The Contribution of the Minimum Wage to US Wage Inequality: A Penalized Spline Approach

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October 2020

Abstract

I reassess the effect of minimum wage on US earnings inequality using data from 1979 to 2012 and a penalized spline technique that addresses potential biases in parametric estimation in prior works. I find that, in contrast with the initial study of Lee (1999) and based on the Current Population Survey, the spillover effect of minimum wage on upper tail and lower tail of wage distribution, where the minimum is nominally non-binding, is small and not significant.

1 Introduction

To what extent has the minimum wage affected US wage distribution? Several studies have tried to estimate the effect of minimum wage policies on shaping inequality. Generally, the literature in this area is divided into two types of modeling. First, there are studies on the general equilibrium impact of minimum wages changes on labor market outcomes. As an example, Flinn (2006) formulated partial and general equilibrium models of wage determination and labor market dynamics to generate an accepted wage distribution with a mass point at the minimum wage and a continuous density to the right of it. Using the federal minimum wage increase in 1997 and the matching function formulation along with Nash bargaining between workers and firms, Flinn (2006) looked at the effect of minimum wages on labor market outcomes, as well as its welfare effects. Not surprisingly these effects were not significant due to the small changes in the magnitude of the minimum wage in US [1]. On the other hand, Engbom and Moser (2018) developed a version of the Burdett and Mortensen (1998) model to evaluate a 119 percent increase in the real minimum wage in Brazil from 1996 to 2012. They concluded that, in the case of Brazil, the spillovers can reach up to 80th percentiles of the earning distribution and the increasing minimum wage policy can explain a large decline in earning inequality[2].

The second strand of literature is focused on reduced-form estimation of the minimum wage effect on inequality. Machin *et al.* (2003) studied the effect of the establishment of a National Minimum Wage (NMW) in 1999 in the UK. NMW affected the residential care homes industry, which contains a large portion of low paid workers. They showed that introducing NMW causes a very big wage compression of the lower end of the wage distribution, while its effect on employment remains negligible. In an influential paper, Lee (1999), By defining the concept of effective minimum wage as a proxy for underlying wage inequality, Lee (1999) estimated to what extent the rise in wage inequality from 1979 to 1988 was due to decreasing real minimum wage. He concluded that if the real minimum wage had been kept constant during this period, the inequality would have fallen instead of having risen. Later, Autor, Manning and Smith (2016, hereafter AMS) reassessed the Lee (1999) model with longer period data (from 1979 to 2012), and they showed that the conclusion of Lee (1999) suffered from estimation bias. More importantly, AMS (2016) concluded that due to the

[1] To read about the changes in the magnitude of the minimum wage in US see Flinn (2006).

[2] To read more about the general equilibrium models see Flinn *et al.* (2017); Abowd *et al.* (1999) and Albrecht and Axell (1984).

data limitation in the Current Population Survey (hereafter CPS), we cannot distinguish between measurement error and spillovers for the case of the US.

My study is in line with the second strand of research. My contribution is to use recent developments in penalized spline estimators[3] and to reassess the Lee (1999) estimation. Compared with Lee (1999) my estimation has the advantage of using longer time period and compared to AMS (2016), I will ease the assumption of parametric form of effective minimum wage. By relaxing the parametric estimation of effective minimum wage using penalized splines, I corroborate the conclusion of AMS (2016) about the estimation bias in Lee's (1999) specification. In the second step of this study, I use instrumental variables recommended by Stock, Wright, and Yogo (2002) and also used in AMS (2016) to suggest that P-Splines estimation clearly shows that based on CPS limitations, no spillovers in wage distribution can be detected from changing the minimum wage in the US.

The reminder of this paper is organized as follows: A brief history of minimum wage in US in provided in Section 2. The method of penalized splines for panel data is introduced in Section 3 and in Section 4, I applied this method on CPS data. Finally, Section 5 summarizes my conclusions.

