Heterogeneous Impact of the Minimum Wage: Implications for Changes in Between- and Within-group Inequality*

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Abstract

Workers who earn at or below the minimum wage in the United States are mostly either less educated, young, or female. This paper shows that changes in the real value of the minimum wage over recent decades have affected the relationship of hourly wages with education, experience, and gender. Changes in the real value of the minimum wage account in part for the patterns of changes in education, experience, and gender wage differentials and mostly for the patterns of changes in within-group wage differentials.

KEYWORDS: Minimum wage; wage inequality; censoring; quantile regression.
JEL CLASSIFICATION: C21, C23, J31, J38, K31.

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1 Introduction

Expectations for the role of the minimum wage in addressing inequality have increased worldwide with concerns over growing inequality in recent decades. The minimum wage has been introduced and expanded in many countries to lift the wages of the lowest paid workers. It has been pointed out, however, that the minimum wage can cause both intended and unintended consequences (Card and Krueger, 1995; Neumark and Wascher, 2008). The intended consequences are the beneficial effects on the distributions of wages and earnings (DiNardo, Fortin, and Lemieux, 1996; Lee, 1999; Teulings, 2003; Autor, Manning, and Smith, 2016; Dube, 2018). The unintended consequences are the adverse effects on employment, consumer prices, and firm entry and exits (Aaronson and French, 2007; Draca, Machin, and Reenen, 2011; Aaronson, French, Sorkin, and To, 2018). Proponents of the policy have typically assumed the view that the intended effects are substantial and the unintended effects are negligible. On the other hand, opponents have raised concerns that the unintended effects are not negligible. Most studies have focused on proving or disproving the existence of adverse effects of the minimum wage, and fewer studies have examined the distributional impact of the minimum wage in recent years (Card and Krueger, 2017). In this paper, we examine the impact of the minimum wage on the wage distribution, which is the most direct and intended consequence of the policy.

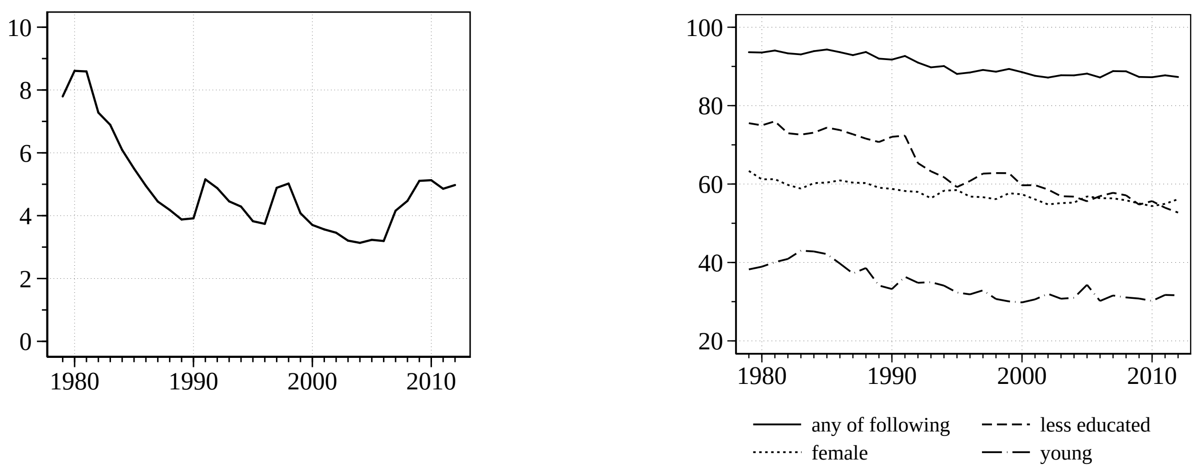
The proportion and characteristics of minimum wage workers serve as starting points for a discussion on the distributional impact of the minimum wage. According to the Current Population Survey (CPS), the proportion of workers who earn at or below the minimum wage in the United States ranges between 3 and 9 percent for the years 1979 to 2012 (Figure 1a). Less than 10 percent of workers have been directly affected by the minimum wage in the U.S. labor market. The extent to which the minimum wage affects the wage structure depends on the magnitude of the spillover effects on workers who earn more than the minimum wage. The minimum wage can exert a substantial influence on the wage structure if there are strong spillover effects.

Perhaps a less well-known fact is that minimum wage workers are concentrated in particular demographic groups. Approximately 90 percent of workers who earned at or below the minimum wage in the United States between the years 1979 and 2012 were high school graduates or less, younger than 25 years old, or female (Figure 1b). The reason was not that the minimum wage policy had been targeted based on education, experience, or gender, but because the lowest paid workers were mostly either less educated, young, or female. In light of this, the minimum wage may affect the relationship of hourly wages with education, experience, and gender.

Figure 1: Proportion and characteristics of minimum wage workers

(a) How many workers earn the minimum wage?

(b) Who earns the minimum wage?



Notes: Figure 1a is reproduced from Figure 2 in Autor, Manning, and Smith (2016). In Figure 1b, less-educated workers are those with a high school degree or less, and young workers are those aged 24 years or less.

In this paper, we show that changes in the real value of the minimum wage over recent decades have affected the relationship of hourly wages with education, experience, and gender in the United States. The impact of the minimum wage is heterogeneous across workers depending on their education, experience, and gender. Consequently, changes in the real value of the minimum wage account in part for the patterns of changes in education, experience, and gender wage differentials. We further show that changes in the real value of the minimum wage over recent decades have affected wage differentials among workers with the same observed characteristics. The impact of the minimum wage is heterogeneous across quantiles of workers' productivity not attributable to their education, experience, or gender. Consequently, changes in the real value of the minimum wage account mostly for the patterns of changes in within-group wage differential among workers with lower levels of experience.

The remainder of the paper is organized as follows. The next section reviews the related literature. Section 3 describes the data and institutional background. Section 4 presents an econometric framework to evaluate the quantitative contribution of the minimum wage to changes in between- and within-group inequality. Section 5 provides the empirical results. The final section concludes.

2 Related Literature

The literature has proven that the minimum wage has an effect on the distribution of hourly wages in the United States, while the magnitude and mechanisms of the effect vary across studies. The seminal work of DiNardo, Fortin, and Lemieux (1996) concludes that a decline in the real value of the minimum wage accounted for, at most, 40 to 65 percent of a rise in the 50/10 wage differential for the years 1979 to 1988. On the other hand, the influential work of Lee (1999) concludes that a decline in the real value of the minimum wage accounted for the entire increase in the 90/10 wage differential during the same period. Teulings (2003) concludes that a decline in the real value of the minimum wage accounted for the entire increase in the 50/10 wage differential in the 1980s. Recently, Autor, Manning, and Smith (2016) conclude that a decline in the real value of the minimum wage accounted for 30 to 40 percent of a rise in the 50/10 wage differential in the 1980s.

These studies develop and adopt different approaches that take into account different degrees of spillover and heterogeneity in the impact of the minimum wage. DiNardo, Fortin, and Lemieux (1996) develop an almost nonparametric approach to estimating discontinuous changes in the wage distribution at the minimum wage. Lee (1999) develop a semiparametric approach to estimating heterogeneous effects of the minimum wage across quantiles of the wage distribution. Teulings (2003) develops a parametric approach to estimating the impact of the minimum wage on the wage distribution. Lee (1999) and Teulings' (2003) approaches allow for spillover effects, while DiNardo, Fortin, and Lemieux's (1996) approach does not. Teulings' (2003) approach allows for heterogeneous effects with respect to workers' observed characteristics, while Lee's (1999) approach does not. Autor, Manning, and Smith (2016) refine and apply Lee's (1999) approach to data covering a longer period, and develop a test for the presence of spillover effects under a distributional assumption.

