for several turning points in the evolution of the minimum. We find that the changes in minimum wage have contributed substantially to the variation in both the return to human capital and wage dispersion in the bottom half of the distribution and that an increase in the minimum wage might be an effective instrument for boosting the labour share in aggregate output. We do not attempt to provide a welfare theoretic framework for weighing the cost and benefits for various parts of the human capital distribution. However, those with a strong preference for an equal wage distribution and a higher labour share and who care less about the disemployment effect for the lowest percentiles of the human capital distribution will find arguments for a high spike in this paper.

The structure of the paper is as follows. Section 2 discusses some theoretical considerations regarding the compression effect in hedonic models. Section 3 discusses the steps of our empirical procedure. The data are discussed in Section 4, while the empirical specification and the estimation results are presented in Section 5. Section 6 contains the counterfactual analysis. Section 7 concludes.

2 Some theoretical considerations

2.1 Walrasian models

Modelling spillover effects of a minimum wage to the wages above the minimum is not straightforward. Rosen (1974) was probably the first to observe that edonic pricing models with heterogeneity on both sides of the market are a prerequisite for assessing the impact of minimum quality standards; a minimum wage is akin to a minimum quality standard for labour. Sattinger (1975) and Teulings (1995, 2005) analyzed equilibrium assignment models of heterogeneous workers to heterogeneous jobs, where the heterogeneity on each side is captured by a *single index*, say, the worker's human capital h and job-complexity z.[1] Gabaix and Landier (2008)'s model of CEO compensation has the same structure. This section shows why an increase in the minimum yields wage compression in these models.

Returns to scale are constant in these models. Let $x(h,z)$ be the log productivity of a worker with human capital h in a job with complexity z; $x(h,z)$ is assumed to be twice differentiable in both arguments. Human capital is assumed to have both an absolute advantage in all job-types, implying $x_h(h,z) > 0$ (more human capital yields more input, irrespective of the job type), and a comparative advantage in more complex jobs, implying $x_{hz}(h,z) > 0$ (log supermodularity: more human capital yields relatively more additional output in more complex jobs). The distributions of the supply of human capital and the demand for product complexity are exogenous; both distri-

[1] A single index is not the same as a single factor of production. In fact, single index models have an infinite number of factors of production, since each value of the index corresponds to a different factor of production. The elasticity of substitution between two factors is a decreasing function of the distance between these factors measured along the index: *DIDES: Distance Dependent Elasticity of Substitution*, see Teulings (2005).

bution functions are assumed to be twice differentiable. For the sake of the argument, we ignore other factors of productions. Finally, there is perfect competition on all markets.

Under these assumptions, absolute advantage implies that the equilibrium log wage function $w(h)$ is differentiable and strictly increasing, $w'(h) > 0$, while comparative advantage implies that the equilibrium assignment of worker- to job-types, $z(h)$, is also a differentiable and strictly increasing function, $z'(h) > 0$, see Teulings (2005) for a proof.

Since types of labour are the only factors of product and since there is perfect competition, wages account for the full value of output and profits are zero. Hence, profit maximization is equivalent to cost minimization. Since production is characterized by constant return to scale, cost minimization for a given quantity is equivalent to cost minimization per unit of output. Let $h(z)$ be the type of worker hired by an employer offering a job of complexity z; this function is therefore the inverse of $z(h)$, which exists since $z'(h) > 0$. The employer chooses the optimal level of human capital $h(z)$ as to minimize cost per unit of output

$$\begin{aligned} h(z) &= \arg\min_h \left[\mathrm{e}^{w(h)-x(h,z)} \right], \\ w'(h) &= x_h[h, z(h)], \end{aligned} \tag{1}$$

where the second line is the first order condition of the program in the first line, substituting z for $z(h)$ and hence $h(z)$ for $h[z(h)] = h$. This is a fundamental insight in this class of models: keeping constant the level of human capital h, the slope of the log wage function $w'(h)$ (or equivalently: the Mincerian return to human capital) is an increasing function of the complexity $z(h)$ of the job which an h-type worker holds in equilibrium. The same result applies in Gabaix and Landier (2008)'s model of CEO pay, where the return to a CEO's talent is proportional to the size of his firm. Keeping constant his managerial talent, the larger are firms, the steeper is the CEO compensation curve.

The impact of a minimum wage is conveniently demonstrated by a simple parameterization of this model: human capital and jobs are uniformly distributed at the unit interval, $h \in [0, 1]$ and $z \in [0, 1]$, and the productivity function satisfies

$$x(h, z) = -\frac{1}{\gamma}\mathrm{e}^{\gamma(z-h)},$$

with $\gamma > 0$; as can be checked easily, this specification satisfies the restriction of absolute and comparative advantage discussed previously. By equation (1) the first order condition reads

$$w'(h) = \mathrm{e}^{\gamma[z(h)-h]}. \tag{2}$$

It is easy to work out that the market equilibrium in this economy is $z(h) = h$. The situation is portrayed in Figure 1. The lower panel shows the assignment $z(h)$ worker- to job-types, while upper panel shows the wage function $w(h)$. All job-types are done and all worker-types are employed, where the worker with the least human capital is assigned to the simplest job, $z(0) = 0$, and the worker with the highest human capital to the most difficult job, $z(1) = 1$. Hence, $w'(h) = 1$. We choose the numeraire of the model such that $w(0) = 0$, so that $w(h) = h$.

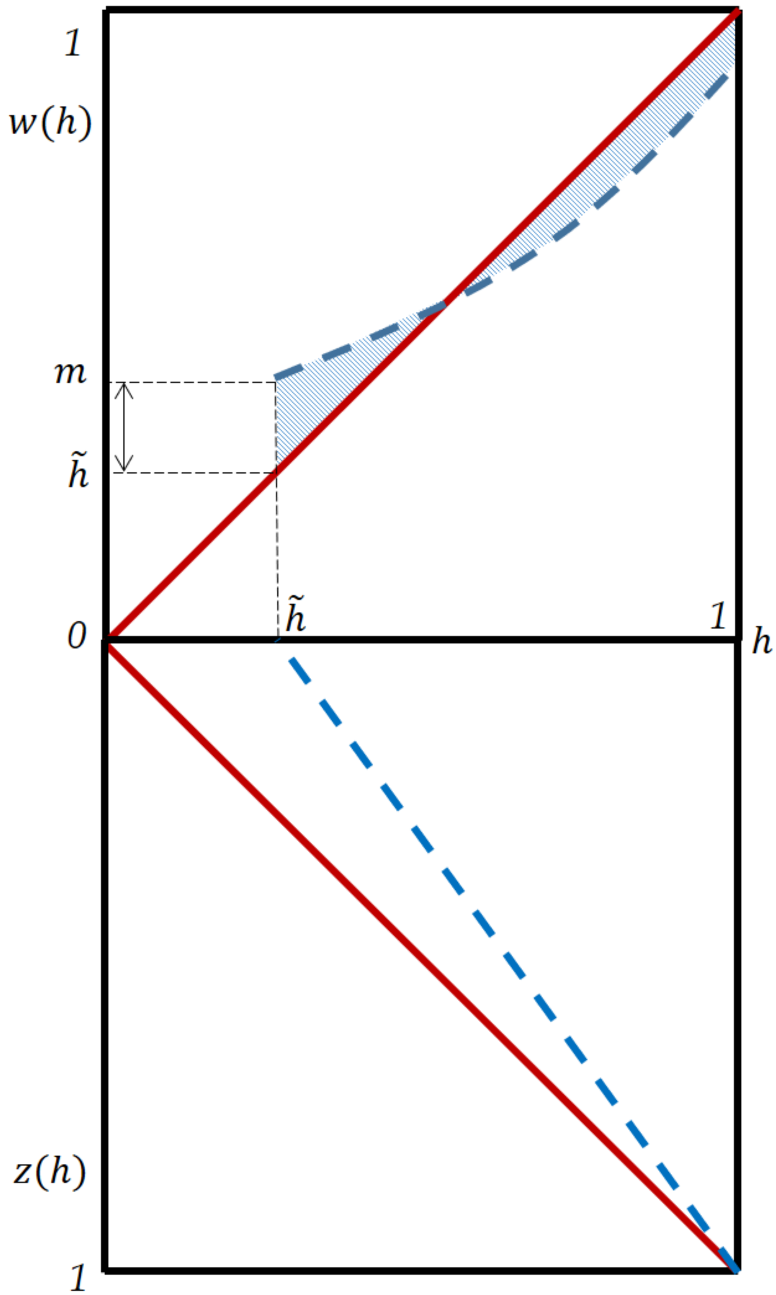

Figure 1: Equilibrium Assignment $z(h)$ and Wages $w(h)$

Consider the effect of log minimum wage m; since $w(0) = 0$, $m > 0$ for this minimum to be binding. The minimum wage causes the least skilled workers to lose their job. Let $\widetilde{h}$ be the worker with the lowest human capital who remains employed. Since h is distributed uniformly on the unit interval, $\widetilde{h}$ is the disemployment effect of the minimum wage as a fraction of total employment. $\widetilde{h}$ measures the *truncation effect* of a minimum wage on the wage distribution: wage dispersion is reduced since the workers with the least human capital lose their job.

Let $\widetilde{w}(h)$ and $\widetilde{z}(h)$ denote the wage function and the equilibrium allocation for this minimum wage. Both functions are also portrayed in Figure 1. Since all jobs have to be done and since $\widetilde{z}'(h) > 0$, the equilibrium assignment $\widetilde{z}(h)$ starts from $z\left(\widetilde{h}\right) = 0$ and ends at $z(1) = 1$. One can show that all worker-types who remain employed (that is: $h \in \left[\widetilde{h}, 1\right]$) hold jobs that are less complex after rather than before the introduction of the minimum wage, $\widetilde{z}(h) \leq z(h)$, where equality holds only for the highest type, $h = 1$. In words: a minimum wage causes the least skilled workers ($h < \widetilde{h}$) to lose their job. Since these jobs have to done anyway, all other workers move to less complex jobs than before the introduction of the minimum wage, except for the worker with the highest human capital who remains doing the most complex job.

Since $\widetilde{w}(h)$ is differentiable and increasing, the wage of the least skilled worker who remains employed is equal to the minimum wage:

$$\widetilde{w}\left(\widetilde{h}\right) = m.$$

Due to equation (2), the decrease in job complexity for all workers (except for $h = 1$) implies that the slope of the wage function declines: $\widetilde{w}'\left(\widetilde{h}\right) \leq w'(h) = 1$, where equality holds for $h = 1$ only. This flattening is the strongest for least skilled worker who remains employed, $\widetilde{h}$. It gradually declines for higher levels of human capital. At the upper support of the human capital distribution, the wage function before and after the introduction of the minimum wage run parallel. Since our example is constructed such that $w(h)$ is linear (and hence $w''(h) = 0$) in the absence of a minimum wage, $\widetilde{w}''(h) > 0$ with a minimum.

These arguments establish the slope of $\widetilde{w}(h)$, but not its level. The latter follows from a Walrasian argument, see Teulings (2005) for a proof. Consider a marginal increase in the minimum wage, forcing workers with $h < \widetilde{h}$ out of employment. Since wages are equal to the value of the marginal product, the fall in aggregate output due to this increase in the minimum must be equal to the wage sum of the workers who loose their job. Hence, the sum of wages for all workers who remain employed must be equal before and after the introduction of the minimum wage:[2]

$$\int_{\widetilde{h}}^{1} \mathrm{e}^{\widetilde{w}(h)} - \mathrm{e}^{w(h)} \mathrm{d}h = 0, \tag{3}$$

Since the wage function flattens, equation (3) implies that the wages at the bottom go up, while these at the top go down. This is the *compression effect* of a minimum wage. Roughly stated, the

[2]The formula holds up to a term of $O\left(m^2\right)$.

two blue shaded areas in Figure 1 between the functions $\widetilde{w}(h)$ and $w(h)$ must have equal surface.[3] We shall use equation (3) to calculate the aggregate shift in value added between labour and other factors of production due to an increase in the minimum wage.

As equation (2) shows, this compression effect is proportional to γ. For $\gamma = 0$, the return to human capital is independent of workers' assignment to jobs $z(h)$. Hence, there is no compression effect in that case.

Summarizing the conclusion of this analysis. For $\gamma > 0$, the introduction of a minimum wage has three effects:

1. *truncation*: workers with the least human capital, $h < \widetilde{h}$, lose their job;
2. *compression*: the return to human capital $w'(h)$ falls for all levels of human capital, except for the highest, the more so the lower h; hence, $w''(h)$ rises;
3. the sum of wages for workers who remain employed remains constant; hence, workers with h slightly above the disemployment threshold $\widetilde{h}$ gain by the introduction of a minimum wage, while workers at the top of the human capital distribution lose.

Note however that the compression effect in this model is driven by the truncation effect: workers take less complex jobs after the introduction of a minimum wage since the least skilled workers are eliminated from the distribution of employed workers. Without a truncation, this model does not generate compression. Note furthermore that this model does not predict a spike in the wage distribution.