2 Minimum Wage in US

The Minimum wage in the US is set at the federal level and the state level. If there is a discrepancy among state and federal level's minimum wage, the higher value would be dominated in that state. Figure 1 shows the number of states with a higher minimum wage compare to federal level from 1979 to 2012. In 1979 just one state (Alaska) had a minimum wage higher than federal level. The number of states with higher minimum wage increased through the time

[3] See Putz and Kneib (2016) and Fahrmeir et al. (2013)

and it hits the maximum of 31 states in 2008, exactly after a historically lowest level of real minimum wage value in 2007.

Minimum wage spillover effects may occur in several different ways. The relative prices of low-skilled labor is increased when the minimum is increased. This may lead to an increased demand for some types of higher-skilled labor, thus leading to increased wages for some types of workers already earning above the minimum. Secondly, firms may reorganize their workforce to realign marginal products of their minimum wage workers to the new minimum, which may affect the marginal products of other workers. A third possibility is that it may lead to wage increases for some workers already earning above the minimum so as to preserve wage differentials that may affect worker motivation and productivity. Finally, it may increase the reservation wages of those looking for jobs in particular sectors, thereby increasing the wages that employers in those sectors must offer in order to successfully recruit.

Following AMS (2016), I use this source of variation among state's minimum wage along with the "bindingness"[4] of the minimum wage to estimate my model. The main idea is the effective minimum wage (whether it is federal or state minimum wage that is implementing in a specific state) should have a larger impact on the wage distribution in states with a lower wage level. Table 1 shows the maximum binding percentiles and minimum binding percentile for different years. In states with lower level of wage, the binding percentile is higher in comparison with higher wage states. I consider the binding percentile as the highest percentile in the wage distribution that the minimum wage binds. This variation among bindingness is the second source of variation for the model estimation.

The database in this study is taken from the Current Population Survey

[4]The log of the difference between the minimum wage and the median, is known as the bindingness of the minimum wage

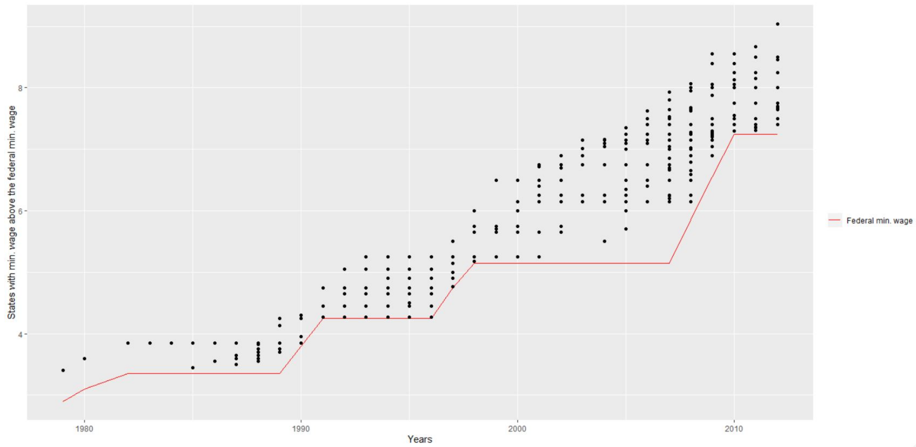

Figure 1: Variation in State Minimum Wages

Notes: Each point corresponds to a state with minimum wage higher than federal minimum wage (the red line).

Merged Outgoing Rotation Group (CPS MORG) and the main outcome of interest is the percentiles of states' annual wage distribution. I follow the approach of Autor, Katz, and Kearney ReStat (2008) to clean the data[5]. I consider only individuals between age 18 to 64 in samples and I winsorize the top two percentiles of wage distribution in each state and year. By pooling all individual responses in CPS MORG for each year, I compute the percentiles of states' annual wage distribution. In some years, the effective minimum wage (state or federal) has been changed twice. In these cases, I consider the minimum wage that was effective longer.

[5]See http://economics.mit.edu/faculty/dautor/data/autkatkear08 for more information about this cleaning process.