Understanding the sources of changes in between- and within-group inequality is key to understanding the mechanisms of changes in wage inequality in the United States (Lemieux, 2006; Autor, Katz, and Kearney, 2008). However, little is known concerning the extent to which changes in between- and within-group wage differentials are attributed to changes in the real value of the minimum wage. In the literature, changes in between-group wage differentials have been typically attributed to changes in technology, workforce composition, and gender discrimination (see Katz and Autor, 1999; Blau and Kahn, 2017, for surveys). There is no consensus on the quantitative contribution of the minimum wage to changes in between-group wage differentials. DiNardo, Fortin, and Lemieux (1996) and Lee (1999) conclude that changes in the educational wage differential are attributable only to a small extent to changes in the real value of the minimum wage, while Teulings (2003) concludes that changes in the educational wage differential are attributable to a large extent to changes in the real value of the minimum wage. DiNardo, Fortin, and Lemieux (1996) demonstrate that the minimum wage was a key factor in accounting for changes in residual inequality in the 1980s. However, the literature identifying the sources of changes in within-group wage differentials have been less conclusive than the literature identifying the sources of changes in between-group wage differentials (Lemieux, 2006; Autor, Katz, and Kearney, 2008).

3 Data

The data used in our analysis are repeated cross-sectional data from the Current Population Survey Merged Outgoing Rotation Group for the years 1979 to 2012. We construct variables in the same way as in Autor, Manning, and Smith (2016). The authors' sample is composed of workers aged between 18 and 64 including males and females, full-time and part-time workers, but excluding self-employed workers. Our sample is composed of employed individuals in the sample of Autor, Manning, and Smith (2016) and non-employed individuals. The yearly sample size ranges from 142,000 to 235,000. Following DiNardo, Fortin, and Lemieux (1996), Lee (1999), and Autor, Manning, and Smith (2016), we weight each individual according to the sampling weight multiplied by hours worked. As we detail later, we use the censored quantile regression model to impute the wages of individuals for whom we cannot observe wages.

Minimum wage laws differ across states and change over time in the United States. The federal government sets the federal minimum wage that applies to all states. State governments can set the state minimum wage higher than the federal minimum wage. The statutory minimum wage is the maximum of the federal minimum wage and the state minimum wage.

Figure 2: Variation and changes in the statutory minimum wage

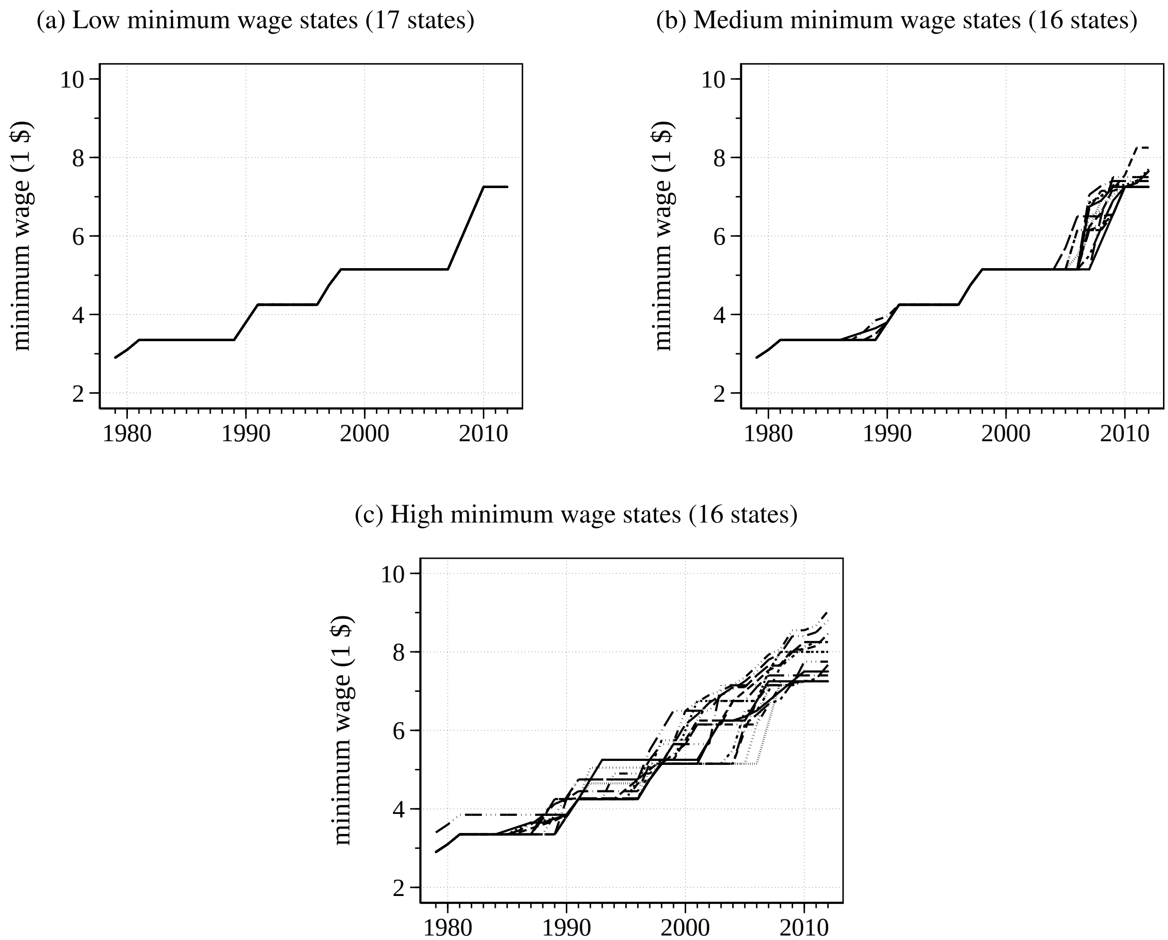


Figure 2 shows the trend in the statutory minimum wage for the years 1979 to 2012. For ease of reference, we divide all 50 states evenly into three groups according to the level of statutory minimum wage. During the period, 17 states had no state minimum wage (Figure 2a). The statutory minimum wage equals the federal minimum wage in these states. The federal minimum wage increased four times: 1979 to 1981, 1989 to 1991, 1996 to 1998, and 2007 to 2010. The remaining 33 states set their state minimum wages (Figures 2b and 2c). The statutory minimum wage has been higher than the federal minimum wage for many years in these states. In the 1980s there was not much variation across states or changes over time in the minimum wage. On the other hand, in the 1990s and the 2000s there was substantial variation and changes in the minimum wage across states over time.

Figure 3: Changes in the real value of the minimum wage, 1979–2012

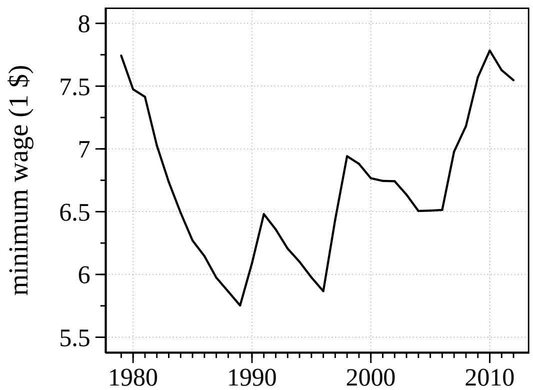


Figure 3 shows the national average trend in the real value of the minimum wage for the years 1979 to 2012. The statutory minimum wage is deflated by the personal consumer expenditure price index using 2012 as the base year. During the period, there was a change in the trend in the year 1989. The real value of the minimum wage fell due to inflation from 1979 to 1989. Subsequently, the real value of the minimum wage exhibits an upward trend due to increases in the statutory minimum wage for the years 1989 to 2012.

4 Econometric Framework

In this section, we present our econometric framework. We start by introducing the (group-level) panel quantile regression model. Then, we describe the censored quantile regression model. We end this section by describing our approach to evaluating the quantitative contribution of the minimum wage to changes in between- and within-group inequality.

4.1 Model

The key feature of our model is that it allows for heterogeneity in the impact of the minimum wage with respect to workers' observed characteristics and unobserved quantiles. The two types of heterogeneity are essential for evaluating the contribution of the minimum wage to changes in between- and within-group inequality.