2.2 Identification from only the wage distribution

Cengiz et al. (2019) seek to establish the disemployment effect of minimum wages just from the shape of the wage distribution. They set out to establish the additional probability mass in the wage distribution just above the minimum due to the compression effect and compare that additional mass to the truncated mass below the minimum. The disemployment effect is measured as the difference between this truncated mass minus the additional mass just above the minimum (workers previously employed below the minimum who found employment in jobs that pay above the minimum after its increase). This section applies the framework developped in the previous section to argue that this method works only under restrictive functional form assumptions.

Empirically, the distribution of human capital is bell shaped (like the normal distribution) rather than uniform. Consider an increase in the minimum wage. Does an increase in the fatness of the lower tail of the wage distribution provide evidence in favour of either truncation or compression? The answer is: hard to tell. Let $w(h, m)$ denote the equilibrium log wage as a function of the human capital h of the worker and the applicable log minimum wage m. It is convenient

[3] The of both blue shaded areas requires

$$\int_{\widetilde{h}}^{1} \widetilde{w}(h) - \widetilde{w}(h)\,\mathrm{d}h = 0.$$

Hence, this condition is not exactly the same as equation (3).

to construct the index h such that for a particular level of the log minimum wage m^o, the function is linear in h: $w_{hh}(h, m^o) = 0$ (the subscript refers to the relevant partial derivative).[4] Let $h(m)$ be lowest level of human capital that is employed for that level of the log minimum m (the equivalent of $\widetilde{h}$ from the previous section). Like in the previous section, we assume that, apart from the truncation at $h(m)$, the supply of human capital $f(h, m)$ is exogenously fixed. Except for the renormalisation due to this truncation, the density of the human capital distribution is therefore invariant to changes in the minimum wage

$$f(h, m) = \frac{f(h)}{1 - F[h(m)]} \text{ for } h \geq h(m),$$

where $f(h)$ denotes the untruncated distribution of human capital that applies in the absence of a minimum wage. The density function of the log wage distribution, $g(w, m)$, is equal to the density of human capital distribution $f(h, m)$ times the Jacobian $\mathrm{d}h/\mathrm{d}w = 1/w_h(h, m)$:

$$g[w(h), m] = f(h, m) / w_h(h, m).$$

The relative change in the density function of log wages at the minimum is therefore equal to

$$\begin{aligned} \frac{\mathrm{d}}{\mathrm{d}m} [\log g(m, m)]_{|m=m^o} &= \left(\frac{f'[h(m^o)]}{f[h(m^o)]} + \frac{f[h(m^o)]}{1 - F[h(m^o)]} \right) h'(m^o) \\ &\quad - \frac{w_{hm}[h(m^o), m^o]}{w_h[h(m^o), m^o]}, \end{aligned} \tag{4}$$

using $w_{hh}(h, m^o) = 0$. The first term is the truncation effect: the change in the lower support of the human capital distribution among employment. The second term is the compression effect: the flattening of the wage function. Since $f'(h)$ is positive in the left tail of a bell shaped distribution, both effects are positive. If the truncation effect is large (that is: low disemployment) and the compression effect is small, then the first term dominates. In the reverse case, the second term dominates. The change in the fatness of the left tail of the wage distribution is therefore an uninformative statistic regarding the relative size of the truncation versus the compression effect.

This argument sketches the outline of a potential solution to this problem in the approach of Cengiz et al. (2019). When information on workers' human capital is available, the lower support $h(m)$ can be established empirically. This allows us to disentangle both effects. This strategy is pursued in remainder of this paper.

3 Empirical specification

We consider a world which consists of multiple regions r which are observed at multiple points in time t; the index s refers to a combination of region r and time t; we refer to each s as an economy. We ignore interregional mobility and dynamic interactions. The market equilibrium in economy s

[4] Following the argument in the previous section, $w(h, m)$ is stricly increasing in h for any m. Hence, such an index does always exist, by setting $h = w(h^*, m^o)$, where h^* is some alternative human capital index. The normalization is not essential, but makes the subsequent argument more easy to follow.

is therefore independent of that in other economies. Each worker i is located in a single economy s, so the index i uniquely identifies the economy s in which she lives.

Similar to the model in Section 2, the human capital of worker i can be summarized in a *single index* h_i. This index has an infinite support on the real domain. The wage-return to this index may vary across economies, but the way in which various components of workers' human capital (like experience and years of education) are aggregated into this single index h_i is invariant across economies. However, the index h_i is observed only partially:

$$h_i = g_i + \varepsilon_i, \tag{5}$$

where g_i is the observable part of the human capital index h_i and $\varepsilon_i \sim N\left(0, \sigma_s^2\right)$ the unobservable component which is orthogonal to g_i. Note that we allow the variance σ_s^2 of ε_i to vary between economies to allow for changes in the role of unobservable components of h_i in the course of time.

Let m_s be the log minimum wage in economy s and let $w_s\left(h, m\right)$ be the log nominal wage for a worker with human capital h in economy s when the log minimum wage is equal to m. Hence, $w_s\left(h\right) \equiv w_s\left(h, m_s\right)$, the log wage function evaluated at the actual log minimum wage m_s in economy s, is the function that generates our data on log wages w_i. Note that we allow the wage function $w_s\left(h, m\right)$ to vary between economies for other reasons than the minimum wage. In line with the analysis Section 2, we assume that this function is twice differentiable and strictly increasing in h everywhere, except for the spike at the minimum wage, where the function is flat. Let $h_s\left(m\right)$ be the upper support of the spike in economy s as a function of the log minimum wage; at $h_s\left(m\right)$, $w_s\left[h_s\left(m\right), m\right]$ is continuous but non-differentiable; the function is flat to the left of $h_s\left(m\right)$; it is increasing to its right. $h_s \equiv h_s\left(m_s\right)$ is the upper support of the spike in our data. Hence:

$$\begin{aligned} w_s\left[h_s\left(m\right), m\right] &= m, \\ w_s\left(h, m\right) &> m, \qquad \forall h > h_s. \end{aligned}$$

The Meyer and Wise (1983) model is the special case of this model where $w_s\left(h, m\right)$ does not depend on m for all $h > h_s\left(m\right)$.

The research questions we address is how $w_s(h, m)$ and the density function of human capital depend on the minimum wage. The standard approach has been to use the Kaitz index (ratio of the median to the minimum wage) as an index for the bindingness of the minimum wage. The problem of this approach is that the median wage itself is endogenous, as it is potentially affected by the truncation and compression effects. Even more problematic, there are systematic differences between economies in their wage distribution unrelated to the minimum wage. In particular, both the mean and dispersion of the wage distribution tend to be higher in cities due to agglomeration externalities and other factors. This yields negative correlation between the Kaitz index and wage dispersion, that is unrelated to the minimum wage. We therefore do not use the Kaitz index, but the spike as a measure of the bindingness of the minimum wage. We view the minimum wage as an instrument of the policy maker to manipulate the level of the spike. Hence, our first stage regression analyses the effect of the minimum wage on the spike, while our second stage regression33s analyze the effect of this instrument for the spike on wages and employment.

Following this argument, we apply a 5-step estimation procedure for addressing our research questions:

1. The construction of the index g_i for observed human capital;

2. The estimation of the upper support of the spike h_s for each economy;

3. The first stage regression for the spike;

4. The second stage regression for the effect of the spike on the wage function $w_s(h, m)$;

5. The second stage regression for the effect of the spike on the distribution of employment.

These steps will be elaborated in the subsequent subsections. Before doing so, we provide a discussion of the data.

4 Data

We draw data from the Current Population Survey, Merged Outgoing Rotation Groups (CPS-MORG) from 1979 till 2019. We use the hourly wage, years of education, occupation, industry and other demography information as gender, age, marital status, and race. Our sample includes all workers aged between 16 and 64.

For our classifications of regions, we first select 34 Metropolitan Statistical Areas (MSAs). We then take the remaining part of each state as one non-city region. The definition of MSAs changes overtime. To make the samples consistent, we match different IDs of these areas over time. From 1979 to 1985, we use 1970 Census ranking to identify MSAs. From 1986 to 1988, we use CMSA and PMSA identifier. From 1989 to 2003, we use MSAFIPS and for the rest of samples we use CBSAFIPS. Out of the total sample of 2,099,847 observations, 36.2% lives in MSAs. We have 47 Non-MSA state regions: as is common practice, we exclude Hawaii and Alaska. Furthermore, we split New Jersey from NY-NJ MSA, and exclude Washington DC, leaving us with 34 MSAs and 47 non-city regions, 81 regions in total. The full list of MSAs is in Appendix Table A1. We use the industry definition by Autor et al. (2003) and the crosswalk constructed by IPUMS.

Let q_s be the spike in the wage distribution at the minimum wage. We operationalize the definition of the spike by including all workers whose log wage is equal to m_s plus or minus .01 (that is 1% above or below the minimum). The details of the construction of the spike are in the Appendix, while summary statistics table are in Table A2.

5 Estimation

5.1 Step 1: the human capital index

For the construction of the index g_i for observed human capital, we apply a second order polynomial for the function $w_i = w_s(h_i)$:[5]

$$\begin{aligned} w_i &= \omega_{0s} + \omega_{1s} h_i + \omega_{2s}\left(h_i^2 - \sigma_s^2\right) \\ &= \omega_{0s} + \omega_{1s} g_i + \omega_{2s} g_i^2 + \varepsilon_{wi}, \\ g_i &= \chi' x_i, \end{aligned} \tag{6}$$

where we substitute equation (5) for h_i in the second line and where x_i is the standard vector of observable personal characteristics like gender, marital status, age, race and education. This specification implies that we allow for a separate fixed effect ω_{0s}, a separate return to human capital ω_{1s} and a separate second order effect ω_{2s} for each economy s, while the parameter vector χ is common to all economies. Using equation (5), we can work out the that the error term $\varepsilon_{w,i}$ satisfies

$$\varepsilon_{wi} = \left(\omega_{1s} + 2\omega_{2s} g_i\right)\varepsilon_i + \omega_{2s}\left(\varepsilon_i^2 - \sigma_s^2\right)$$

and has zero mean. Empirically, the error term captures not only unobserved human capital, but also measurement error and the effect of search frictions. Angrist and Krueger (1991) show that the measurement error accounts for 30% of the variance in log wages, while Gottfries and Teulings (2021) show that search frictions account for another 10%. The actual interpretation of ε_i does not matter for our estimation results, since we are only interested in the parameter vector χ aggregating the components of x_i into a single index for observed human capital g_i.

Equation (6) allows full flexibility ω_{0s} and ω_{1s} across economies s. There are good reasons for this: the return to human capital has increased between 1979 and 2019, in particular for higher levels of human capital, see Autor and Dorn (2013). However, equation (6) allows too much flexibility. In fact, it is under-identified.[6] We therefore impose further structure:

$$\begin{aligned} \mathrm{E}\left(x_i\right) = 0 \quad &\Rightarrow \quad \mathrm{E}\left(g_i\right) = 0, \\ \mathrm{E}\left(\omega_{1s}\right) = 1, & \end{aligned} \tag{7}$$

where the expectations are taken over all individuals in the sample in the first line and over all economies in the second line.[7] These assumptions imply that human capital index h_i is scaled as such that the "*average*" worker in our sample (with $h_i = g_i = 0$) has a return to this index of unity "*on average*" across regions and over the time span of our sample. This choice is just a normalisation

[5] Strictly speaking, this specification violates our assumption that $w_s(h)$ is strictly increasing. In practice, the support of h is limited to the domain $[-2, 2]$, so that this will not be a problem as long as $|\omega_{2s}| < 4\omega_{1s}$.

[6] We can apply a linear transformation to g_i, $g_i^* = \chi_0 + \chi_1 g_i$, that is observationally equivalent to equation (6) by an appropriate change in the parameters ω_{0s}, ω_{1s} and ω_{2s}:.$\omega_{0s}^* = \omega_{0s} - \omega_{1s}\chi_0 - \omega_{2s}\chi_0^2$, $\omega_{1s}^* = \left(\omega_{1s} - 2\omega_{2s}\chi_0\right)/\chi_1$ and $\omega_{2s}^* = \omega_{2s}/\chi_1^2$

[7] $\mathrm{E}\left(x_i\right) = 0$ implies that x_i cannot contain an intercept.

facilitating the interpretation of our results. Furthermore we impose additional structure on ω_{2s}

$$\omega_{2s} = \omega_x (t - \mathrm{E}t), \tag{8}$$

implying that ω_{2s} is the same across regions, while the variation over time is restricted to a linear time trend with zero mean over the time span of our sample. Hence, we impose *"on average linearity"* of $w_s(h, m)$ in h for the construction of the human capital index g_i. Again, this is not really a restriction, but a convenient normalisation, since we can include everything and its square in the vector x_i to capture any non-linearity in the relation between g_i and w_i to an arbitrary degree of precision. We do so in our empirical specification, by allowing for a number of well known non-linearities, e.g. the experience profile and the interaction between years of education and experience and by using dummies for each value of years of education. Moreover, deviating slightly from our assumption that χ is constant across economies, we included cross effects of marital status, gender, and a time trend to account for the changes in the attitude towards working women. Similarly, we account for the differential impact of being black in Southern states.