Table 1: Bindingness of State and Federal Minimum Wages

	Minimum binding percentile	Maximum binding percentile		Minimum binding percentile	Maximum binding percentile
1979	3.5	17.0	1996	1.5	10.0
1980	4.0	15.5	1997	2.0	8.0
1981	2.5	14.5	1998	2.0	7.0
1982	3.5	12.5	1999	1.5	7.5
1983	3.0	11.5	2000	1.5	7.0
1984	2.0	10.5	2001	1.5	7.5
1985	1.5	9.5	2002	1.5	6.5
1986	1.5	10.0	2003	1.5	6.0
1987	1.5	8.0	2004	1.5	6.5
1988	1.0	7.0	2005	1.0	7.5
1989	0.5	9.0	2006	1.0	8.5
1990	1.0	12.5	2007	1.5	7.5
1991	1.5	9.5	2008	1.0	8.5
1992	1.5	7.5	2009	2.0	8.0
1993	2.0	7.5	2010	3.0	7.5
1994	1.5	6.0	2011	2.5	9.0
1995	1.5	9.0	2012	2.0	8.0

3 Methodology

3.1 Reduced Form Estimation

Following AMS (2016), the main model I estimate is the change of inequality at any point in the wage distribution, which is defined as the difference between the log wage at the pth percentile and the log of the median for state s in year t. This model is formulated as follows:

$$w_{st}(p) - w_{st}(50) = f(w_{st}^m - w_{st}(50)) + \gamma_s(p) + \gamma_t(p) + u_{it} \tag{1}$$

where $w_{st}(p)$ is the log real wage at percentile p ($p = 50$ stands for the median) in state s at time t, w_{st}^m is the log minimum wage and $w_{st}(50)$ is the log median

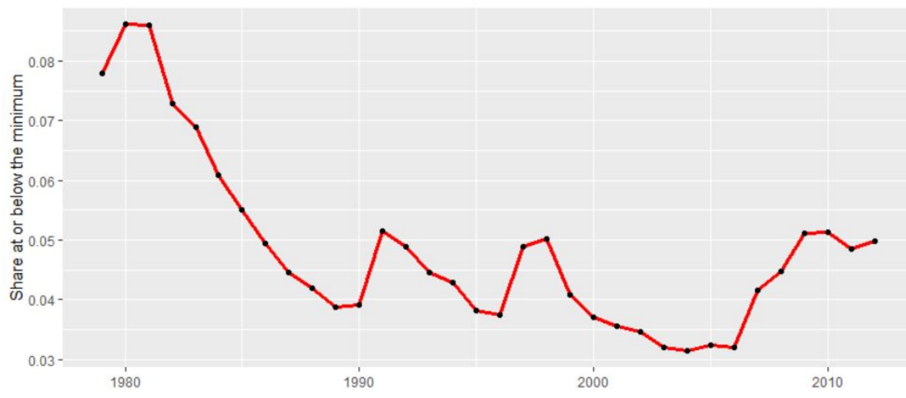

Figure 2: Share of Hours at or Below the Minimum Wage

wage for that state-year . $\gamma_s(p)$ and $\gamma_t(p)$ represent the time-invariant state effects and state-invariant time effects respectively. u_{it} represents transitory effects which I assume to be independent of the state and year effects.

The expression $w_{st}^m - w_{st}(50)$ in equation (1), the log of the difference between the minimum wage and the median, is known as the bindingness of the minimum wage in the wage inequality literature. Lee (1999) modeled this as a quadratic term to capture the idea that minimum wage would have a higher effect whenever it is more binding. Following Lee (1999), equation (1) in this case is specified as:

$$
\begin{aligned}
w_{st}(p) - w_{st}(50) =& \beta_1(p)[w_{st}^m - w_{st}(50)] + \beta_2(p)[w_{st}^m - w_{st}(50)]^2 \\
&+ \gamma_s(p) + \gamma_t(p) + u_{it}
\end{aligned} \tag{2}
$$

The general idea behind equations (1) and (2) is that minimum wage is not binding on for example $w(20) - w(50)$ distribution[6], so if we find a significant effect of the bindingness of the minimum wage on $w(20) - w(50)$, it has to come from the spillover effect of the minimum wage. An inspection of US data

[6]The distribution of the difference between the bottom 20th percentile wage and the median wage.

between 1979 and 2012 shows that there is no year in which more than 10 percent of the share of hours worked for the reported wages is equal to or less than the applicable state or federal minimum wage (see figure (2)). Historical data confirm that the minimum wage has an impact on a small proportion of workers and if we see its effect on higher percentiles, this effect should be a spillover of the minimum wage.