For the purpose of our analysis, we adopt the quantile regression approach pioneered by Koenker and Bassett (1978).[1] We consider the following quantile regression model that allows for interactions between the minimum wage and workers' observed characteristics.

$$Q_{st}\left(\tau|z_{ist}\right) = m_{st}\left(\beta_0\left(\tau\right) + z'_{-,ist}\beta_{-}\left(\tau\right)\right) + z'_{ist}\delta_{st}\left(\tau\right) + x'_{st}\gamma_0\left(\tau\right) + \varepsilon_{0,st}\left(\tau\right) \qquad \text{for} \quad \tau \in (0,1), \qquad (1)$$

where $Q_{st}\left(\tau|z_{ist}\right)$ is the τth conditional quantile of the log of real hourly wages, w_{ist}, given the log of the real value of the minimum wage, m_{st}, a J-vector of individual characteristics, $z_{ist} = \left(1, z'_{-,ist}\right)'$, and a K-vector of state characteristics, x_{st}. We observe individuals $i = 1, \ldots, N_{st}$ in states $s = 1, \ldots, S$, and time $t = 1, \ldots, T$. The disturbance term, $\varepsilon_{0,st}\left(\tau\right)$, includes unobserved state characteristics. Appendix A.1 describes the conceptual framework that underlies the econometric model (1).

We include the linear and quadratic terms in years of education and of potential experience (age minus education minus six), and an indicator for being male in individual characteristics, $z_{-,ist}$. There are three reasons we use these variables. First, they are determined prior to the entry of the labor market. Second, they are commonly used as regressors in the quantile regression of wages (Buchinsky, 1994; Angrist, Chernozhukov, and Fernández-Val, 2006). The quantile regression model (1) is more flexible in that it allows all intercept and slope coefficients to vary across states and years. We choose not to include more regressors in the quantile regression model, because the sample becomes smaller and more homogeneous when it is split by state and year.[2] Finally, and most importantly, they are useful to distinguish minimum wage workers. Following Autor, Manning, and Smith (2016), we include state and year dummies and state-specific linear trends in state characteristics, x_{st}.

The impact of the minimum wage can vary across individuals according to their observed characteristics z_{ist} and unobserved quantiles τ. The heterogeneous impact of the minimum wage can be represented by a set of parameters, $\beta\left(\tau\right) = \left(\beta_0\left(\tau\right), \beta'_{-}\left(\tau\right)\right)' = \left(\beta_0\left(\tau\right), \beta_1\left(\tau\right), \ldots, \beta_J\left(\tau\right)\right)'$. Note that

[1] Koenker (2017) recently notes that "somewhat neglected in the econometrics literature on treatment response and program evaluation is the potentially important role of the interactions of covariates with treatment variables."

[2] When we add an indicator of being white in individual characteristics, we find that the minimum wage has no effect on the racial wage differential. The proportion of black workers was less than 20 percent among minimum wage workers throughout the sample period. Even if the linear and quadratic terms in years of education and years of experience are interacted with the indicator for being male, the results reported remain essentially unchanged.

the first element of the vector z_{ist} is one. The second to last elements, $\beta_1(\tau)$ to $\beta_J(\tau)$, of the vector $\beta(\tau)$ measure the extent to which the impact of the minimum wage varies across individuals according to their observed characteristics. If there is no heterogeneity in the impact of the minimum wage with respect to observed characteristics, the parameter vector is $\beta(\tau) = (\beta_0(\tau), 0, \ldots, 0)'$ for a given τ. The quantile τ measures the position in the distribution of workers' productivity not attributable to their observed characteristics. If there is no heterogeneity in the impact of the minimum wage with respect to unobserved quantiles, the parameter vector is $\beta(\tau) = (\beta_0, \beta_1, \ldots, \beta_J)'$ for all τ.

Following Chetverikov, Larsen, and Palmer (2016), we consider estimating the quantile regression model (1) in two steps to avoid imposing a distributional assumption on $\varepsilon_{0,st}(\tau)$. In a similar way to Chetverikov, Larsen, and Palmer (2016), we rewrite the quantile regression model (1) as

$$Q_{st}(\tau | z_{ist}) = z'_{ist}\alpha_{st}(\tau), \tag{2}$$

and

$$\alpha_{jst}(\tau) = m_{st}\beta_j(\tau) + x'_{st}\gamma_j(\tau) + \varepsilon_{jst}(\tau) \qquad \text{for } j = 0, \ldots, J. \tag{3}$$

As can be seen by substituting equation (3) into equation (2), the vector of coefficients on z_{ist} in equation (1) corresponds to $\delta_{st}(\tau) = (x'_{st}\gamma_1(\tau) + \varepsilon_{1,st}, \ldots, x'_{st}\gamma_J(\tau) + \varepsilon_{J,st}(\tau))'$. Equations (2) and (3) imply that equation (1) can be estimated in two steps. In the first step, we perform separate quantile regressions of w_{ist} by state s and year t for each quantile τ using the individual-level cross-sectional data. We then obtain a set of parameters $\alpha_{st}(\tau) = (\alpha_{0,st}(\tau), \alpha_{1,st}(\tau), \ldots, \alpha_{J,st}(\tau))'$. In the second step, we perform the mean regression of $\alpha_{st}(\tau)$ for each quantile τ using the state-level panel data. Relative to several applications discussed in Chetverikov, Larsen, and Palmer (2016), we allow for interactions between the treatment variable and individual characteristics, while we assume the exogeneity of the treatment variable. The minimum wage is commonly assumed to be exogenous in the literature (DiNardo, Fortin, and Lemieux, 1996; Lee, 1999; Teulings, 2003; Autor, Manning, and Smith, 2016). We, however, examine the possibility that differences in changes in the real value of the minimum wage across states may be driven by differences in changes in unobserved state characteristics.

The approach described above is related to the approach used in Lee (1999), who estimates the model of the form:

$$Q_{st}(\tau) - Q_{st}(0.5) = \left(m_{st} - Q_{st}(0.5)\right)\beta(\tau) + x'_{st}\gamma(\tau) + \varepsilon_{st}(\tau), \tag{4}$$

where $Q_{st}(\tau)$ is the τth unconditional quantile of w_{ist}. If the median wage, $Q_{st}(0.5)$, is absent, this model corresponds to the case in which all individual characteristics are excluded from equation (2). The main reason for the use of the median wage is presumably that there was insufficient variation in the state minimum wage during the period of the author's analysis, 1979 to 1988.

4.2 Estimation

We address the issues of censoring and truncation, building on the approach described above.

Censoring The wage distribution has been left-censored due to the minimum wage in many states (DiNardo, Fortin, and Lemieux, 1996; Lee, 1999). This issue is evident from the data but typically ignored when estimating the wage equation. The main reason, presumably, is that the magnitude of the bias due to left-censoring at the minimum wage is negligible if the interest lies at the mean impact. However, the magnitude of the bias may not be negligible if the interest lies at the distributional impact. The left-censoring due to the minimum wage can cause the fitted wage equation to be flat. In this case, the intercept coefficient becomes larger, while the slope coefficients become smaller. This effect is stronger at quantiles closer to the minimum wage. As a likely consequence, the censoring effect (the impact of the minimum wage at the minimum wage) may suffer from a downward bias, while the spillover effect (the impact of the minimum wage above the minimum wage) may suffer from an upward bias.

In addition, the earnings data from the CPS is right-censored due to top-coding. This issue has been widely recognized in the literature. Many studies using the CPS data make some adjustments for top-coding. Among others, Hubbard (2011) develops a maximum likelihood approach to addressing this issue under a distributional assumption. He shows that an increase in top-coded observations causes a serious bias in the trend in the gender wage differential.

We adopt the censored quantile regression approach developed in Powell (1986), Chernozhukov and Hong (2002), and Chernozhukov, Fernández-Val, and Kowalski (2015) to address the issue of censoring. This approach is semiparametric in the sense that it does not require a distributional assumption. We consider the following censored quantile regression model to deal with left-censoring due to the minimum wage and right-censoring due to top-coding.

$$Q_{st}(\tau | z_{ist}) = \begin{cases} m_{st} & \text{if } w_{ist} \leq m_{st}, \\ z_{ist}' \alpha_{st}(\tau) & \text{if } m_{st} \leq w_{ist} < c_{it}, \\ c_{it} & \text{if } w_{ist} \geq c_{it}, \end{cases} \tag{5}$$

where c_{it} denotes the top-coded value.[3] The key concept of this approach is to estimate the quantile regression model using the subsample of individuals who are unlikely to be left- or right-censored.[4] Appendix A.2 details the estimation procedure.