Equation (6)-(8) is a simple NLLS model. It can be estimated in an iterative way, by first estimating a standard OLS earnings with economy fixed effects

$$w_i = \omega_{0s} + \chi' x_i + \varepsilon_{wi}.$$

These first round estimate of χ can be used to construct g_i, which is then use to estimate ω_{0s}, ω_{1s} and ω_x by one OLS regression for all economies simultaneously

$$w_i = \omega_{0s} + \omega_s g_i + \omega_x (t - \mathrm{E}t) g_i^2 + \varepsilon_{wi}, \tag{9}$$

These estimates for ω_{0s}, ω_s and ω_x can be used to reestimate the vector χ, etc., until the procedure converges. The converged results are the maximum likelihood estimates of the NLLS model. In practice, we stop after the first two steps, since the value of χ obtained after the second iteration hardly differs from the first iteration.

We run this regression for a subsample of the economies with the lowest spikes. We have two reasons for doing so. First, a large spike implies that the wage function is flat for a substantial part of the wage distribution, disturbing the estimation of χ. Second, we have a mild preference for a human capital index h_i which is *"on average"* linear in the counterfactual economy, where the minimum wage is only mildly binding. We approximate this by omitting the economies with the highest spikes from sample used for the estimation of χ. Note that this is only a matter of presentation and does not affect the validity of our method, since we will control for non-linearities in the relation between log wages and the human capital index later on. We have experimented a bit by omitting 10%, 20%, 30%, and even 40% of the economies with the highest spike. It does not matter much for our estimates of the parameters χ. Moving from 30% to 40% does not affect our estimates of χ in a significant way. We choose to use the estimation results excluding 30% of the economies with the highest spike in the subsequent steps. Tables A3 and A4 shows the number states and years that is included in bottom 70% regarding spike for each year and state respectively.

The coefficients χ are presented in Table A5 in Appendix.

The mean of the distribution of g_i in economy s evolves over time due the rise in educational attainment and it differs between regions, due to strong agglomeration of highly educated workers in metropolitan areas. For reasons discussed later on, it is convenient to define g_i relative to a proxy for its mean $\overline{g}_s$. However, we want to avoid demeaning by the sample mean, for similar reasons as we want to avoid using the Kaitz index as a measure of the bindingness of the minimum wage, since the mean is endogenous. Hence, we regress g_i on fixed time and region effects and an instrument, based on a companion paper on the size of regional agglomeration externalities, see Chen and Teulings (2021). In line with the evidence in Gennaioli et al. (2013), we show that higher educated agglomerate in particular regions. We use a Bartik instrument for $\overline{g}_s$, using the idea that its evolution is driven by its industry mix. We use nationwide changes in the level of human capital in a each industry. We hypothesize that regions where industries with rising human capital are overrepresented experience a rise in $\overline{g}_s$.[8] We exclude the own region from the calculation of nation wide mean of these instruments, see Chen and Teulings (2021) for details. The coefficient of this Bartik instrument is 0.410 ($t = 12.62$), implying that when for the industry mix of state, the nation wide mean of g increases by one unit, the regional mean is predicted to increase by 0.410. In the remainder of the paper, g_i refers to this regionally demeaned version of the index.

Figure 2 shows the overall distribution of g_i, controlled for the local mean in the way described above. This distribution is approximately normal. It has zero mean by construction, see equation (7), and its variance and standard deviation are 0.135 and 0.367 respectively.

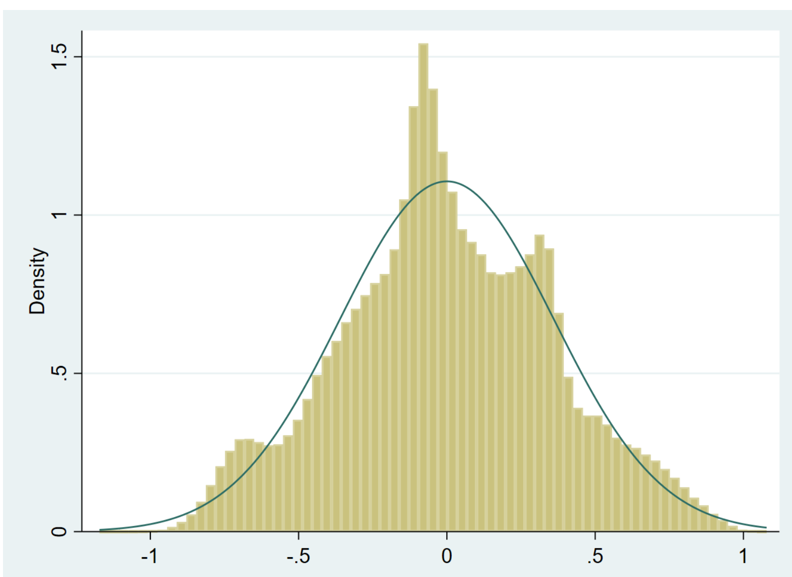

Figure 2: Histogram of $g_i - \bar{g}_s$

[8]Along the same lines, one can develop a second instrument, using nation wide changes in the industry mix rather than nation wide changes in $\overline{g}_s$ within industries. When entering both instrument, this second instrument was insignificant, so we omit it from our estimation results.

5.2 Step 2: the upper support of the spike

The next step in our empirical strategy is to establish the uppersupport of the spike h_s for each economy. The challenge here is that we have to account for the fact that h_i is only partially observed. Equation (6) implies

$$w_i = w_s(h_i) = w_s(g_i + \varepsilon_i).$$

Since $w_s(h_i) > m_s$ for $h_i > h_s$, h_s can be estimated by means of a simple Probit model:

$$\Pr(w_i < m_s + .01|g_i) = \Pr(g_i + \varepsilon_i < h_s|g_i) = \Phi\left(\frac{h_s - g_i}{\sigma_s}\right), \tag{10}$$

where we add add $.01$ to m_s to be consistent with the definition of the spike. The Probit-parameter on g_i is an estimate of $-\sigma_s^{-1}$; the intercept is an estimate of h_s/σ_s.

For small values of q_s, the number of observations in the spike is low: an average economy has slightly less than 1500 observations on workers in our data. A spike of 1.5% is equivalent to roughly 25 workers. For a smaller number, the estimate of h_s becomes highly unreliable. We estimate the model for all economies with $q_s > 1.5\%$; 1414 economies meet this restriction. In all subsequent stages where we use the estimation results on h_s, we report both the results for the full sample of economies and for the restricted sample for which the spike q_s exceeds 1.5%.

Since the distribution of g_i is approximately normal, see Figure 2, and using our assumption that the distribution of ε_i is normal, we can calculate the share of observations that earn less or equal to the minimum

$$\Pr(w_i < m_s + .01) = \Pr(h_i < h_s) = \Phi\left(\frac{h_s - \overline{g}_s}{\sigma_{hs}}\right), \tag{11}$$

$$\sigma_{hs}^2 = \sigma_s^2 + \sigma_{gs}^2,$$

where σ_{gs}^2 and σ_{hs}^2 are the variances of g_i and h_i respectively for economy s. We use $\mathrm{E}(\varepsilon_i|s) = 0$ and hence $\mathrm{E}(h_i|s) = \overline{g}_s$. The estimation results for equation (10) provide an estimate of σ_s, while $\overline{g}_s$ and σ_{gs} can be calculated from the data. Since σ_{hs}^2 is subject to substantial measurement error, we instrument σ_{hs} by region and time fixed effects; a hat on a variable denotes the instrument (the explained part of a first stage regression)

$$\sigma_{hs} = \widehat{\sigma}_{hs} + \varepsilon_{\sigma hs},$$

$$\widehat{\sigma}_{hs} = \sigma_{hr} + \sigma_{ht}.$$

where σ_{hr} and σ_{ht} denote vectors of region and time fixed effects.

There is convenient way to evaluate the estimates of h_s. Ignoring non-compliance (the part of the wage distribution below the minimum wage) for the sake of the argument, $\Pr(w_i < m_s + .01)$ is equal to the spike q_s. Define h_{qs} as the inverse of q_s with respect to the normal distribution:

$$h_{qs} = \widehat{\sigma}_{hs}\Phi^{-1}(q_s). \tag{12}$$

Hence

$$h_{qs} \cong h_s - \overline{g}_s. \tag{13}$$

Equation (13) can be tested. Since $\text{Var}\,(h_{qs}) = 0.128 > \text{Var}\,(h_s) = 0.042$, the measurement error in h_{qs} is likely to be larger than in h_s. Hence, we run equation (13) as a regression taking h_{qs} as the endogenous variable. The estimation results for the restrictive sample of economies are reported Table 1. Since h_{qs} is a non-linear transformation of q_s, we expect outliers among the error terms of this regression. We therefore estimate this equation by both OLS and a robust method allowing for non-normality of the error term.

Table 1: OLS and Robust Regression results for $\bar{x}_s$

	(1)	(2)
VARIABLES	h_{qs}	h_{qs}
h_s	1.014	1.019
	(59.45)	(56.89)
$\bar{g}_s$	0.320	0.322
	(2.04)	(1.96)
R-squared	0.721	0.703
RMSE	0.108	0.114
Regression	OLS	Robust
Observations	1,414	1,414

t-statistics in parentheses

The coefficient for h_s is indeed equal to unity. The coefficient for $\overline{g}_s$ is positive, but much smaller unity. However, a large share of the variation $\overline{g}_s$ is already absorbed by the demeaning of g_i by means of fixed region and time effects and the Bartik, see the discussion of Step 1. OLS or robust estimation makes little difference. We conclude that our estimation results for h_s and the index h_{qs}, which derived from the data for q_s, are mutually consistent.

5.3 Step 3: the first stage regression for the spike

We use the previous analysis of the relation between the spike q_s and its upper support h_s as benchmark for the construction of an instrument for the spike. Suppose that Meyer and Wise (1983)'s model had applied. Then, the wage function above the minimum wage minimum wage would be independent of the minimum. Due to our normalisation of the index g_i, it would be linear *"on average"* in w_i with a unit slope. The coefficient of a regression of h_{qs} on m_s would therefore be equal to unity in that case. The transform h_{qs} is therefore a natural starting point for the construction of an instrument.

Three factors determine the evolution of the real regional minimum wage:

1. Increases in the nominal federal minimum wage; since the federal minimum is not binding in all states, changes in the federal minimum are not fully absorbed by the inclusion of time fixed effects;

2. Increases in the nominal state minimum wage;

3. The gradual increase in nominal wages reduces the real value of a fixed nominal minimum wage. Since the nominal minimum wage is adjusted at irregular intervals, this factor plays an important role in the variation of the minimum. In fact, the fall in the real minimum wage during the Reagan presidency was fully due to the nominal freeze of the federal minimum. To the extent that the evolution of real wages is the same across regions, it is fully absorbed by time dummies. However, we can expect interregional heterogeneity in the evolution of wages.

Our first stage regression allows for these three factors.

$$h_{qs} = \alpha_r + \alpha_t + \alpha_m m_s + \alpha_w w_{\mathrm{IV}s} + \varepsilon_{qt}, \tag{14}$$

where α_r and α_t are region and time fixed effects and where $w_{\mathrm{IV}s}$ is an instrument for the real wage. The variable m_s covers both the effect of the federal and the state minimum wage. The variable takes the value of either the federal or the state minimum wage that is binding. The third factor is covered both by the region and time fixed effects and by the Bartik instrument discussed in Step 2.

Table 2: Instrumental Variable First Stage Regression

	(1)	(2)	(3)	(4)
VARIABLES	h_{qs}	h_{qs}	h_{qs}	h_{qs}
m_s	1.211	1.357	1.396	1.414
	(21.97)	(24.80)	(34.24)	(40.30)
Bartik IV	-4.040	-4.319	-2.576	-3.138
	(-7.01)	(-7.55)	(-3.60)	(-5.09)
Observations	1,414	1,414	3,321	3,321
RMSE	0.886	0.890	0.838	0.870
RMSE	0.0724	0.0719	0.147	0.126
Time Dummy	Y	Y	Y	Y
Region Dummy	Y	Y	Y	Y
Regression	OLS	Robust	OLS	Robust

t-statistics in parentheses

Table 2 presents the results for equation (14). We present results for both the full and the restricted sample of economies [9]. Again, we present both OLS and robust estimation results. The regression results are very similar for all four regressions. The coefficient on m_s is between 1.2 and 1.4, where the estimation results for the full sample are in the upper part of that bracket. Had Meyer and Wise (1983)'s model had applied, the coefficient would have been equal to unity. The estimation results are in that range. More remarkable is the coefficient on the Bartik instrument. The sign is accordance with the theoretical expectations (higher nominal wages reduce the spike),

[9] For some economies, the measured value of q_s is zero. Hence, h_{qs} cannot be calculated. For these economies, h_{qs} is set at the lowest value observed among other economies

but its magnitude is much higher. For demeaning of g_i, its coefficient was 0.410. Since the wage function has "*on average*" a unit slope in g_i, this effect is "*reinstalled*" by a coefficient of -0.410. The actual coefficient is 6 to 10 times larger. This points to substantial agglomeration benefits, compare Chen and Teulings (2021). Since this effect is discussed extensively in our companion paper and in Gennaioli et al. (2013), we do not discuss this finding in the current paper.