3.2 Penalized Splines Estimation of Reduced Form

For estimation of the nonlinear part in equation (1), I consider the weighted sum of d_h B-spline basis functions, $B_{h_1}, ..., B_{d_h}$, such that:

$$f(w_{st}^m - w_{st}(50)) = \sum_{j=1}^{d_h} B_j(w_{st}^m - w_{st}(50))\beta_j = z^T(w_{st}^m - w_{st}(50))\beta \tag{3}$$

where β_h is a d_h-dimensional column vector of basis coefficients and $z_h(w_{st}^m - w_{st}(50))$ is the evaluation of the basis functions at the observed covariate value. We can write equation (3) in a matrix form:

$$f(w_{st}^m - w_{st}(50)) = Z\beta \tag{4}$$

Z is a design matrix of dimension $NT \times d_h$, N is the number of states and T is the time period. To use the above B-spline basis in panel data, I follow Putz and Kneib (2016) by considering the one period time lag of equation (1):

$$\begin{aligned} w_{s(t-1)}(p) - w_{s(t-1)}(50) =& f(w_{s(t-1)}^m - w_{s(t-1)}(50)) \\ &+ \gamma_s(p) + \gamma_{t-1}(p) + u_{i(t-1)} \end{aligned} \tag{5}$$

To cancel out the state-specific effects γ_s, I subtract (5) from (1):

$$\begin{aligned}
\Delta(w_{st}(p) - w_{st}(50)) =& (w_{st}(p) - w_{st}(50)) - (w_{s(t-1)}(p) - w_{s(t-1)}(50)) \\
=& \gamma_s - \gamma_s + [f(w^m_{st} - w_{st}(50)) - f(w^m_{s(t-1)} - w_{s(t-1)}(50))] \\
&+ (\gamma_t(p) - \gamma_{t-1}(p)) + u_{it} - u_{i(t-1)} \\
=& \sum_{j=1}^{d_h} B_{h_j}(w^m_{st} - w_{st}(50))\beta_j - \\
& \sum_{j=1}^{d_h} B_{h_j}(w^m_{s(t-1)} - w_{s(t-1)}(50))\beta_j + \Delta\gamma_t(p) + \Delta u_{it} \\
=& [z(w^m_{st} - w_{st}(50)) - z(w^m_{s(t-1)} - w_{s(t-1)}(50))]^T\beta + \\
& \Delta\gamma_t(p) + \Delta u_{it} \\
=& [\Delta z(w^m_{st} - w_{st}(50))]^T\beta + \Delta\gamma_t(p) + \Delta u_{it}
\end{aligned} \tag{6}$$

Δ is the first-difference operator over time and design matrix Z of the evaluated basis function is given by:

$$Z = \begin{pmatrix}
B_1((w^m_{11} - w_{11}(50))) & \dots & B_{d_h}((w^m_{11} - w_1(50))) \\
\vdots & \ddots & \vdots \\
B_1((w^m_{1T} - w_{1T}(50))) & \dots & B_{d_h}((w^m_{1T} - w_{1T}(50))) \\
\vdots & \ddots & \vdots \\
B_1((w^m_{N1} - w_{N1}(50))) & \dots & B_{d_h}((w^m_{N1} - w_{N1}(50))) \\
\vdots & \ddots & \vdots \\
B_1((w^m_{NT} - w_{NT}(50))) & \dots & B_{d_h}((w^m_{NT} - w_{NT}(50)))
\end{pmatrix} \tag{7}$$