Missing wages There are diverse views on the employment effect of the minimum wage (Card and Krueger, 1995; Neumark and Wascher, 2008). Given the importance of this issue, a valid question may be whether changes in the wage distribution are due in part to a potential loss of employment resulting from a rise in the minimum wage. For the sake of discussion, we suppose that workers lose their jobs in the order of those with the lowest to highest productivity. In this case, percentile wages can mechanically increase even without any actual increase in wages. This implies that if the sample is restricted to employed individuals, the censoring effect and the spillover effect might be subject to an upward bias. The magnitude of the bias depends on the magnitude of the employment effect. We control for potential bias by imputing the wages of non-employed individuals.

Our approach builds on the quantile imputation approach developed in Yoon (2010) and Wei (2017). For the purpose of imputation, we use the censored quantile regression model, instead of the standard

[3]The CPS sample is composed of hourly paid workers and monthly paid workers. Earnings for monthly paid workers are top-coded, while wages for hourly paid workers are not. For monthly paid workers, earnings are divided by hours worked to calculate hourly wages. Although the top-coded value of earnings is constant for a given year, the top-coded value of wages differs according to hours worked. We, thus, allow the top-coded value to vary across individuals.

[4]In practice, it does not matter which values are assigned to the wages of workers who earn below the minimum wage in the range less than or equal to the minimum wage. Similarly, it does not matter which values are assigned to the wages of workers who earn above the top-coded value in the range greater than or equal to the top-coded value.

quantile regression, to take into account left- and right-censoring. In the process of imputation, we assume that non-employed individuals are less productive than median employed individuals, as is common in the literature on the gender wage differential (Johnson, Kitamura, and Neal, 2000).[5] We are concerned that a potential loss of employment may result from a rise in the minimum wage. This assumption is also a result of theoretical predictions that state that workers who might lose their jobs due to a rise in the minimum wage are more likely to be low-productivity workers in the lower quantiles. In this sense, we allow for selection on unobservables. Appendix A.2 details the imputation procedure.

Procedure The estimation procedure is divided into three stages. First, we estimate the censored quantile regression model (5) using the sample of employed individuals and impute the wages of individuals for whom we cannot observe wages. Second, we estimate the censored quantile regression model (5) using the sample of employed and non-employed individuals, and obtain the estimates for intercept and slope coefficients $\widehat{\alpha}_{jst}(\tau)$ in the wage equation for $j = 0, 1, \ldots, 5$, $s = 1, 2, \ldots, 50$, $t = 1979, 1980, \ldots, 2012$, and $\tau = 0.04, 0.05, \ldots, 0.97$. Both in the first and second stages, we perform the separate regressions by state and year for each quantile. Finally, we estimate the linear regression model (3) of $\widehat{\alpha}_{jst}(\tau)$ using the state-level panel data.

Inference Chetverikov, Larsen, and Palmer (2016) derive the asymptotic properties of estimators for parameters in equation (3). The authors show that estimation errors from the individual-level quantile regression are asymptotically negligible, if the size of the sample used in the individual-level quantile regression is sufficiently large relative to the size of the sample used in the state-level mean regression. Because the sample size may not be sufficiently large in the least populous states, we choose to report bootstrapped confidence intervals. We construct bootstrapped intervals from 50,000 bootstrap estimates obtained by repeating the individual-level censored quantile regression 500 times and then repeating the state-level mean regression 1,000 times for each quantile regression estimate. We allow for arbitrary forms of heteroscedasticity and serial correlation.

[5] The results reported remain essentially unchanged if we assume that non-employed individuals are less productive than 30 or 70 percent of employed individuals.

Specification checks As is common when estimating the impact of the minimum wage on the wage distribution (DiNardo, Fortin, and Lemieux, 1996; Lee, 1999; Teulings, 2003; Autor, Manning, and Smith, 2016), we focus primarily on the contemporaneous effect of the minimum wage. We estimate the following model in which we add the lag and lead variables, $m_{s,t-1}$ and $m_{s,t+1}$, to assess the validity of the model specification.

$$\alpha_{jst}(\tau) = m_{s,t-1}\beta_{j,-1}(\tau) + m_{st}\beta_{j,0}(\tau) + m_{s,t+1}\beta_{j,+1}(\tau) + x_{st}'\gamma_j(\tau) + \varepsilon_{jst}(\tau) \quad \text{for } j = 0,\ldots,J. \tag{6}$$

If model (3) is correctly specified, we expect two restrictions to be satisfied. First, the long-term effect, $\beta_{j,-1}(\tau) + \beta_{j,0}(\tau)$, in model (6), would be the same as the contemporaneous effect, $\beta_j(\tau)$, in model (3). This restriction will be valid if the policy effect is well captured by the contemporaneous effect. Second, there would be no leading effect in model (6); that is, $\beta_{j,+1}(\tau) = 0$. This restriction will not hold if changes in the real value of the minimum wage are driven by changes in unobserved state characteristics. We, thus, examine whether the long-term effect differs from the contemporaneous effect, and whether the leading effect differs from zero.

4.3 Measures of inequality

The aim of this paper is to evaluate the quantitative contribution of the minimum wage to changes in between- and within-group inequality. Here, we provide the definition of the two types of inequality and describe the way to measure the contribution of the minimum wage along the lines of the model described above.

Between-group inequality is the wage differential among workers with different observed characteristics. Consider two groups of workers, one of which consists of workers with individual characteristics, $z_{ist} = z_A$, and the other consists of workers with individual characteristics, $z_{ist} = z_B$. Between-group inequality can be defined as:

$$\Delta_{st}^{B}(\tau | z_A, z_B) := Q_{st}(\tau | z_A) - Q_{st}(\tau | z_B) \tag{7}$$

for a given quantile τ. Let $\widetilde{\Delta}_{st}^{B}$ denote the counterfactual between-group wage differential if the real value of the minimum wage were kept constant at a certain level. The contribution of the minimum wage can be measured by taking the difference between the actual wage differential and the counterfactual wage differential: $\Delta_{st}^{B}\left(\tau|z_A, z_B\right) - \widetilde{\Delta}_{st}^{B}\left(\tau|z_A, z_B\right)$.

Within-group inequality is the wage differential among workers with the same observed characteristics. Consider a range between two quantiles, τ_A and τ_B, as a measure of inequality. Within-group inequality can be defined as:

$$\Delta_{st}^{W}\left(\tau_A, \tau_B|z\right) := Q_{st}\left(\tau_A|z\right) - Q_{st}\left(\tau_B|z\right) \tag{8}$$

for a group of workers with individual characteristics, $z_{ist} = z$. Let $\widetilde{\Delta}_{st}^{W}$ denote the counterfactual within-group wage differential if the real value of the minimum wage is kept constant at a certain level. The contribution of the minimum wage can be measured by taking the difference between the actual wage differential and the counterfactual wage differential: $\Delta_{st}^{W}\left(\tau_A, \tau_B|z\right) - \widetilde{\Delta}_{st}^{W}\left(\tau_A, \tau_B|z\right)$.