We use the results for the robust regression on the full sample and the inverse of equation (12) to calculate the instrument $\widehat{q}_s$

$$\widehat{q}_s = \Phi\left(\widehat{h}_{qs}/\widehat{\sigma}_s\right). \tag{15}$$

5.4 Step 4: the second stage regression for wages

A simple approach to the estimation of the effect of the spike on the wage function would be to regress individual log wages w_i on a second order polynomial in g_i similar to equation (6) for all individuals earning more than the minimum wage, $w_i > m_s + 0.01$, and then to use simple regressions to analyse how the coefficients ω_{0s}, ω_{1s} and ω_{2s} depend on $\widehat{q}_s$. This approach fails, however, due to the selectivity at the lower bound: the individuals in the sample are positively selected on earning a wage above the minimum wage. This problem could be resolved by estimating a non-linear Tobit model for all economies simultaneously. This approach is computationally infeasible, however, since there are several thousand economies in the full sample. Instead, we apply a 2-step procedure to correct for this selection bias similar to the classic 2-step Heckman-method.

First, we regress log wages on a second order polynomial in g_i as suggested above for each economy s, simply ignoring the problem of selection bias:

$$w_i = \widetilde{w}_s(g_i) + \widetilde{\varepsilon}_{wi},$$
$$\widetilde{w}_s(g_i) = \widetilde{\omega}_{0s} + \widetilde{\omega}_{1s} g_i + \widetilde{\omega}_{2s} g_i^2.$$

Here $\widetilde{w}(g_i) >\mathrm{E}(w_i|g_i)$ due to the selection bias introduced by including only individuals for which $w_i > m_s + .01$. Let $\mathrm{Bias}_s(g_i)$ be this selection bias in economy s as a function of the observed component of the human capital index g_i

$$\mathrm{Bias}_s(g_i) = \widetilde{w}_s(g_i) - w_s(g_i).$$

The bias at the upper support of the spike h_s can calculated using the fact that by construction $w_s(h_s) = m_s$. Hence

$$\mathrm{Bias}_s(h_s) = \widetilde{w}_s(h_s) - w_s(h_s) = \widetilde{w}_s(h_s) - m_s. \tag{16}$$

Alternatively, $\mathrm{Bias}_s(h_s)$ can be calculated from a first order Taylor expansion of $w_s(h)$ around $h = h_s$:

$$\begin{aligned}\mathrm{Bias}_s(h_s) &= \mathrm{E}\left[w_s(h_s+\varepsilon)|\varepsilon>0\right] \cong w_s'(h_s)\,\mathrm{E}\left[\varepsilon|\varepsilon>0\right] \\ &= \widehat{\sigma}_s w_s'(h_s)\frac{\phi(0)}{\Phi(0)},\end{aligned} \tag{17}$$

This Taylor expansion would hold exactly if $w_s(h)$ were linear in h. This expansion is a reasonable approximation for small non-linearities in the wage function and for small $\widehat{\sigma}_s$.

Equation (17) for $\mathrm{Bias}_s(h_s)$ can be generalized to the calculation of the bias $\mathrm{Bias}_s(g_i)$ for $g_i \neq h_s$ as follows:

$$\begin{aligned}\mathrm{Bias}_s(g_i) &= \mathrm{E}\left[w_s(g_i+\varepsilon)\,|\varepsilon > h_s - g_i\right] \cong w_s'(h_s)\,\mathrm{E}\left[\varepsilon|\varepsilon > h_s - g_i\right] \\ &= \widehat{\sigma}_s w_s'(h_s)\frac{\phi\left[(g_i-h_s)/\widehat{\sigma}_s\right]}{\Phi\left[(g_i-h_s)/\widehat{\sigma}_s\right]} = \left[\widetilde{w}(h_s)-m_s\right]\frac{\Phi(0)}{\phi(0)}\frac{\phi\left[(g_i-h_s)/\widehat{\sigma}_s\right]}{\Phi\left[(g_i-h_s)/\widehat{\sigma}_s\right]},\end{aligned}$$

where the last step follows from combining equation (16) and (17). Similar to the second step of the 2-step Heckman method, we use the last expression to calculate

$$\widehat{w}_i = w_i - \mathrm{Bias}_s(g_i),$$

and then run the wage regression

$$\widehat{w}_i = \omega_{0s} + \omega_{1s}g_i + \omega_{2s}g_i^2 + \varepsilon_{wi}.$$

The estimate for ω_{0s}, ω_{1s} and ω_{2s} do not suffer from selection bias.

Next, we run a regression of the parameters ω_{0s} for each economy s on a polynomial in $\widehat{q}_s$, the Bartik instrument and fixed region and time effects, and the same for ω_{1s} and ω_{2s}. Again, we run this regression for both the full and the restricted sample of economies and we use both OLS and robust regression techniques. The estimation results are in Table 3.

A comparison of Panel A and Panel B shows that the estimated coefficients are very similar in OLS and robust regression, but that they are estimated more precisely when accounting for outliers by using robust regression. We therefore focus on the latter results. Next, the results for the full and the restricted sample are qualitatively similar, but the coefficients are larger when using the full sample. This is to be expected, since the variance in the explanatory variable $\widehat{q}_s$ is reduced in the restricted sample. This yields a lower signal-noise ratio. Hence, we focus on the results for the full sample.

The difference between Panel B and C, is the former uses a second order polynomial in $\widehat{q}_s$, while the latter uses a third order polynomial. Since the coefficients on the third order terms in Panel C are significant for all three regressions for ω_{0s}, ω_{1s} and ω_{2s}, we use the latter for our counterfactual simulations in Section 6. However, the results for the second order polynomial are more easy to interpret. The subsequent discussion therefore focuses on these results.

Recall that $\overline{g}_s$ (the mean value of g_i for economy s) is roughly normalized to zero for each economy by means of region and time fixed effects and by the Bartik instrument (see Step 1). Hence, ω_{0s} is the log wage for mean worker in economy s, ω_{1s} is the return to human capital for this worker, while $2\omega_{2s}$ is the second derivative of the log wage function $w_s(h_i, m_s)$. The regression results imply therefore that for a low spike $\widehat{q}_s$, an increase in the spike raises the wage of the median worker, reduces the return to additional human capital for this worker, while the second derivative goes up. Due to the positive second derivative, the negative effect on the first derivative is lower

Table 3: Regression with Bias_s corrected $\widehat{\omega}_{0s}$ $\widehat{\omega}_{1s}$ and $\widehat{\omega}_{2s}$

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ω_{0s}	ω_{1s}	ω_{2s}	ω_{0s}	ω_{1s}	ω_{2s}
Panel A: with 2SLS Regression						
$\widehat{q}_s$	2.333	-2.403	2.864	2.720	-4.834	5.268
	(4.16)	(-3.79)	(2.99)	(9.87)	(-13.82)	(10.99)
$\widehat{q}_s^2$	-4.753	28.30	-43.94	-7.524	46.35	-60.22
	(-0.96)	(5.06)	(-5.20)	(-2.73)	(13.23)	(-12.55)
Bartik IV	5.945	0.134	-6.216	4.071	0.224	-3.659
	(15.49)	(0.31)	(-9.48)	(17.49)	(0.76)	(-9.04)
R-squared	0.988	0.701	0.624	0.985	0.579	0.497
RMSE	0.0454	0.0514	0.0776	0.0464	0.0589	0.0807
Panel B: with Robust OLS Regression						
$\widehat{q}_s$	2.506	-0.829	0.785	3.322	-4.914	5.297
	(5.75)	(-1.36)	(0.86)	(13.62)	(-14.21)	(10.94)
$\widehat{q}_s^2$	-6.710	16.18	-29.02	-16.68	53.46	-68.89
	(-1.84)	(3.17)	(-3.78)	(-6.89)	(15.57)	(-14.34)
Bartik IV	6.933	0.00568	-6.333	4.329	0.496	-3.910
	(23.09)	(0.01)	(-10.03)	(23.35)	(1.89)	(-10.63)
R-squared	0.993	0.731	0.663	0.991	0.676	0.575
RMSE	0.0366	0.0512	0.0769	0.0369	0.0524	0.0733
Panel C: with Robust OLS Regression						
$\widehat{q}_s$	0.427	3.484	-6.510	-1.262	7.527	-9.283
	(0.85)	(4.96)	(-6.19)	(-4.29)	(18.22)	(-15.75)
$\widehat{q}_s \times \ln\widehat{q}_s$	-0.739	1.410	-2.284	-1.488	3.731	-4.111
	(-2.79)	(3.81)	(-4.11)	(-11.06)	(19.75)	(-15.25)
Bartik IV	6.987	-0.323	-5.784	4.889	-1.008	-2.255
	(22.86)	(-0.76)	(-9.03)	(26.21)	(-3.85)	(-6.03)
R-squared	0.993	0.731	0.665	0.991	0.689	0.579
RMSE	0.0366	0.0511	0.0767	0.0364	0.0511	0.0729
Time Dummy	Y	Y	Y	Y	Y	Y
Region Dummy	Y	Y	Y	Y	Y	Y
Observations	1,414	1,414	1,414	3,321	3,321	3,321

t-statistics in parentheses

for higher levels of g_i; it has disappeared for $g_i = 0.46$,[10] which is one and a quarter standard deviations of g_i above its mean. This fits the theoretical notion developed in Section 2.1 that the effect should be zero at the uppersupport of the distribution of g_i.

For a higher spike, the marginal effect of a further increase in the spike switches signs for all three variables; for the level ω_{0s}, this occurs at a spike of 10%; for the return to human capital at 5%; and for the second derivative at 4%. The wage of the mean worker is 16% higher[11] for a spike of 10% rather than 0%, while the return to the human capital index g_i is 11% lower[12] for a spike of 5% rather than 0%. At the upper support of the spike, the compression of the return to human capital is even 30%. Summarizing: we find strong compression effects for wage levels above the minimum, in accordance with the theoretical model in Section 2, which persist even for quite high levels of the spike.

5.5 Step 5: the second stage regression for employment

The final step is to estimate the employment effect. We use regressions on quantiles of the human capital distribution to address this problem. Let g_{sp} be the p-quantile of the distribution of g_i in economy s. We estimate g_{sp} for the first 20 percentiles ($p = .01, .02, .03...., .20$), applying the specification below:

$$\begin{aligned} g_{sp} &= \beta_r + \beta_t + \beta_w w_{\mathrm{IV}s} + (\beta_{rp} + \beta_{tp} + \beta_{wp} w_{\mathrm{IV}s})\, p + \beta_{pp} p^2 + \beta_{3p} p^3 + \beta_{4p} p^4 \\ &\quad + \left(\beta_q + \beta_{qp} p + \beta_{qpp} p^2 + \beta_{q3p} p^3\right) \widehat{q}_s + (\beta_{qq} + \beta_{qqp} p)\, \widehat{q}_s^2 + \varepsilon_{gsp}. \end{aligned} \tag{18}$$

This specification allows for region and time fixed effects and for the effect of the Bartik instrument, both in the level and the slope with respect to p and the fourth order polynomial in p to allow for the non-linearity in the general shape of the quantile function. The interesting terms are in the second line where we analyze the effect of the spike on employment at various quantiles of human capital distribution.

The estimation results are presented in Table 4, standard errors are clustered at the economy level. A comparison of column (1) and (2) shows that the inclusion of p^4 as an additional regressor does not affect the cross-terms with $\widehat{q}_s$ and $\widehat{q}_s^2$. This is important, since it shows that cross-terms are not a proxy for an incomplete specification of the functional form of g_{sp} as function of p. Since the coefficient on p^4 is highly significant, we retain it in subsequent columns.

The terms for $\widehat{q}_s$ and $\widehat{q}_s^2$ not crossed with p are not or only weakly significant (compared to the t-values for other coefficients). They are hard to interpret as they measure the effect of $\widehat{q}_s$ on g in the lowest quantile in economy s. This can only be true if all employment below that lower support is completely eliminated by an increase in the spike, which is unlikely, in particular in the presence of unobserved heterogeneity. Hence, we consider the regression excluding these effects in column (3) and (4): $\beta_q = \beta_{qq} = 0$.

[10] $4.9/(2 \times 5.3)$

[11] $3.3 \times 0.1 - 16.5 \times (0.1)^2$

[12] $-4.9 \times 0.05 + 53.5 \times (0.05)^2$. Note that the return to the human capital index g_i is normalized to unity "*on average*". Hence, this effect can be interpreted as a relative change in the return to human capital.