So we get:

$$\Delta(w(p) - w(50)) = \Delta Z\beta + \Delta\gamma_t + \Delta u \tag{8}$$

in matrix form where $\Delta(w(p)-w(50))$ is a $N(T-1)$-dimensional column vector and ΔZ is obtained by building the difference between matrix Z in (7) and its one period lagged counterpart. Defining $\Delta y = \Delta(w_{st}(p) - w_{st}(50))$, then the first-difference penalized spline estimator for β is defined as the minimization of:

$$[\Delta y - \Delta Z\beta - (I_{t-1} \otimes I_N)\Delta\gamma_t]^T[\Delta y - \Delta Z\beta - (I_{t-1} \otimes I_N)\Delta\gamma_t] + \lambda\beta^T\mathbf{K}\beta \quad (9)$$

where λ is the smoothing parameter that controls for variance-bias trade off and $\mathbf{K}$ is a $d_h \times d_h$-dimensional matrix that controls for over-fitting by penalizing differences of directly contiguous coefficients[7]. I employ the following form for $\mathbf{K}$[8]:

$$\mathbf{K} = \begin{pmatrix} 1 & -1 & & & \\ -1 & 2 & -1 & & \\ & \ddots & \ddots & \ddots & \\ & & -1 & 2 & -1 \\ & & & -1 & 1 \end{pmatrix}$$

Let $(w^m - w(50))_0$ be an arbitrary value on the domain of $(w^m - w(50))$, by defining the smoothing matrix $\mathbf{L}((w^m - w(50))_0)$ as:

$$\mathbf{L}((w^m - w(50))_0) = \Delta Z[\Delta Z^T\Delta Z + \lambda\mathbf{K}]^{-1}\Delta z^T((w^m - w(50))_0) \quad (10)$$

[7] This penalty term promotes smoothness in estimation.

[8] For more details about the different types of penalties for B-spline functions see Eilers and Marx (1996).

where Δz is the first difference of (3), the estimator of $f((w^m_{st} - w_{st}(50))_0)$ can be written as:

$$\hat{f}((w^m - w(50))_0) = \mathbf{L}^T((w^m - w(50))_0)((w(p) - w(50))) \tag{11}$$

If we assume $u_i \sim N(0, \sigma^2_u)$, it follows that:

$$Var[\hat{f}((w^m - w(50))_0)] = \mathbf{L}^T((w^m - w(50))_0)\sigma^2_u \mathbf{I}_n \mathbf{L}^T((w^m - w_(50))_0)$$

To find the marginal effect, in case of B-spline basis functions, the derivative of the smoothing matrix in (10) is given by[9]:

$$\mathbf{L}'((w^m - w(50))_0) = \Delta Z[\Delta Z^T \Delta Z + \lambda \mathbf{K}]^{-1}[\Delta z'((w^m - w(50))_0)]^T \tag{12}$$

where $[\Delta z'((w^m - w(50))_0)]^T$ is the row vector of the derivatives of the first difference of the initial basis function, evaluated at $(w^m - w(50))_0)$.

There are two challenges with using the B-spline functions for estimation. The first challenge is tuning the value of λ which is smoothing parameter. There are several methods to choose the optimal value of λ, for example, cross validation and mixed model. Due to the exploratory nature of this study and limitation on data, I cannot use cross validation to find the optimal λ value. The second challenge is building confidence bands for penalized splines to measure the uncertainty of the parameter estimates. To address these obstacles, I use a mixed model method proposed first by Krivobokova et al. (2010) and then extended by Wiesenfarth et al. (2012) which I will briefly describe here. Following Putz and Kneib (2016), the general idea is to rewrite:

$$f^m((w^m - w(50))) = Z\beta = Z(F_f\alpha_f + F_r\alpha_r) = X_f\alpha_f + X_r\alpha_r \tag{13}$$

[9]See Putz and Kneib (2016) for details.

where α_f is fixed coefficients and α_r is a vector of i.i.d random coefficients with variance σ_r^2, which are assumed to be independent from the errors u_i. With this representation of mixed model, we can use a restricted maximum likelihood estimator to obtain both coefficients and smoothing parameter. In addition, using the fact that the model errors u_i are normally distributed with zero expectation and constant variance, the marginal distribution of $(w(p) - w(50))$ is given by:

$$(w(p) - w(50)) \sim N(\beta_0 1_n + X_f \alpha_f, \sigma_u^2 I_n + \sigma_r^2 X_r X_r^T) \tag{14}$$