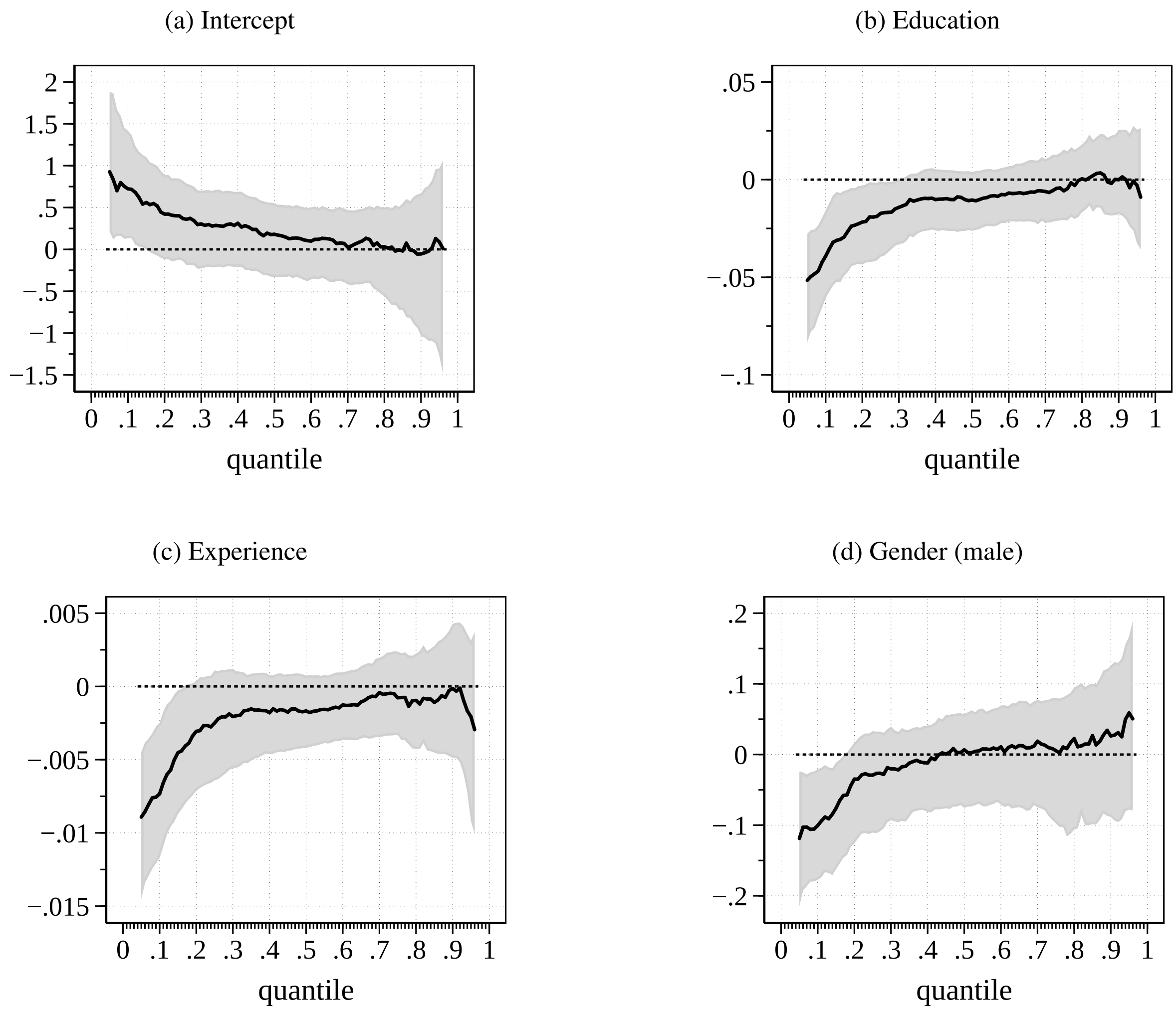
5 Results

Our results are divided into two parts. The first part is a collection of the results regarding the impact of the minimum wage on the wage structure. The second part is a collection of the results regarding the contribution of the minimum wage to changes in between- and within-group inequality.

5.1 Impact on the wage structure

We first present the results of estimating equation (3). Figure 4 shows the impact of the minimum wage on the intercept and slope coefficients in the wage equation across quantiles. The four panels show the estimates for $\beta_0(\tau)$, $\beta_1(\tau) + 2\beta_2(\tau)\overline{educ}$, $\beta_3(\tau) + 2\beta_4(\tau)\overline{exper}$, and $\beta_5(\tau)$, respectively, where the bar represents the sample mean over all states and years. We summarize the impact of the minimum wage on the coefficients of linear and quadratic terms in education and experience as the impact on their marginal effects.

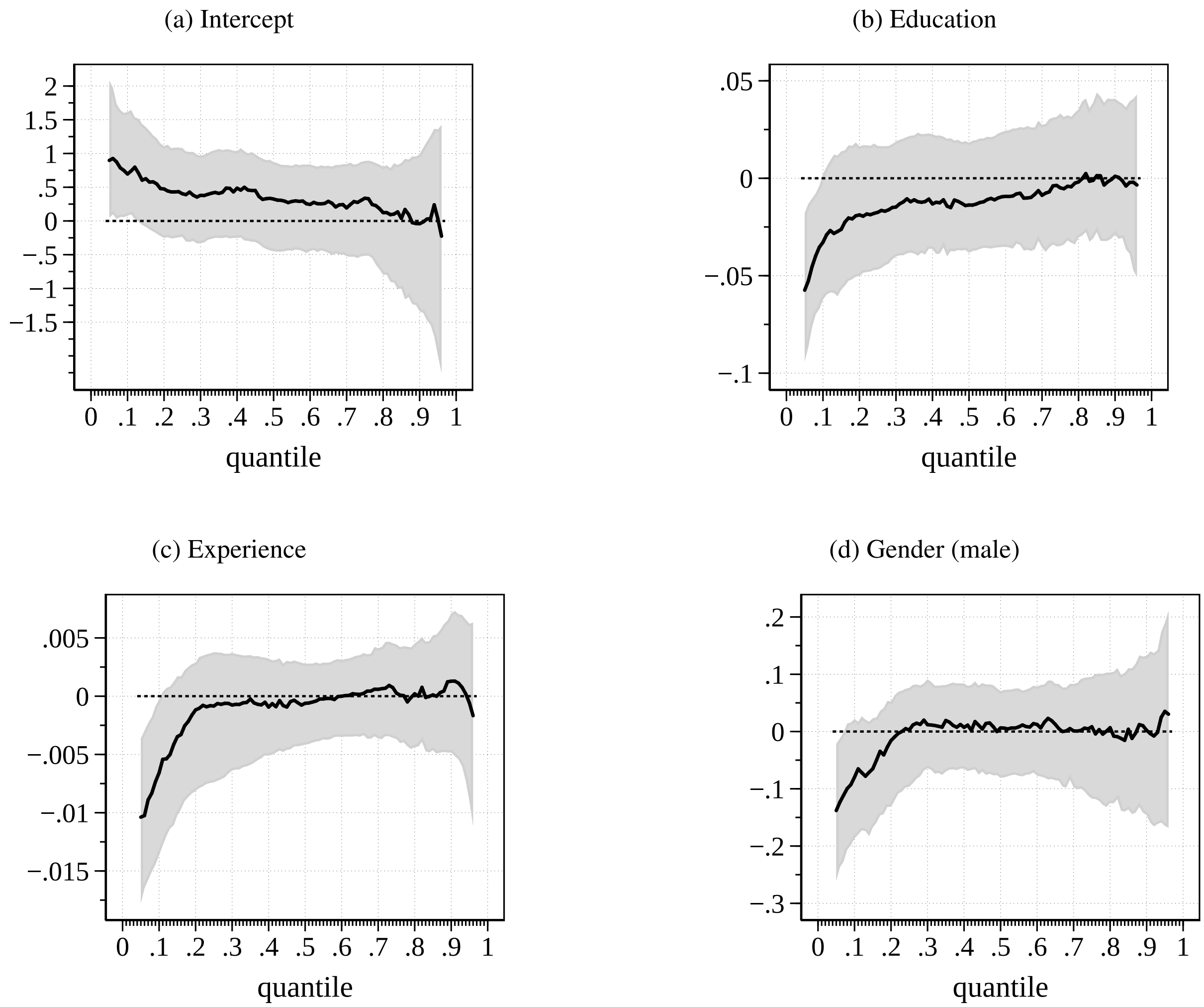
Figure 4: Impact of the minimum wage on the wage structure



Notes: The shaded area represents the 95 percent confidence interval.

Both the intercept and slope coefficients in the wage equation are affected by the real value of the minimum wage. The intercept coefficient increases with a rise in the minimum wage (Figure 4a), while the slope coefficients of education, experience, and gender decrease with a rise in the minimum wage (Figures 4b, 4c, and 4d). The former result implies that a rise in the minimum wage results in a rise in the wages of the least-skilled workers in terms of observed characteristics. The latter result implies that a rise in the minimum wage weakens the relationship of hourly wages with education, experience, and gender. These results are consistent with the fact that less-educated, less-experienced, and female workers are more directly affected by a rise in the minimum wage than more-educated, more-experienced, and male workers. Furthermore, the magnitude of changes in the intercept and slope coefficients varies across quantiles. In all cases, the impact of the minimum wage is greatest at the lowest quantile and gradually declines in absolute value to zero by the 0.3 quantile. Spillover effects are present but limited mostly to the first quintile.