Table 4: Employment Regression

VARIABLES	(1) g_{sp}	(2) g_{sp}	(3) g_{sp}	(4) g_{sp}	(5) g_{sp}
$\widehat{q}_s$	-0.644	-0.644			
	(-4.83)	(-4.83)			
$\widehat{q}_s \times p$	36.15	36.15	21.32	28.78	-6.068
	(19.86)	(19.86)	(12.51)	(11.21)	(-1.83)
$\widehat{q}_s \times p^2$	-446.0	-446.0	-322.6	-507.2	-753.3
	(-29.24)	(-29.24)	(-22.99)	(-11.59)	(-12.03)
$\widehat{q}_s \times p^3$	1,359	1,359	1,008	2,449	8,460
	(32.04)	(32.03)	(25.27)	(8.15)	(19.92)
$\widehat{q}_s \times p^4$				-3,579	-22,917
				(-5.18)	(-23.96)
$\widehat{q}_s^2$	-1.118	-1.118			
	(-0.93)	(-0.93)			
$\widehat{q}_s^2 \times p$	33.19	33.19	25.01	25.01	65.02
	(3.46)	(3.46)	(2.74)	(2.74)	(6.71)
p^2	3.637	41.61	39.25	42.78	49.51
	(8.27)	(47.31)	(44.94)	(36.40)	(35.91)
p^3	-35.32	-311.9	-305.2	-332.8	-297.5
	(-28.82)	(-57.25)	(-55.90)	(-41.57)	(-30.52)
p^4		658.5	658.5	727.0	690.7
		(54.96)	(54.96)	(39.62)	(30.75)
Bartik IV	0.0631	0.0631	0.247	0.277	-1.060
	(0.60)	(0.60)	(2.29)	(2.55)	(-7.23)
Bartik IV $\times p$	2.154	2.154	0.812	0.589	7.263
	(2.81)	(2.81)	(1.04)	(0.75)	(8.89)
Time $\times p$	Y	Y	Y	Y	Y
Region $\times p$	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y
Region	Y	Y	Y	Y	Y
Observation	66,420	66,420	66,420	66,420	66,420
R-squared	0.969	0.970	0.970	0.970	0.958
RMSE	0.0278	0.0274	0.0275	0.0274	0.0313

Robust t-statistics in parentheses

For the interpretation of these results we consider a "*representative*" economy, so that we can drop the subscript s. Below, all subscripts refer to the relevant partial derivatives. We assume that employment for the upper 80 percentiles of the human capital distribution is not affected by changes in the spike. In that case, the change in the density function in the lowest percentiles is a first order approximation of the relative change in the employment at that percentile.

Let $F(g,q)$ and $f(g,q) \equiv F_g(g,q)$ be the distribution and density function respectively of the observed part g of the human capital index in the representative economy, and let $g(p,q)$ be the observed human capital index g for quantile p, both as a function of the spike q. These definitions imply that the function $F(g,q)$ is the inverse of $g(p,q)$ with respect to p:

$$\begin{aligned} F[g(p,q),q] &= p, \\ g[F(g,q),q] &= g. \end{aligned}$$

These relations hold identically for all p, g and q, and hence their derivatives apply. Totally differentiating the first equation with respect p and q and rearranging terms yields

$$\begin{aligned} f[g(p,q),q] &= 1/g_p(p,q), \\ F_q(g,q) &= -\frac{g_q[F(g,q),q]}{g_p[F(g,q),q]}. \end{aligned} \tag{19}$$

The latter equation is the effect of q on total employment for all workers with observed human capital less than g. This expression can be applied for the evaluation of the relative effect of a change in the spike on the employment for particular percentiles of human capital distribution. Substitution of $g = g(p,g)$ and hence $F(g,q) = p$ yields the relative change in employment

$$\frac{F_q[g(p,q),q]}{p} = -\frac{g_q(p,q)}{p \cdot g_p(p,q)} = -\frac{f[g(p,q),q]}{p} g_q(p,q) \cong -\frac{\phi\left[\Phi^{-1}(p)\right]}{\sigma_g p} g_q(p,q), \tag{20}$$

where we substitute equation (19) in the second step and where we use the fact that the distribution of g is approximately normal in the final step; hence $f(g,\cdot) \cong \sigma_g^{-1}\phi(g)$. The expression in the first step requires the evaluation of $g_q(p,q)$ and $g_p(p,q)$. The evaluation of $g_q(p,q)$ is straightforward, using the estimated coefficients in Table 4. The evaluation of $g_p(p,g)$ is more complicated, since it involves all terms in the first line of equation (18), including the economy specific fixed effects. The expression in the third step is therefore convenient since it only requires an estimate of σ_g, which can be taken directly from the data, while the factor $\phi\left[\Phi^{-1}(p)\right]/p$ is a number depending on the quantile p only.[13]

Employment goes down for the lowest quantiles of the human capital distribution, up to $p = 6\%$, but it increases for higher quantiles, up to $p = 17\%$. The increase employment for these higher quantiles outweighs the loss in employment for the lower quantiles. The marginal employment effects for each quantile are in Figure 3 (see the Appendix for the derivation of the effect on the

[13]We obtain

$$p^{-1}F_q[g(p,q),0] = -(.367)^{-1}\phi\left[\Phi^{-1}(p)\right]\left(28.8 - 507p + 2450p^2 - 3579p^3\right)$$

Table 5: Estimated marginal employment effect

p	.01	.05	.10	.20
$p^{-1}\phi\left[\Phi^{-1}(p)\right]$	2.67	2.06	1.75	1.40
$p^{-1}F_q\left[g(p,q),0\right]$	−1.74	−2.55	0.50	2.55

density).

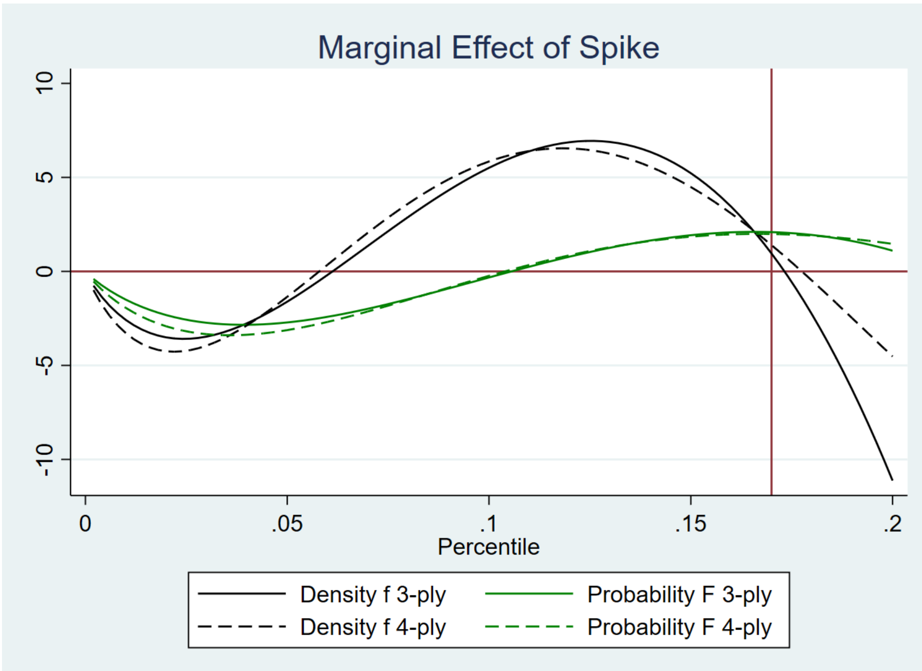

Figure 3: Estimated marginal employment effects using Table 4 columns 3-4

Suppose there exists a value $q_{Fg}^{\max} > 0$ of q for which employment $F(g,q)$ reaches a maximum. This $q_{Fg}^{\max}$ maximize therefore total employment for workers with human capital g_i less or equal than g. $q_{Fg}^{\max}$ solves $F_q\left(g, q_{Fg}^{\max}\right) = 0$, or equivalently

$$g_q\left[F\left(g, q_{Fg}^{\max}\right), q_{Fg}^{\max}\right] = 0. \tag{21}$$

The second order condition of this problem is

$$g_{qq}\left[F\left(g, q_{Fg}^{\max}\right), q_{Fg}^{\max}\right] > 0 \Rightarrow \beta_{qqp} > 0,$$

using equation (18) in the second step. Substitution of $F\left(g, q_{Fg}^{\max}\right) = p$, we obtain

$$q_{Fg}^{\max} = -\frac{1}{2}\frac{\beta_{qp} + \beta_{qpp}p + \beta_{q3p}p^2}{\beta_{qqp}},$$
$$g = g\left(p, q_{Fg}^{\max}\right),$$

where we use column (3) from Table 4 for the sake of the argument. This is a system of two equations, that can be solved recursively for $q_{Fg}^{\max}$ and then for g as functions of p. Let $q_F^{\max}$ be the maximum value that $q_{Fg}^{\max}$ can attain; such a maximum exists if $\beta_{qpp} < 0$ and $\beta_{q3p} > 0$. The value of $p_F^{\max}$ for which that maximum is attained and the implied value of $q_F^{\max}$ reads

$$\begin{aligned} p_F^{\max} &= -\frac{\beta_{qpp}}{2\beta_{q3p}} = \frac{322.6}{2 \times 1008} = 16\%, \\ q_F^{\max} &= \frac{\beta_{qpp}^2 - 4\beta_{qp}\beta_{q3p}}{8\beta_{qqp}\beta_{q3p}} = \frac{322.6^2 - 4 \times 21.3 \times 1008}{8 \times 25 \times 1008} = 9\%. \end{aligned} \tag{22}$$

Let $\Delta p^{\max} = F\left(g_F^{\max}, q_F^{\max}\right) - F\left(g_F^{\max}, 0\right)$ is the gain in employment for workers with observed human capital less than $g\left(p_F^{\max}, q_F^{\max}\right)$ by setting $q = q_F^{\max}$. It satisfies

$$\begin{aligned} \Delta p^{\max} &= p_F^{\max} - p_0, \\ g\left(p_0, 0\right) &= g\left(p_F^{\max}, q_F^{\max}\right). \end{aligned}$$

The first equation calculates the growth in employment as the difference between employment for workers with observed human capital less than $g_F^{\max}$ with a spike equal to $q_F^{\max}$ rather than equal to zero. The second equation implicitly solves for the employment without a spike. This equation can be solved by applying a Taylor expansion of $g\left(p_0, 0\right)$ around $g\left(p_F^{\max}, 0\right)$, using again the approximate normality of the distribution of g_i:

$$\begin{aligned} g\left(p_0, 0\right) &= g\left(p_F^{\max}, 0\right) + g_p\left(p_F^{\max}, 0\right) \Delta p^{\max}, \\ \Delta p^{\max} &= \frac{g\left(p_F^{\max}, 0\right) - g\left(p_F^{\max}, q_F^{\max}\right)}{g_p\left(p_F^{\max}, 0\right)} = \frac{\phi\left[\Phi^{-1}\left(p_F^{\max}\right)\right]}{\sigma_g}\left[g\left(p_F^{\max}, 0\right) - g\left(p_F^{\max}, q_F^{\max}\right)\right]. \end{aligned}$$

Again, the evaluation of $g\left(p_F^{\max}, 0\right) - g\left(p_F^{\max}, q_F^{\max}\right)$ is straightforward, as it only involves the terms in the second line of equation (18), using the expression for $p_F^{\max}$ and $q_F^{\max}$ in equation (22).[14]

$$\Delta p^{\max} = 2\%.$$

Summarizing our conclusions, starting from a spike of zero, an increase in the spike reduces employment at the lowest quantiles up until the seventh percentile, but it increases employment at higher quantiles. This increase outweighs the employment loss at lower quantiles. The highest value of the spike that maximizes employment up to some quantile p is 9%. The corresponding value of p is 16%. The total gain in employment up to $p = 0.16$ by setting the spike at 9% rather than zero is 2% of total employment, or 12% of employment up for the bottom 16% of the human capital distribution.

[14]

$$\begin{aligned} \Delta p^{\max} &= -(.367)^{-1}\phi\left[\Phi^{-1}(.16)\right]\left(28.8 - 508\,(.16) + 2455\,(.16)^2 - 3592\,(.16)^3 - 25 \times .09\right)(.16)\,(.09) \\ &= -(.367)^{-1}.24\left(28.8 - 508\,(.16) + 2455\,(.16)^2 - 3592\,(.16)^3 + 25 \times .09\right)(.16)\,(.09) \end{aligned}$$

6 Counterfactuals

Our empirical results can be used for an analysis of the impact of the changes in the spike on the distribution of wages and employment over the past forty years. The results of this exercise are summarized in Table 7. We consider the average impact across all regions in 1980, 1991, 1998, 2004, 2010 and 2019. These years are chosen since they mark turning point in the policy regarding minimum wages, see Table A2 in the Appendix. The calculation of a counterfactual with a smaller spike for workers in the spike is involved since there is no one-to-one correspondence of the actual wage to the counterfactual wage, because part of the workers in the spike will earn a wage above the spike after the reduction of the spike. We therefore focus on counterfactuals with an increase in the spike. Since 1980 is the year with the highest spike, we take this year as the point of reference. The counterfactuals for other years raise the spike in all regions by the difference between nation mean of the spike in that year and in 1980, so that the nation mean in the counterfactual becomes equal to that in 1980. We also present the counterfactuals using the level of 2010 spike as the reference. We adjust the share q_s^- of workers earning less than the minimum by the same methodology, using a simple regression

$$q_s^- = \beta_0 + \beta q_s + \varepsilon_q.$$

We find $\beta = 0.52$ ($t = 34.8$).[15]

For the calculation of the changes in employment, we apply equation (20) and using the coefficients from Table 4, column (4). For the calculation of the changes in log wages, we use the coefficients from Table 3, Panel C for the full sample of economies. For the sake of simplicity we assume that the average log wage of workers earning less than the minimum wage in economy s is the same in the actual and the counterfactual. The precise numerical procedure for the calculation is summarize below.

we take out all workers who earn less than the minimum., since we have not modeled this part of the distribution. Our subsequent discussion refers to changes in the wage distribution for the remaining workers. This limitation does not affect the change in the log wage differentials very much, since the lowest percentile we consider (5%) is above the percentage paid below the minimum wage for all economies. We first calculate for each individual i the counterfactual wage that would have applied with this higher spike, using the regression results in Table 3, We derive the implied value of counter factual log minimum wage $m_s^{\text{c.fact.}}$ by observing that this must be equal to the highest counterfactual log wage in the bottom $q_s^{\text{c.fact.}}$ share of the wage distribution (the superfix c.fact denotes the counterfactual value). Having established $m_s^{\text{c.fact.}}$, we set the log wages of workers in this bottom $q_s^{\text{c.fact.}}$ share of equal to $m_s^{\text{c.fact.}}$. With this counterfactual log wage for every worker, the calculation of the summary statistics in Table 7 is straightforward.