The fixed coefficients estimators are unbiased, so we can derive a zero mean Gaussian process:

$$G(w^m - w(50)) = \frac{Z^m(\hat{\beta}^m - \beta^m)}{\sqrt{Z^m Cov(\hat{\beta}^m - \beta^m)(Z^m)^T}} \sim N(0, \Sigma) \tag{15}$$

Wiesenfarth et al. (2012) showed that using (14) and (15), we can derive simultaneous confidence bands around the estimated functions with critical value that is the $(1-\alpha)$-quantile of the random variable:

$$\sup_{x_{min} \leq x \leq x_{max}} \frac{|\hat{f}(x) - f(x)|}{\sqrt{Var[\hat{f}(x)]}} \tag{16}$$

where $x = (w^m - w(50))$ here. In the next section, I will apply penalized splines explained above to estimate (1).

4 Estimation

Using penalized spline estimator and the wage percentiles data of US from 1979 to 2012, I estimate the relation between $log(Min) - log(50)$ and $log(p) -$

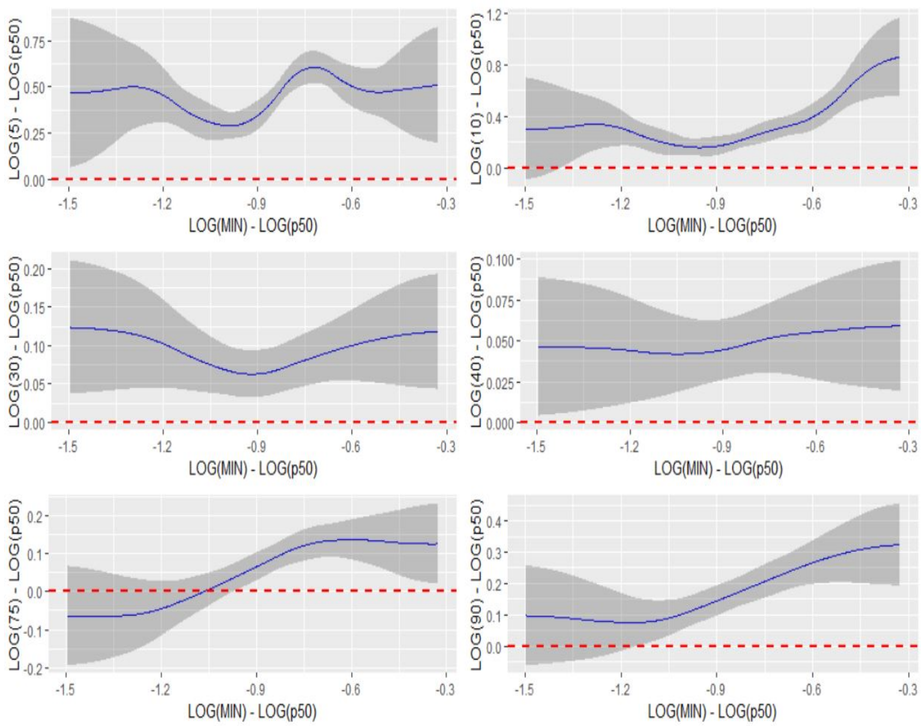

Figure 3: Estimates of the Relation Between LOG(p) - LOG(p50) and LOG(MIN) - LOG(p50)

$log(50)$. If there is spillover from binding minimum wage, I expect to see a positive relation (in negative direction) between the $50-p$ inequality and binding minimum wage for $p < 50$ and negative relation for $p > 50$[10]. Figure (3) shows the estimate of the marginal effect of $log(minimum.wage) - log(50)$ for the selected percentiles, evaluated across states and years with their 95% confidence interval. The marginal effect of minimum wage is positive on $50 - 5$ and $50 - 10$ inequality which confirms the Lee (1999) findings about the spillover effect of minimum wage on the lower tail of minimum wage. The effect of minimum wage is diminishing as we move to the higher percentiles. It is not significant in the middle of wage distribution, but this effect again becomes positive in

[10]For $p > 50$, $log(p) - log(50)$ would be negative, so the direction should should switch.