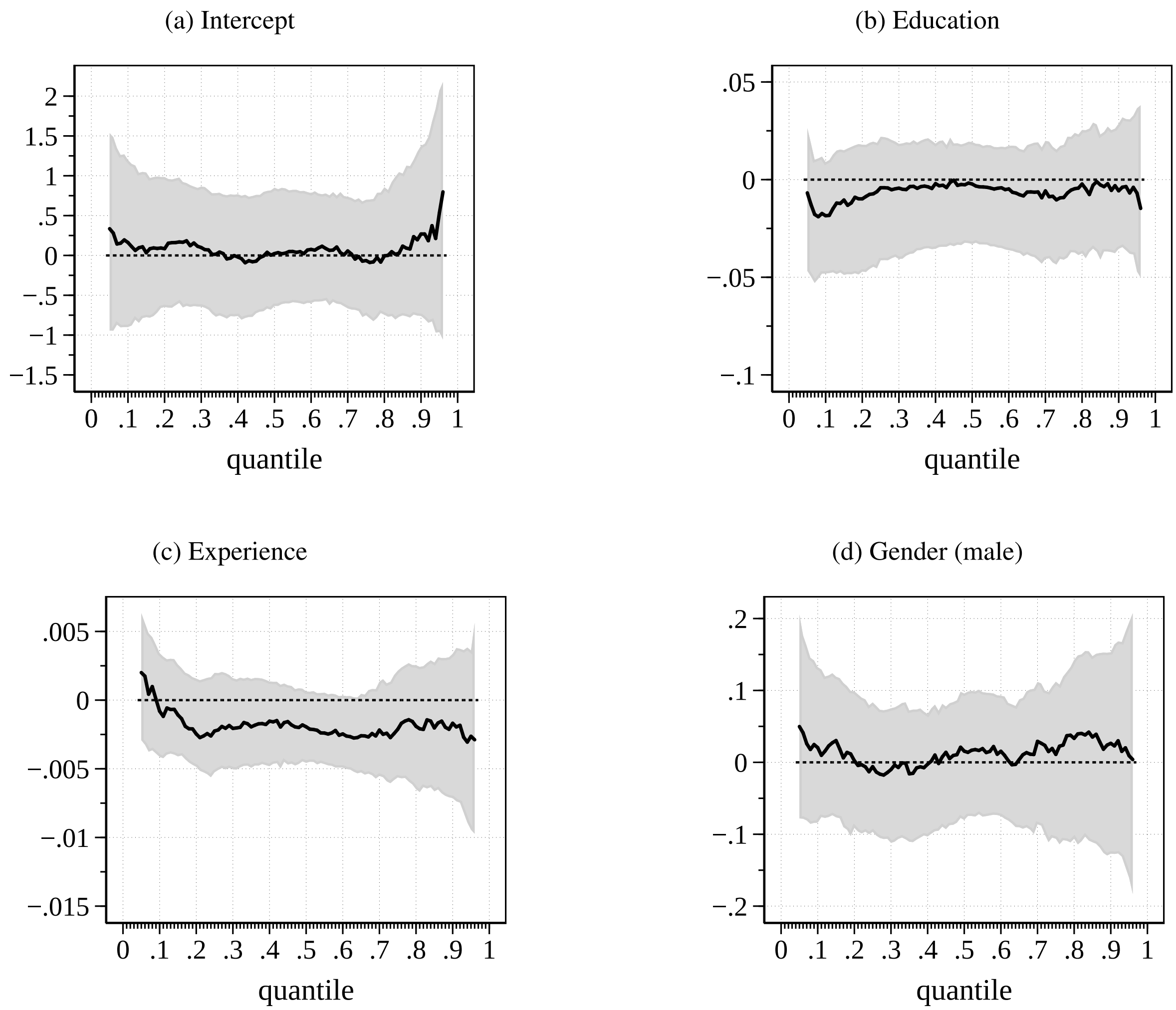
Figure 5: Long-term effect of the minimum wage on the wage structure



Notes: The shaded area represents the 95 percent confidence interval.

Lag and lead Before discussing the contribution of the minimum wage to changes in between- and within-group inequality, we present the results of estimating the augmented equation (6). The four panels in Figure 5 show the estimates of the long-term effects. All estimates remain essentially unchanged, although they become less precise. Indeed, the long-term effects fall inside the 95 percent confidence intervals of the contemporary effects. The four panels in Figure 6 illustrate the estimates of the lead-

Figure 6: Placebo effect on the wage structure



Notes: The shaded area represents the 95 percent confidence interval.

ing (placebo) effects. All estimates are close to zero for virtually all quantiles, and none of them are statistically significant. These results support our specification.

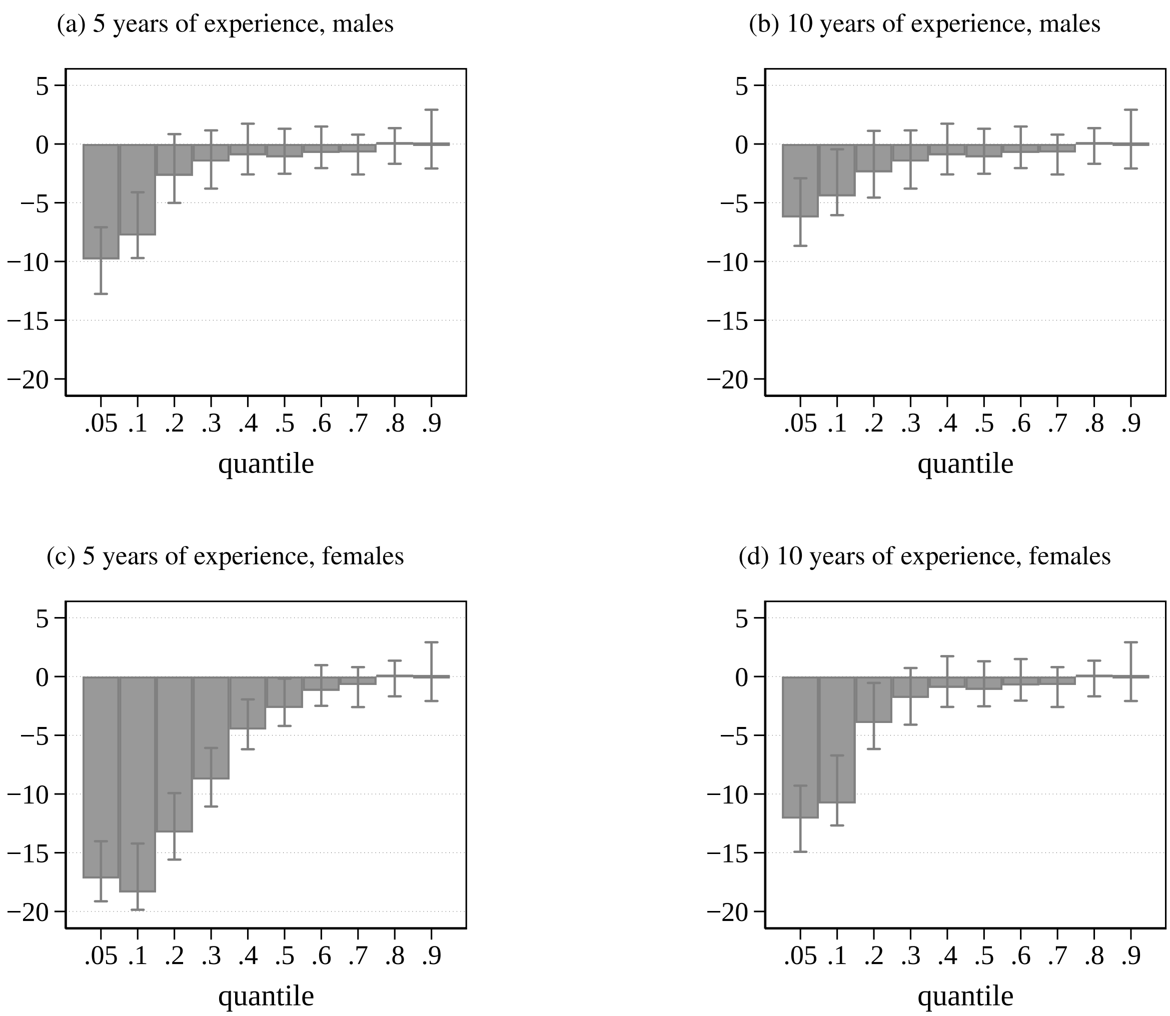
5.2 Contribution to changes in between- and within-group inequality

Finally, we discuss the quantitative contribution of the minimum wage to changes in between- and within-group inequality. As in Figure 3, the real value of the minimum wage declined by 30 log points due to inflation for the years 1979 to 1989 and subsequently increased by 28 log points due to increases in the statutory minimum wage for the years 1989 to 2012. Here, we provide the results for workers with 10 years of experience or less, who are subject to the influence of the minimum wage, for the latter period. Appendix A.3 shows the results for the former period.