1. For each economy, sort observations by w_i ($i = 1$ is the lowest wage).

[15] Let a superfix o denote the counterfactual and let $\overline{q}_t$ denote the mean of the spike for year t across all regions. Then

$$\begin{aligned} q_s^o &= q_s + \overline{q}_{1980} - \overline{q}_t, \\ q_s^{-o} &= q_s^- + \beta\left(\overline{q}_{1980} - \overline{q}_t\right). \end{aligned}$$

2. Calculate $p_i = i/N_s$ where N_s is the number of observations for economy s.

3. Calculate:

   (a) for all $p_i < 0.17$: $f_i = 1 + \sigma_g^{-1} \left[\Phi^{-1}(p)\, g_q(p,q) - \phi\left[\Phi^{-1}(p)\right] g_{qp}(p,q)\right](q_s^o - q_s)$;

   (b) for higher values of p_i, $f_i = 1$.

4. Calculate $p_i^o = \Sigma_{j=1}^{i} f_j / \Sigma_{i=1}^{N_s} f_i$ (the counterfactual for p_i).

5. Calculate $w_i^+ = w_i + w_s(g_i, q_s^o) - w_s(g_i, q_s)$

6. Calculate w_i^o: define j_s such that $p_{j_s}^o = q_s^{-o} + q_s^o$ (the value of i at the uppersupport of the spike in the counterfactual)

   (a) for $p_i^o < q_s^{-o}$(workers earning less than the minimum in the counterfactual): w_i^o =E$(w_i|p_i < q_s^-)$.

   (b) w_s^- (the wage for the subminimum wage worker is unaffected)

   (c) for $q_s^{-o} \leq p_i^o \leq q_s^{-o} + q_s^o : w_i^o = m_s^o = w_{j_s}^+$

   (d) for $q_s^{-o} + q_s^o < p_i^o : w_i^o = w_i^+$

7. Define j_{sp} such that $p_{j_{sp}} = p$ and j_{sp}^o such that $p_{j_{sp}}^o = p$ for $p = .01, .05, .10, .20., .50, .90$

8. Calculate: $f_{j_{sp}} - 1$ (the change in the density of employment; it is zero for $p > .10$ by construction)

9. Calculate: $p^{-1}\Sigma_{i=1}^{j_{sp}}(f_i - 1)$ (the relative change in employment)

10. Calculate log wage differential (trunc.): $\Delta \log w_{sp\text{trunc}} = \max w_{j_{sp}^o} - w_{j_{sp}}$ and $\Delta \log W_{t\text{trunc}} = \log \Sigma_{i\in t} f_i \mathrm{e}^{w_i} - \log \Sigma_{i\in t} \mathrm{e}^{w_i}$

11. Calculate log wage differential (compres.): $\Delta \log w_{sp\text{comp}} = w_{j_{sp}^o}^o - w_{j_{sp}^o}$ and $\Delta \log W_{t\text{comp}} = \log \Sigma_{i\in t} f_i \mathrm{e}^{w_i^o} - \log \Sigma_{i\in t} f_i \mathrm{e}^{w_i}$

Table 6: Counterfactual Estimation with q

							Δlog employment[(2)]					log wage differential[(3)]					
year	s.d.g_i		$\overline{q}_t$[(1)]	$\overline{q}_t^-$	$\Delta\overline{m}_t$[(4)]		1%	5%	10%	20%		50-5	50-10	50-15	50-20	90-50	$\Delta\ln \Sigma W_i$[(5)]
1980	0.345	actual	0.054	0.061							actual	0.652	0.570	0.516	0.441	0.671	
1991	0.359	actual	0.006	0.024		dens	-0.142	-0.033	0.321	0.000	actual	0.110	0.084	0.048	0.031	0.053	
		c.fact.	0.054	0.051	0.368	distr	-0.109	-0.116	0.031	0.108	trunc.	-0.033	-0.016	0.008	0.017	0.009	0.011
											compr.	-0.060	-0.034	-0.019	-0.014	-0.020	0.110
1998	0.367	actual	0.013	0.041		dens	-0.121	-0.035	0.259	0.000	actual	0.150	0.094	0.049	0.029	0.064	
		c.fact.	0.054	0.064	0.299	distr	-0.093	-0.102	0.020	0.084	trunc.	-0.031	-0.016	0.007	0.010	0.009	0.008
											compr.	-0.048	-0.051	-0.019	-0.014	-0.014	0.093
2004	0.372	actual	0.006	0.025		dens	-0.137	-0.032	0.312	0.000	actual	0.144	0.116	0.065	0.041	0.094	
		c.fact.	0.054	0.053	0.465	distr	-0.106	-0.112	0.031	0.106	trunc.	-0.045	-0.017	0.006	0.016	0.008	0.010
											compr.	-0.042	-0.043	-0.024	-0.020	-0.018	0.122
2010	0.366	actual	0.018	0.040		dens	-0.108	-0.035	0.221	0.000	actual	0.161	0.117	0.070	0.053	0.117	
		c.fact.	0.054	0.061	0.241	distr	-0.084	-0.093	0.013	0.069	trunc.	-0.031	-0.013	0.005	0.007	0.006	0.007
											compr.	0.014	-0.036	-0.013	-0.007	-0.011	0.081
2019	0.368	actual	0.010	0.055		dens	-0.126	-0.034	0.277	0.000	actual	0.123	0.107	0.051	0.030	0.142	
		c.fact.	0.054	0.080	0.354	distr	-0.098	-0.106	0.023	0.091	trunc.	-0.042	-0.016	0.008	0.012	0.008	0.009
											compr.	-0.138	-0.035	-0.034	-0.022	-0.020	0.106
2010	0.366	actual	0.018	0.040							actual	0.803	0.691	0.585	0.494	0.788	
1991	0.359	actual	0.006	0.024		dens	-0.034	-0.008	0.078	0.000	actual	-0.051	-0.033	-0.022	-0.022	0.053	
		c.fact.	0.018	0.030	0.152	distr	-0.027	-0.029	0.008	0.027	trunc.	-0.009	-0.004	0.004	0.004	0.002	0.003
											compr.	-0.017	-0.010	-0.007	-0.005	-0.006	0.030
1998	0.367	actual	0.013	0.041		dens	-0.015	-0.004	0.031	0.000	actual	-0.005	-0.024	-0.021	-0.024	0.064	
		c.fact.	0.018	0.044	0.065	distr	-0.011	-0.013	0.002	0.010	trunc.	-0.004	-0.002	0.002	0.001	0.001	0.001
											compr.	-0.005	-0.003	-0.001	-0.000	-0.005	0.013
2004	0.372	actual	0.006	0.025		dens	-0.034	-0.008	0.077	0.000	actual	0.025	-0.001	-0.004	-0.012	0.094	
		c.fact.	0.018	0.032	0.199	distr	-0.027	-0.028	0.008	0.027	trunc.	-0.012	-0.005	0.003	0.003	0.003	0.003
											compr.	-0.022	-0.012	-0.009	-0.007	-0.007	0.044
2019	0.368	actual	0.010	0.055		dens	-0.021	-0.006	0.046	0.000	actual	0.020	-0.014	-0.020	-0.022	0.142	
		c.fact.	0.018	0.059	0.119	distr	-0.017	-0.018	0.004	0.015	trunc.	-0.008	-0.003	0.002	0.002	0.002	0.002
											compr.	-0.045	-0.021	-0.009	-0.007	-0.007	0.027
2019	0.368	actual	0.010	0.055		dens	-0.079	-0.020	0.176	0.000	actual						
		c.fact.	0.037	0.070	0.234	distr	-0.061	-0.066	0.016	0.058	trunc.	-0.022	-0.008	0.006	0.009	0.005	0.006
											compr.	-0.077	-0.027	-0.022	-0.010	-0.014	0.066

Note: 1: The unweighed average of the spike q_s across regions for a particular year. 2: Δ ln employment: (c.fact.) see equation (20) 3: The actual and counter-factual log wage differentials among the workers. 4: The unweighed average of the log minimum wage m_s across regions for a particular year. 5: The difference between the actual and the counter-factual log of the sum of wage for all workers earning more than the minimum wage.

7 Conclusion

Followed the extensive literature on the impact of minimum wages on wage distribution and the employment, we examined the new evidence for spillover effects on wages and mixed results for employment. We further addressed the issues on endogenous minimum wage policies, endogenous median wage, discuss the shifts in the wage distribution, and to combine the spillover effects with an upward sloped labour supply curve. Increase the minimum wage contribute to the increase of wage in the lower part of the wage distribution, flatting the curve and reduce the dispersion. We further provide a method to evaluate the counterfactual scenario using instruments and the specification of the heterogeneity in employment effects. We find strong evidence both for the compression of wage differentials above the minimum and for heterogeneous employment effects. For the lowest quantiles of the human capital distribution, the employment effect of the minimum wage is negative irrespective the level of the spike. However, the sum of the employment effect for all lower percentiles of a not too high minimum wage is positive. The additional employment of this spike relative to a situation without a minimum wage is 2.2% of total employment. Conditional on the specification of the model, these effects are precisely measured. We argue that this strong positive employment effect demonstrates the relevance of monopsony models above the hedonic pricing models, where the driving force of compression is disemployment.

We provide a counterfactual simulation for several turning years since 1980. We find that the changes in minimum wage have contributed substantially to the variation in the return to human capital and wage dispersion in the bottom half of the distribution and that an increase in the minimum wage might be an effective instrument for boosting the labour share in aggregate output. We do not attempt to provide a welfare theoretic framework for weighing the cost and benefits of various subgroups. Whatever level of the spike one prefers, is up to the reader, depending on his or her political preferences. However, those with a strong preference for an equal wage distribution and a substantial labour share and who care less about the disemployment effect for the lowest percentiles of the human capital distribution can derive arguments for a high spike from this paper.

References

AHLFELDT, G., D. ROTH, AND T. SEIDEL (2018): "The Regional Effects of a National Minimum Wage," CESifo Working Paper Series 6924, CESifo.

ANGRIST, J. D. AND A. B. KRUEGER (1991): "Does Compulsory School Attendance Affect Schooling and Earnings?" *The Quarterly Journal of Economics*, 106, 979–1014.

AUTOR, D. H. AND D. DORN (2013): "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103, 1553–97.

AUTOR, D. H., L. F. KATZ, AND M. S. KEARNEY (2006): "The Polarization of the U.S. Labor Market," *American Economic Review*, 96, 189–194.

——— (2008): "Trends in US wage inequality: Revising the revisionists." *The Review of economics and statistics*, 90, 300–323.

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118, 1279–1333.

AUTOR, D. H., A. MANNING, AND C. L. SMITH (2016): "The Contribution of the Minimum Wage to US Wage Inequality over Three Decades: A Reassessment," *American Economic Journal: Applied Economics*, 8, 58–99.

AZAR, J., E. HUET-VAUGHN, I. MARINESCU, B. TASKA, AND T. VON WACHTER (2019): "Minimum Wage Employment Effects and Labor Market Concentration," Working Paper 26101, National Bureau of Economic Research.

BAILEY, M. J., J. DINARDO, AND B. A. STUART (2020): "The Economic Impact of a High National Minimum Wage: Evidence from the 1966 Fair Labor Standards Act," Working Paper 26926, National Bureau of Economic Research.

BONTEMPS, C., J.-M. ROBIN, AND G. J. VAN DEN BERG (2000): "Equilibrium Search with Continuous Productivity Dispersion: Theory and Nonparametric Estimation," *International Economic Review*, 41, 305–358.

BOUND, J. AND A. B. KRUEGER (1991): "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?" *Journal of Labor Economics*, 9, 1–24.

BROCHU, P., D. A. GREEN, T. LEMIEUX, AND J. TOWNSEND (2015): "The Minimum Wage, Turnover, and the Shape of the Wage Distribution," .

CARD, D. AND A. B. KRUEGER (1994): "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania," *American Economic Review*, 84, 772–93.

——— (1995): "Time-Series Minimum-Wage Studies: A Meta-analysis," *American Economic Review*, 85, 238–43.

——— (2000): "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Reply," *American Economic Review*, 90, 1397–1420.

——— (2016): *Myth and Measurement: The New Economics of the Minimum Wage Twentieth-Anniversary Edition*, Princeton University Press, 2 ed.