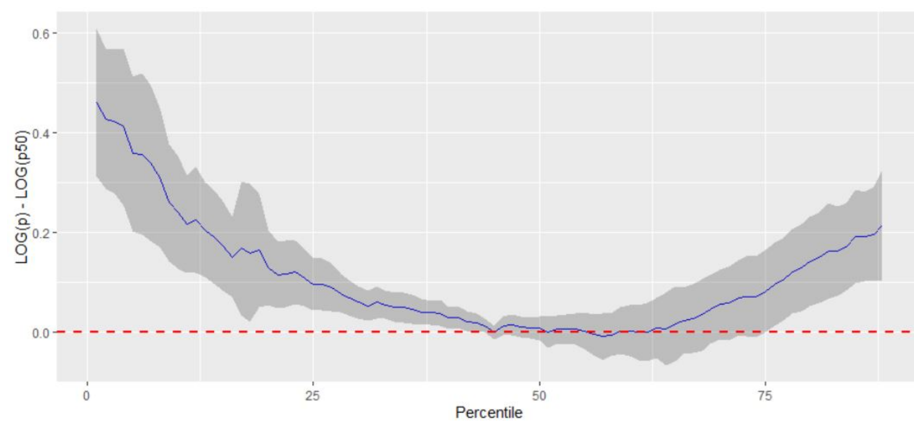

Figure 4: The Average Marginal Effect of the Relation Between LOG(p) - LOG(p50) and LOG(MIN) - LOG(p50)

the upper tail of wage distribution, which is troubling since we expect to see a negative effect. Notice that the $log(p) - log(50)$ is negative for percentiles less than median and positive for percentiles higher than median, so if the minimum wage is supposed to reduce inequality, the marginal effect in equation (1) should be positive for percentiles less than the median and negative for percentiles more than median. This issue with the upper tail of distribution is more pronounced in Figure 4. This figure shows the average marginal effect for each percentile: the average marginal effect of minimum wage approaches to zero after the 25th percentile, but again becomes positive after the 75th percentile. This mixed findings is the main result of AMS (2016) and comes from the fact that equation (1) specification suffers from endogeneity. The issue is that states with higher wage tend to have lower effective minimum wages and that creates an endogeneity in the right hand side of equation (1) and penalized spline estimation in Figure 4 can depicts this fact very well.

Knowing that there is bias in equation (1), I follow the Card, Katz and Krueger (1993) approach to consider an IV estimation. As did AMS (2016), I use the effective minimum wage and the interaction of effective minimum wage with