5.2.1 Between-group inequality

Educational wage differential We measure the educational wage differential by comparing workers with 16 years of education (equivalent to college graduates) and those with 12 years of education (equivalent to high school graduates), holding experience and gender constant. The four panels in Figure 7 show the national means of changes in the educational wage differential due to increases in the real value of the minimum wage for the years 1989 to 2012 by experience and gender for each decile $\tau = 0.05, 0.1, 0.2, ..., 0.9$.

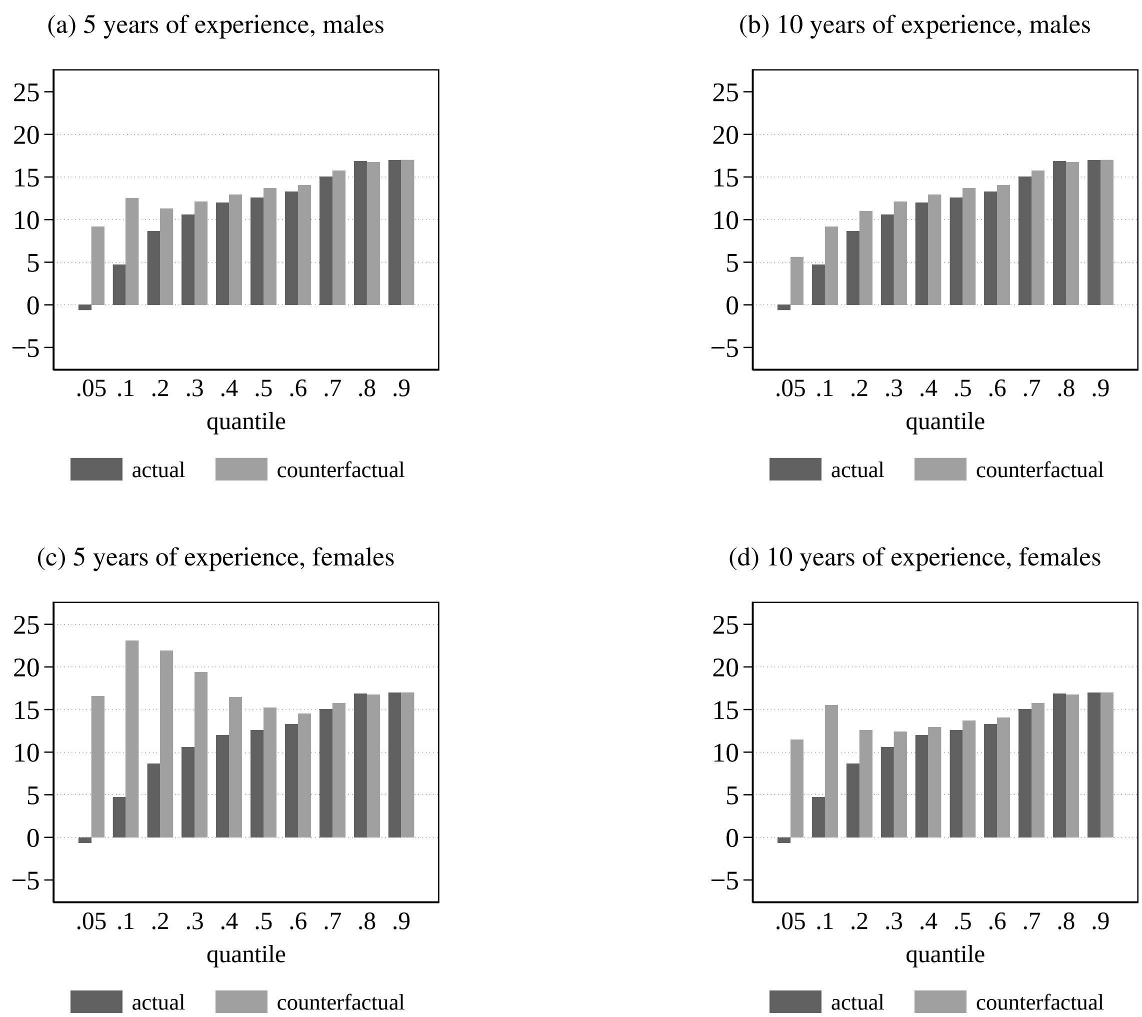
Figure 7: Contribution to the educational wage differential (16 versus 12 years of education)



Notes: The error bar represents the 95 percent confidence interval.

The minimum wage contributes to a reduction in the educational wage differential in the lower quantiles. The contribution of the minimum wage to a reduction in the educational wage differential is greater for more-experienced, female workers than less-experienced, male workers. For each group of workers, the contribution of the minimum wage is greatest at the 0.05th quantile and gradually declines in absolute value to zero by the 0.2th to 0.5th quantiles. For female workers with five years of experience, however, it is slightly greater at the 0.1th quantile than the 0.05th quantile. The reason is that, at the 0.05th quantile in this group, both more- and less-educated workers are affected by a rise in the real value of the minimum wage.

Figure 8: Changes in the educational wage differential (16 versus 12 years of education), 1989–2012