CENGIZ, D., A. DUBE, A. LINDNER, AND B. ZIPPERER (2019): "The Effect of Minimum Wages on Low-Wage Jobs*," *The Quarterly Journal of Economics*, 134, 1405–1454.

CHEN, Y. AND C. N. TEULINGS (2021): "Agglomeration, Sorting and the Return to Human Capital," Working paper series, University of Cambridge.

DICKENS, R., S. MACHIN, AND A. MANNING (1998): "Estimating the effect of minimum wages on employment from the distribution of wages: A critical view," *Labour Economics*, 5, 109–134.

DICKENS, R. AND A. MANNING (2004): "Has the National Minimum Wage Reduced UK Wage Inequality?" *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 167, 613–626.

DICKENS, R., A. MANNING, AND T. BUTCHER (2012): "Minimum Wages and Wage Inequality: Some Theory and an Application to the UK," Working paper series, Department of Economics, University of Sussex Business School.

DINARDO, J., N. M. FORTIN, AND T. LEMIEUX (1996): "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, 64, 1001–1044.

DOLADO, J., F. KRAMARZ, S. MACHIN, A. MANNING, D. MARGOLIS, C. TEULINGS, G. SAINT-PAUL, AND M. KEEN (1996): "The Economic Impact of Minimum Wages in Europe," *Economic Policy*, 11, 319–372.

DUBE, A., T. W. LESTER, AND M. REICH (2010): "Minimum Wage Effects across State Borders: Estimates using Contiguous Counties," *The Review of Economics and Statistics*, 92, 945–964.

——— (2016): "Minimum Wage Shocks, Employment Flows, and Labor Market Frictions," *Journal of Labor Economics*, 34, 663–704.

ENGBOM, N. AND C. MOSER (2018): "Earnings Inequality and the Minimum Wage: Evidence from Brazil," Working paper series, CESifo.

FISHBACK, P. V. AND A. SELTZER (2020): "The Rise of American Minimum Wages, 1912-1968," Working Paper 26937, National Bureau of Economic Research.

FLINN, C. J. (2006): "Minimum Wage Effects on Labor Market Outcomes under Search, Matching, and Endogenous Contact Rates," *Econometrica*, 74, 1013–1062.

GABAIX, X. AND A. LANDIER (2008): "Why has CEO Pay Increased So Much?*," *The Quarterly Journal of Economics*, 123, 49–100.

GENNAIOLI, N., R. LA PORTA, F. LOPEZ-DE SILANES, AND A. SHLEIFER (2013): "Human Capital and Regional Development," *The Quarterly Journal of Economics*, 128, 105–164.

GOLDSMITH-PINKHAM, P., I. SORKIN, AND H. SWIFT (2020): "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 110, 2586–2624.

GOOS, M., A. MANNING, AND A. SALOMONS (2010): "Explaining Job Polarization in Europe: The Roles of Technology, Globalization and Institutions," Cep discussion papers, Centre for Economic Performance, LSE.

GOTTFRIES, A. AND C. N. TEULINGS (2021): "Returns to on-the-job search and the dispersion of wages," Working paper series, CEPR.

HAANWINCKEL, D. (2017): "Supply, Demand, Institutions, and Firms: A Theory of Labor Market Sorting and the Wage Distribution," Working paper series, CEPR.

HAANWINCKEL, D. AND R. R. SOARES (2021): "Workforce Composition, Productivity, and Labor Regulations in a Compensating Differentials Theory of Informality," *The Review of Economic Studies*, rdab017.

HAGEDORN, M., I. MANOVSKII, AND Y. WANG (2018): "Search Frictions and Wage Dispersion," Working paper series, University of Oslo.

JUHN, C., K. M. MURPHY, AND B. PIERCE (1993): "Wage Inequality and the Rise in Returns to Skill," *Journal of Political Economy*, 101, 410–442.

KATZ, L. F. AND K. M. MURPHY (1992): "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 107, 35–78.

LEE, D. S. (1999): "Wage Inequality in the United States during the 1980s: Rising Dispersion or Falling Minimum Wage?" *The Quarterly Journal of Economics*, 114, 977–1023.

MACHIN, S. AND A. MANNING (1994): "The Effects of Minimum Wages on Wage Dispersion and Employment: Evidence from the U.K. Wages Councils," *Industrial and Labor Relations Review*, 47, 319–329.

MACHIN, S., A. MANNING, AND L. RAHMAN (2003): "Where the Minimum Wage Bites Hard: Introduction of Minimum Wages to a Low Wage Sector," *Journal of the European Economic Association*, 1, 154–180.

MEYER, R. H. AND D. A. WISE (1983): "Discontinuous Distributions and Missing Persons: The Minimum Wage and Unemployed Youth," *Econometrica*, 51, pp. 1677–1698.

NEUMARK, D. AND L. F. M. CORELLA (2019): "Do Minimum Wages Reduce Employment in Developing Countries? A Survey and Exploration of Conflicting Evidence," NBER Working Papers 26462, National Bureau of Economic Research, Inc.

NEUMARK, D., J. I. SALAS, AND W. WASCHER (2014): "More on Recent Evidence on the Effects of Minimum Wages in the United States," *IZA J Labor Policy*, 3.

NEUMARK, D. AND P. SHIRLEY (2021): "Myth or Measurement: What Does the New Minimum Wage Research Say about Minimum Wages and Job Loss in the United States?" Tech. rep., National Bureau of Economic Research.

NEUMARK, D. AND W. WASCHER (2000): "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Comment," *American Economic Review*, 90, 1362–1396.

ROSEN, S. (1974): "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, 82, 34–55.

RUGGLES, S., K. GENADEK, R. GOEKEN, J. GROVER, AND M. SOBEK (2017): "Integrated Public Use Microdata Series: Version 7.0 [dataset]," Tech. rep., Minneapolis: University of Minnesota.

SATTINGER, M. (1975): "Comparative Advantage and the Distributions of Earnings and Abilities," *Econometrica*, 43, 455–68.

STEWART, M. B. (2012): "Quantile Estimates of Counterfactual Distribution Shifts and the Effect of Minimum Wage Increases on the Wage Distribution," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 175, 263–287.

TEULINGS, C. N. (1995): "The Wage Distribution in a Model of the Assignment of Skills to Jobs," *Journal of Political Economy*, 103, 280–315.

——— (2000): "Aggregation Bias in Elasticities of Substitution and the Minimum Wage Paradox," *International Economic Review*, 41, 359–398.

——— (2003): "The Contribution of Minimum Wages to Increasing Wage Inequality," *The Economic Journal*, 113, 801–833.

——— (2005): "Comparative Advantage, Relative Wages, and the Accumulation of Human Capital," *Journal of Political Economy*, 113, 425–461.

TEULINGS, C. N. AND T. VAN RENS (2008): "Education, Growth, and Income Inequality," *The Review of Economics and Statistics*, 90, 89–104.

Appendix

The effect of q on the employment $f(g,q)$ for a fixed value of g satisfies

$$f_q(g,q) = \frac{\mathrm{d}\left[g_p\left[F(g,q),q\right]^{-1}\right]}{\mathrm{d}q} = -\frac{g_{pp}\left[F(g,q),q\right]F_q(g,q) + g_{qp}\left[F(g,q),q\right]}{g_p\left[F(g,q),q\right]^2} \tag{23}$$
$$= f(g,q)^2 \times \left\{g_{pp}\left[F(g,q),q\right]g_q\left[F(g,q),q\right]f(g,q) - g_{qp}\left[F(g,q),q\right]\right\},$$

where we use equation (19) in the second step. Differentiating the inverse of equation (19) with respect to g, rearranging terms and substitution of equation (19) for $g_p(p,q)$ yields

$$g_{pp}(p,g) = -\frac{f_g\left[g(p,q),q\right]}{f\left[g(p,q),q\right]^3} \cong \sigma_g \frac{\Phi^{-1}(p)}{\phi\left[\Phi^{-1}(p)\right]^2},$$

where we use the fact that g is distributed approximately normal in the final step.[16] Substitution of this relation and $p = F(g,q)$ in equation (23) yields an expression for the relative change of the density at quantile p

$$\sigma_g \frac{f_q\left[g(p,q),q\right]}{\phi\left[\Phi^{-1}(p)\right]} \cong \sigma_g^{-1}\left[\Phi^{-1}(p)\,g_q(p,q) - \phi\left[\Phi^{-1}(p)\right]g_{qp}(p,q)\right]. \tag{24}$$

Using the assumption of approximate normality and $\lim_{x\to-\infty}\frac{\phi(x)}{x\Phi(x)} = -1$, equation (24) and (19) imply

$$\lim_{p\to0}\left\{\left[\Phi^{-1}(p)\,g_q(p,q)\right]^{-1}\frac{f_q\left[g(p,q),q\right]}{f\left[g(p,q),q\right]}\right\} \cong \sigma_g^{-1}\lim_{g\to-\infty}\left\{1 - \frac{\phi\left[\Phi^{-1}(p)\right]}{\Phi^{-1}(p)}\frac{g_{qp}(p,q)}{g_q(p,q)}\right\} = \sigma_g^{-1},$$
$$\lim_{p\to0}\left\{\left[\Phi^{-1}(p)\,g_q(p,q)\right]^{-1}\frac{F_q\left[g(p,q),q\right]}{F\left[g(p,q),q\right]}\right\} = \lim_{g\to-\infty}\left\{-\left[\Phi^{-1}(p)\,p g_p(p,q)\right]^{-1}\right\}$$
$$\cong \sigma_g^{-1}\lim_{g\to-\infty}\left\{-\frac{\phi\left[\Phi^{-1}(p)\right]}{\Phi^{-1}(p)\,p}\right\} = \sigma_g^{-1}.$$

The relative change of the distribution and the density converge to each other for $p \to 0$ (or equivalently: $g \to -\infty$)

$$\frac{f_q(g,q)}{f(g,q)} \cong \frac{F_q(g,q)}{F(g,q)} \cong \frac{g}{\sigma_g^2}g_q\left[F(g,q),q\right].$$

We use the estimation results from table 4 and estimate the marginal effect of change of spike on the density $\frac{f_q(g,q)}{f(g,q)}$ equation (24) and probability functions $\frac{F_q(g,q)}{F(g,q)}$:

$$\frac{F_q(g,q)}{F(g,q)} = -\frac{\phi\left[\Phi^{-1}(p)\right]}{\sigma_g p}g_q(p,g)$$

[16]
$$f_g\left[g(p,q),q\right] \cong -\sigma_g^{-2}\Phi^{-1}(p)\,\phi\left[\Phi^{-1}(p)\right].$$

Table A1: CBSA Observations Distribution Among States

CBSA	State I	State II	State III	State IV	Pct SI	Pct SII	Pct SIII	Pct SIV	NAME
31100	CA				100.00%				Los Angeles-Long Beach-Anaheim, CA
40140	CA				100.00%				Riverside-San Bernardino-Ontario, CA
41740	CA				100.00%				San Diego-Carlsbad, CA
41860	CA				100.00%				San Francisco-Oakland-Hayward, CA
41940	CA				100.00%				San Jose-Sunnyvale-Santa Clara, CA
19740	CO				100.00%				Denver-Aurora-Lakewood, CO
47900	DC	VA	MD		45.91%	25.90%	28.19%		Washington-Arlington-Alexandria, DC-VA-MD-WV
33100	FL				100.00%				Miami-Fort Lauderdale-West Palm Beach, FL
45300	FL				100.00%				Tampa-St. Petersburg-Clearwater, FL
12060	GA				100.00%				Atlanta-Sandy Springs-Roswell, GA
16980	IL	IN	WI		98.23%	1.77%	0.00%		Chicago-Naperville-Elgin, IL-IN-WI
26900	IN				100.00%				Indianapolis-Carmel-Anderson, IN
35380	LA				100.00%				New Orleans-Metairie, LA
14460	MA	NH			86.75%	13.25%			Boston-Cambridge-Newton, MA-NH
12580	MD				100.00%				Baltimore-Columbia-Towson, MD
19820	MI				100.00%				Detroit-Warren-Dearborn, MI
33460	MN	WI			99.99%	0.01%			Minneapolis-St. Paul-Bloomington, MN-WI
28140	MO	KS			45.36%	54.64%			Kansas City, MO-KS
41180	MO	IL			80.98%	19.02%			St. Louis, MO-IL
24660	NC				100.00%				Greensboro-High Point, NC
15380	NY				100.00%				Buffalo-Cheektowaga-Niagara Falls, NY
35620	NY	NJ			69.24%	30.76%			New York-Newark-Jersey City, NY-NJ
40380	NY				100.00%				Rochester, NY
17140	OH	KY			77.70%				Cincinnati, OH-KY-IN
17460	OH				100.00%				Cleveland-Elyria, OH
18140	OH				100.00%				Columbus, OH
38900	OR	WA			91.57%	8.43%			Portland-Vancouver-Hillsboro, OR-WA
37980	PA	NJ	DE	MD	62.06%	23.32%	14.62%	0.00%	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
38300	PA				100.00%				Pittsburgh, PA
19100	TX				100.00%				Dallas-Fort Worth-Arlington, TX
26420	TX				100.00%				Houston-The Woodlands-Sugar Land, TX
47260	VA				100.00%				Virginia Beach-Norfolk-Newport News, VA-NC
42660	WA				100.00%				Seattle-Tacoma-Bellevue, WA
33340	WI				100.00%				Milwaukee-Waukesha-West Allis, WI

Note: Information for 34 city areas: CBSA code in 2013, city belong to which state(s) and the percentage of sample observations in the CPS 1979-2015, name of cities. *Data sources*: the Current Population Survey MORG and the US Census Bureau.