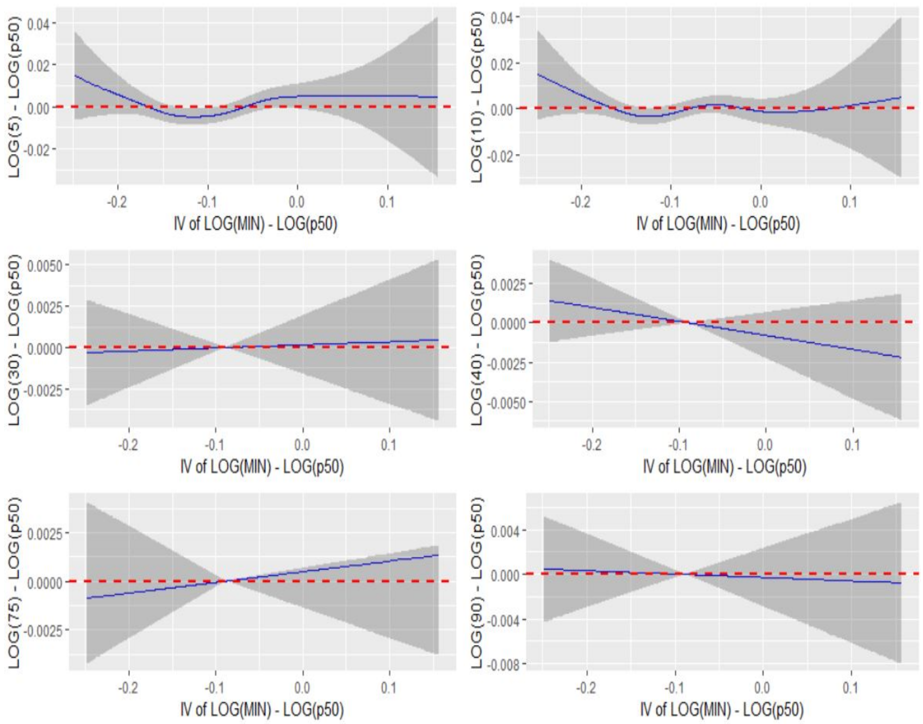

Figure 5: Spline Regression with Instrument of the Relation Between LOG(p) - LOG(p50) and LOG(MIN) - LOG(p50)

state median wage as instruments for the bindingness of the minimum wage[11]. Henderson and Souto (2018) suggest a method to use spline regression with instruments. I use their method along with the mentioned instruments. Figure 5 represents the results for selected percentiles. As one may see in Figure 5, the marginal effect of the minimum wage on wage distribution is not significant through all parts of wage distribution. This fact is more clear in Figure 6 which shows the average marginal effects for each percentile. According to Figure 6, the average marginal effects is zero even for lower tail of wage distribution. This finding exactly confirms the discussion of AMS (2016), although they failed to

[11] According to Card, Katz and Krueger (1993), these instruments passed tests for weak instruments.

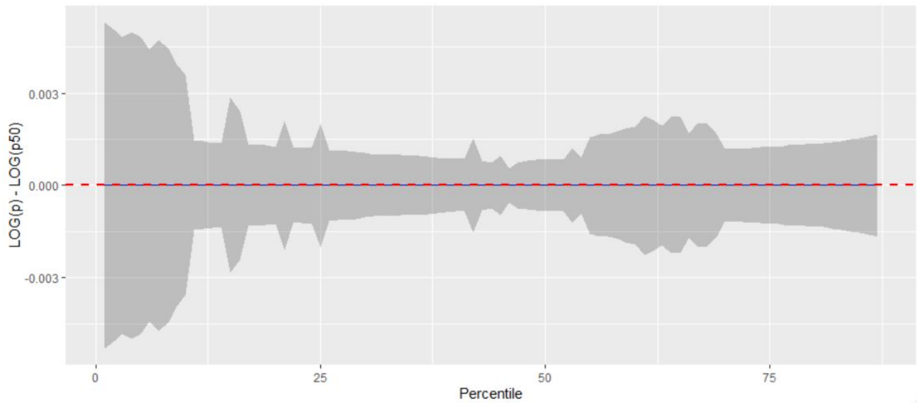

Figure 6: The Average of Marginal Effect of the Relation Between LOG(p) - LOG(p50) and LOG(MIN) - LOG(p50) for P-Spline with Instruments

show that. By using IV, AMS (2016) were successful to show that, based on CPS data, we cannot detect any spillover effect of the minimum wage for upper tail of wage distribution. Further, they argued that any observed spillover effect of the minimum wage for lower tail of wage distribution should simply comes from measurement error[12]. The IV estimation in AMS (2016) failed to show this measurement error, while the spline regression due to its flexibility and denoising ability is successful to show that the spillover effect based on CPS data is not detectable even for lower tail of wage distribution.

5 Conclusion

The main purpose of this study is to estimate the effect of effective the minimum wage on different percentiles of wage distribution. My contribution rests on two recent developments: 1) a recent paper by AMS (2016) which shows the spillover effect of minimum wage on upper tail of minimum wage is not significant by CPS data and state level effective minimum wage; 2) a penal-

[12]This measurement error is coming from the fact that there is always a spike in wage distribution around minimum wage.

ized spline estimator for fixed effects panel data, developed by Putz and Kneib (2016) which is advantageous in estimating the unknown nonlinear covariates effects. Combining these two recent developments, I show that penalized spline methods support the claim of AMS (2016) that, based on CPS data from 1979 to 2012, the spillover effect of minimum wage is not detectable even in the lower tail of the wage distribution.

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