Table A5: Individual Level Mincer Regression

VARIABLES β	(1) $\tilde{w}$ Full Obs.	(2) $\tilde{w}$ excl. 10%	(3) $\tilde{w}$ excl. 20%	(4) $\tilde{w}$ excl. 30%	(5) $\tilde{w}$ excl. 40%
Male	0.310	0.303	0.285	0.269	0.260
	(179.08)	(155.45)	(129.15)	(106.57)	(92.36)
Male × Trend	0.00548	0.00499	0.00419	0.00354	0.00321
	(131.11)	(104.32)	(75.88)	(54.84)	(43.75)
Single	0.0126	0.0121	0.00997	0.00863	0.00975
	(9.11)	(7.51)	(5.31)	(3.84)	(3.82)
Single × Trend	-0.00242	-0.00223	-0.00206	-0.00197	-0.00197
	(-44.50)	(-36.34)	(-29.48)	(-24.20)	(-21.32)
Divorced	0.0257	0.0296	0.0267	0.0269	0.0268
	(16.78)	(16.36)	(12.59)	(10.61)	(9.29)
Divorced × Trend	-0.00164	-0.00175	-0.00164	-0.00162	-0.00160
	(-25.43)	(-24.00)	(-19.67)	(-16.86)	(-14.67)
Male × Single	-0.211	-0.216	-0.213	-0.207	-0.206
	(-112.79)	(-99.02)	(-83.67)	(-67.93)	(-59.17)
Male × Single × Trend	0.00398	0.00399	0.00380	0.00353	0.00345
	(54.11)	(48.10)	(39.97)	(31.84)	(27.43)
Male × Divorced	-0.113	-0.117	-0.116	-0.115	-0.117
	(-45.36)	(-40.38)	(-34.22)	(-28.59)	(-25.48)
Male × Divorced × Trend	0.00164	0.00182	0.00176	0.00173	0.00182
	(15.94)	(15.70)	(13.41)	(11.42)	(10.61)
South	0.00609	0.00583	0.00716	0.00736	0.00714
	(1.76)	(1.67)	(1.98)	(2.01)	(1.89)
Black	-0.100	-0.104	-0.110	-0.117	-0.120
	(-103.19)	(-103.42)	(-102.89)	(-100.16)	(-96.59)
Other Race	-0.0764	-0.0790	-0.0820	-0.0815	-0.0826
	(-73.75)	(-73.54)	(-71.08)	(-64.42)	(-60.07)
South × Black	-0.0349	-0.0314	-0.0246	-0.0158	-0.00996
	(-25.71)	(-21.57)	(-16.05)	(-9.59)	(-5.63)
South ×Others	0.00133	0.00405	0.00889	0.00739	0.0104
	(0.58)	(1.71)	(3.60)	(2.84)	(3.70)
Edu = 0	-0.637	-0.637	-0.622	-0.602	-0.594
	(-107.31)	(-98.90)	(-88.62)	(-77.16)	(-69.69)
Edu = 1	-0.532	-0.518	-0.500	-0.465	-0.423
	(-36.52)	(-27.67)	(-22.09)	(-15.16)	(-12.28)
Edu = 2	-0.530	-0.531	-0.509	-0.467	-0.456

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Table A5 – continued from previous page

VARIABLES β	(1) $\tilde{w}$ Full Obs.	(2) $\tilde{w}$ excl. 10%	(3) $\tilde{w}$ excl. 20%	(4) $\tilde{w}$ excl. 30%	(5) $\tilde{w}$ excl. 40%
	(-72.20)	(-60.87)	(-50.08)	(-35.15)	(-30.42)
Edu = 3	-0.525	-0.523	-0.520	-0.513	-0.509
	(-80.23)	(-65.61)	(-55.10)	(-40.58)	(-35.31)
Edu = 4	-0.453	-0.459	-0.449	-0.419	-0.429
	(-68.01)	(-55.38)	(-45.67)	(-32.23)	(-29.15)
Edu = 5	-0.465	-0.468	-0.451	-0.449	-0.436
	(-103.70)	(-88.79)	(-75.07)	(-59.31)	(-50.99)
Edu = 6	-0.427	-0.436	-0.437	-0.412	-0.418
	(-118.86)	(-101.40)	(-87.31)	(-62.13)	(-55.21)
Edu = 7	-0.357	-0.371	-0.365	-0.362	-0.363
	(-109.67)	(-93.89)	(-80.11)	(-66.97)	(-60.03)
Edu = 8	-0.262	-0.268	-0.278	-0.277	-0.282
	(-119.28)	(-98.37)	(-84.43)	(-67.22)	(-60.17)
Edu = 9	-0.259	-0.270	-0.272	-0.270	-0.272
	(-166.68)	(-155.34)	(-142.54)	(-127.25)	(-117.00)
Edu = 10	-0.194	-0.200	-0.204	-0.206	-0.208
	(-167.84)	(-155.40)	(-143.73)	(-131.43)	(-121.51)
Edu = 11	-0.157	-0.163	-0.166	-0.171	-0.172
	(-148.07)	(-138.94)	(-129.94)	(-120.72)	(-111.43)
Edu = 13	0.0574	0.0549	0.0508	0.0439	0.0423
	(60.89)	(52.55)	(43.56)	(33.33)	(29.18)
Edu = 14	0.165	0.170	0.174	0.176	0.178
	(187.37)	(177.70)	(166.44)	(151.76)	(139.95)
Edu = 15	0.209	0.217	0.223	0.224	0.226
	(135.36)	(126.84)	(116.73)	(104.21)	(95.54)
Edu = 16	0.420	0.429	0.433	0.435	0.437
	(369.70)	(347.58)	(324.91)	(298.35)	(275.43)
Edu = 17	0.399	0.409	0.421	0.425	0.432
	(167.36)	(148.71)	(129.95)	(107.31)	(95.26)
Edu = 18	0.574	0.586	0.593	0.594	0.597
	(330.35)	(311.82)	(291.81)	(267.91)	(247.55)
Year of Experience (Exp)	0.0248	0.0243	0.0220	0.0188	0.0181
	(40.85)	(36.61)	(30.49)	(23.61)	(20.82)
$Exp^2/100$	-0.0400	-0.0354	-0.0229	-0.00666	-0.00221
	(-14.39)	(-11.59)	(-6.89)	(-1.81)	(-0.55)
$Exp^3/100000$	0.235	0.174	0.00153	-0.216	-0.283

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Table A5 – continued from previous page

VARIABLES β	(1) $\tilde{w}$ Full Obs.	(2) $\tilde{w}$ excl. 10%	(3) $\tilde{w}$ excl. 20%	(4) $\tilde{w}$ excl. 30%	(5) $\tilde{w}$ excl. 40%
	(6.44)	(4.31)	(0.03)	(-4.43)	(-5.31)
Exp $\times$ Edu	0.00165	0.00169	0.00181	0.00197	0.00200
	(37.30)	(35.07)	(34.65)	(34.30)	(32.10)
$Exp^2/100 \times$ Edu	-0.00888	-0.00919	-0.00983	-0.0106	-0.0108
	(-43.79)	(-41.37)	(-40.80)	(-39.96)	(-37.47)
$Exp^3/100000 \times$ Edu	0.107	0.111	0.120	0.130	0.134
	(39.56)	(37.39)	(37.22)	(36.63)	(34.48)
Male $\times$ Exp	0.00581	0.00568	0.00605	0.00657	0.00683
	(22.72)	(20.51)	(20.26)	(20.16)	(19.27)
$Exp^2/100 \times$ Male	0.00459	0.00356	0.000249	-0.00338	-0.00564
	(3.52)	(2.51)	(0.16)	(-2.02)	(-3.10)
$Exp^3/100000 \times$ Male	-0.233	-0.216	-0.168	-0.119	-0.0838
	(-12.13)	(-10.31)	(-7.41)	(-4.81)	(-3.11)
Observations	5,803,821	5,146,824	4,541,693	3,916,580	3,351,354
R-squared	0.584	0.547	0.515	0.489	0.474
R-MSE	0.449	0.453	0.456	0.458	0.460
Time x Region Dummy	Y	Y	Y	Y	Y

t-statistics in parentheses

Table A2: Summary Statistics

Year	s.d. g_i	mean $q_s(=)$	mean $q_s(<)$	#Region $q_s > 1.5\%$	#≤FedMW
1979	0.346	0.045	0.060	79	80
1980	0.346	0.054	0.061	81	80
1981	0.345	0.050	0.066	81	80
1982	0.345	0.047	0.052	78	78
1983	0.344	0.048	0.045	79	80
1984	0.344	0.045	0.040	80	80
1985	0.345	0.038	0.035	76	79
1986	0.345	0.036	0.035	69	75
1987	0.347	0.032	0.032	69	74
1988	0.346	0.026	0.029	55	72
1989	0.359	0.018	0.025	41	56
1990	0.360	0.012	0.038	26	0
1991	0.360	0.006	0.024	7	63
1992	0.353	0.023	0.026	50	76
1993	0.354	0.020	0.024	50	75
1994	0.361	0.012	0.036	22	73
1995	0.366	0.011	0.030	18	72
1996	0.367	0.008	0.027	7	69
1997	0.368	0.008	0.033	10	70
1998	0.369	0.013	0.041	24	0
1999	0.371	0.011	0.034	19	0
2000	0.371	0.010	0.030	14	0
2001	0.370	0.007	0.030	10	0
2002	0.371	0.006	0.029	7	0
2003	0.372	0.007	0.026	7	0
2004	0.372	0.006	0.025	6	0
2005	0.371	0.007	0.025	9	0
2006	0.371	0.006	0.026	8	0
2007	0.371	0.008	0.032	12	0
2008	0.370	0.009	0.034	16	25
2009	0.368	0.011	0.038	19	34
2010	0.367	0.018	0.040	41	55
2011	0.370	0.016	0.039	38	51
2012	0.377	0.016	0.040	39	48
2013	0.368	0.015	0.038	33	46
2014	0.369	0.014	0.052	29	32
2015	0.369	0.014	0.043	28	32
2016	0.369	0.015	0.043	22	32
2017	0.368	0.013	0.040	21	32
2018	0.368	0.011	0.045	18	32
2019	0.368	0.010	0.055	16	32

Table A3: Frequency table by year with the spike in the bottom 70%

Year	Regions	Year	Regions	Year	Regions
1979	7	1993	54	2007	75
1980	1	1994	71	2008	72
1981	4	1995	75	2009	73
1982	8	1996	81	2010	62
1983	4	1997	77	2011	67
1984	7	1998	70	2012	69
1985	14	1999	73	2013	71
1986	17	2000	74	2014	73
1987	24	2001	77	2015	69
1988	42	2002	77	2016	68
1989	57	2003	77	2017	68
1990	72	2004	77	2018	70
1991	76	2005	77	2019	71
1992	45	2006	78	Total	2324

Table A4: Frequency table by region with the spike in the bottom 70%

Region ID	Freq.	Region ID	Freq.	Region ID	Freq.
Atlanta, GA	35	St Louis, MO	31	Delaware	31
Baltimore, MD	33	San Diego, CA	18	Maryland	29
Boston, MA	35	San Francisco, CA	35	Virginia	31
Buffalo, NY	28	San Jose, CA	33	West Virginia	20
Chicago, IL	36	Seattle, WA	39	North Carolina	31
Cincinnati, OH	32	Tampa, FL	31	South Carolina	28
Cleveland, OH	31	Virginia Beach, VA	31	Georgia	24
Columbus, OH	33	Maine	30	Florida	31
Dallas, TX	37	New Hampshire	35	Kentucky	26
Denver, CO	35	Vermont	32	Tennessee	27
Detroit, MI	32	Massachusetts	29	Alabama	25
Greensboro, NC	33	Rhode Island	32	Mississippi	24
Houston, TX	33	Connecticut	34	Arkansas	24
Indianapolis, IN	32	New York	31	Louisiana	22
Kansas City, MO	33	Pennsylvania	30	Oklahoma	26
Los Angeles, CA	5	Ohio	26	Texas	21
Miami, FL	32	Indiana	30	Montana	28
Milwaukee, WI	33	Illinois	23	Idaho	28
Minneapolis, MN	39	Michigan	28	Wyoming	29
New Orleans, LA	30	Wisconsin	31	Colorado	29
New York, NY	36	Minnesota	28	New Mexico	21
New Jersey, NJ	33	Iowa	28	Arizona	28
Philadelphia, PA	34	Missouri	26	Utah	29
Pittsburgh, PA	29	North Dakota	29	Nevada	31
Portland, OR	28	South Dakota	28	Washington	18
Riverside, CA	10	Nebraska	30	Oregon	13
Rochester, NY	29	Kansas	27	California	9