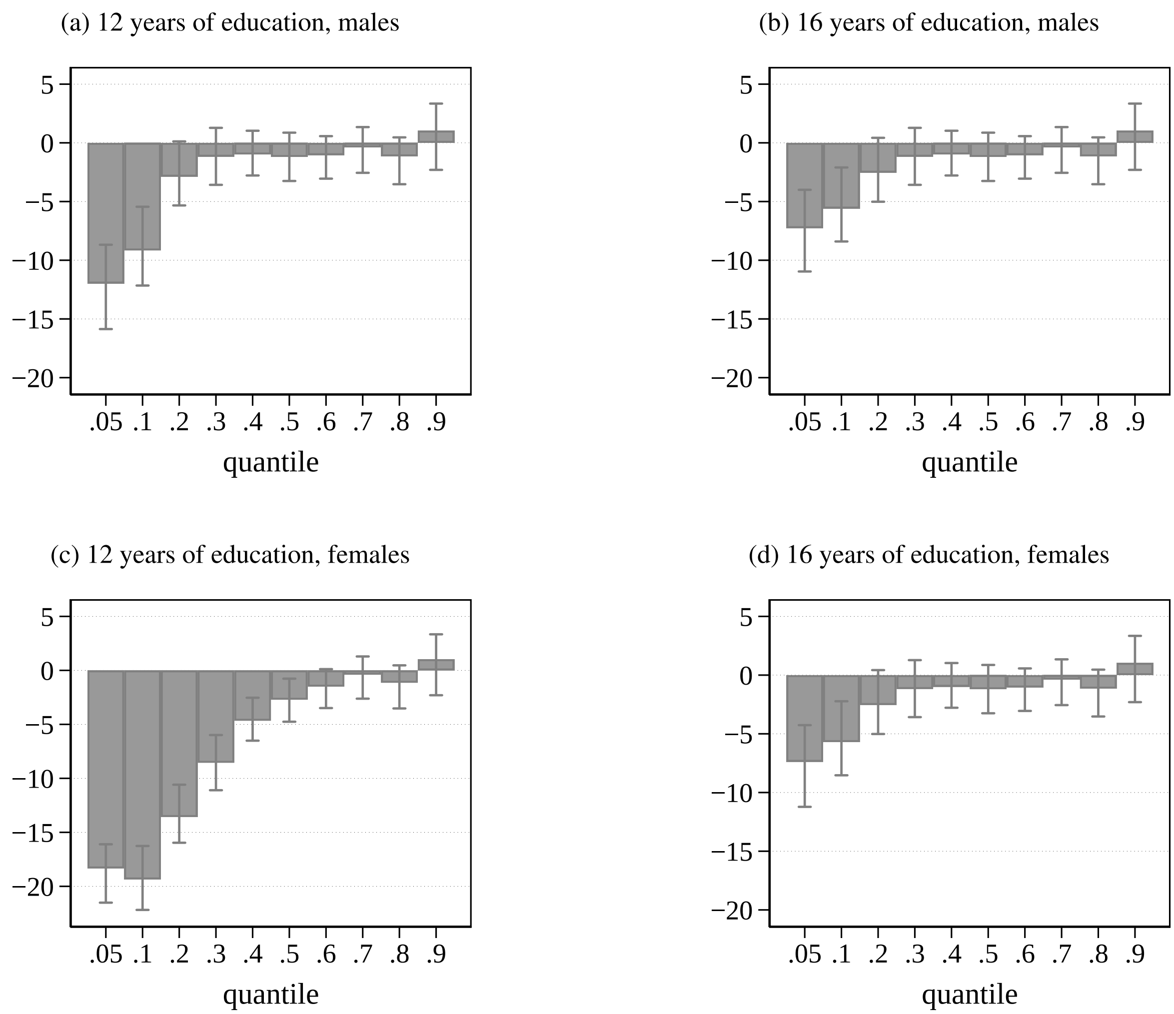


The educational wage differential increased during the 1989–2012 period (Figure 8). The trend in the educational wage differential is known to be important in accounting for the rise in wage inequality in the United States (Autor, Katz, and Kearney, 2008). The increase in the educational wage differential is typically attributed in the literature to skill-biased technological change and compositional changes in the workforce (Bound and Johnson, 1992; Katz and Murphy, 1992; Autor, Katz, and Kearney, 2008). The magnitude of the increase in the educational wage differential is greater in the higher quantiles than the lower quantiles during the period, as also shown by Buchinsky (1994) and Angrist, Chernozhukov, and Fernández-Val (2006). The educational wage differential did not increase at the 0.05 quantile and increased only moderately at the 0.1 quantile, while it increased more in the higher quantiles. If there were no increase in the real value of the minimum wage, however, the educational wage differential would increase at the 0.05 quantile and more than double at the 0.1 quantile for all groups. Consequently, in the counterfactual case in which the real value of the minimum wage is kept constant, the increase in the educational wage differential is more uniform across quantiles. Our results indicate that the minimum wage is another factor in accounting for the patterns of changes in the educational wage differential.

Experience wage differential We measure the experience wage differential by comparing workers with 25 years of experience and those with five years of experience, holding education and gender constant. The four panels in Figures 9 show the national means of changes in the experience wage differential due to increases in the real value of the minimum wage for the years 1989 to 2012 by education and gender.

The minimum wage contributes to a reduction in the experience wage differential in the lower quantiles. The contribution of the minimum wage to a reduction in the experience wage differential is greater for less-educated, female workers than more-educated, male workers. For each group of workers, the contribution of the minimum wage is greatest at the 0.05th quantile and gradually declines in absolute value to zero by the 0.2th to 0.5th quantiles. For female workers with 12 years of education, however, it is slightly greater at the 0.1th quantile than the 0.05th quantile. The reason is that, at the 0.05th quantile in this group, both more- and less-experienced workers are affected by a rise in the real value of the minimum wage.

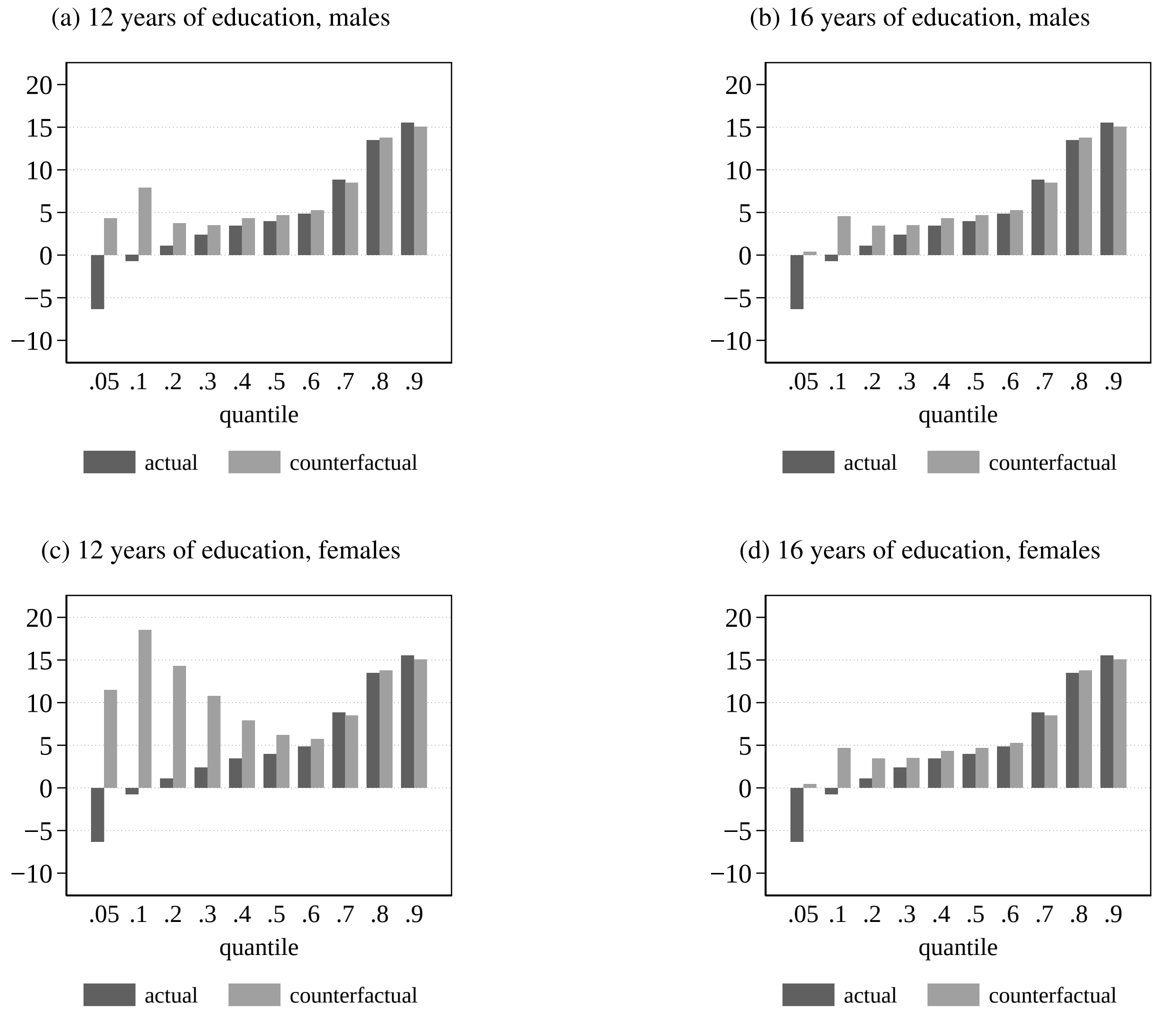
Figure 9: Contribution to the experience wage differential (25 versus 5 years of experience)



Notes: The error bar represents the 95 percent confidence interval.

The experience wage differential increased during the 1989–2012 period with the exception of the lowest quantile (Figure 10). Changes in the experience wage differential are typically attributed in the literature to compositional changes in the workforce (Welch, 1979; Jeong, Kim, and Manovskii, 2015). The magnitude of the increase in the experience wage differential is greater in the higher quantiles than the lower quantiles during the period. The experience wage differential declined at the 0.05th quantile and increased only moderately at the median, while it increased more at the 0.7th and higher quantiles. If there were no increase in the real value of the minimum wage, however, the experience wage differential would increase in the lower as well as higher quantiles. Consequently, in the counterfactual case in which the real value of the minimum wage is kept constant, the increase in the educational wage

Figure 10: Changes in the experience wage differential (25 versus 5 years of experience), 1989–2012

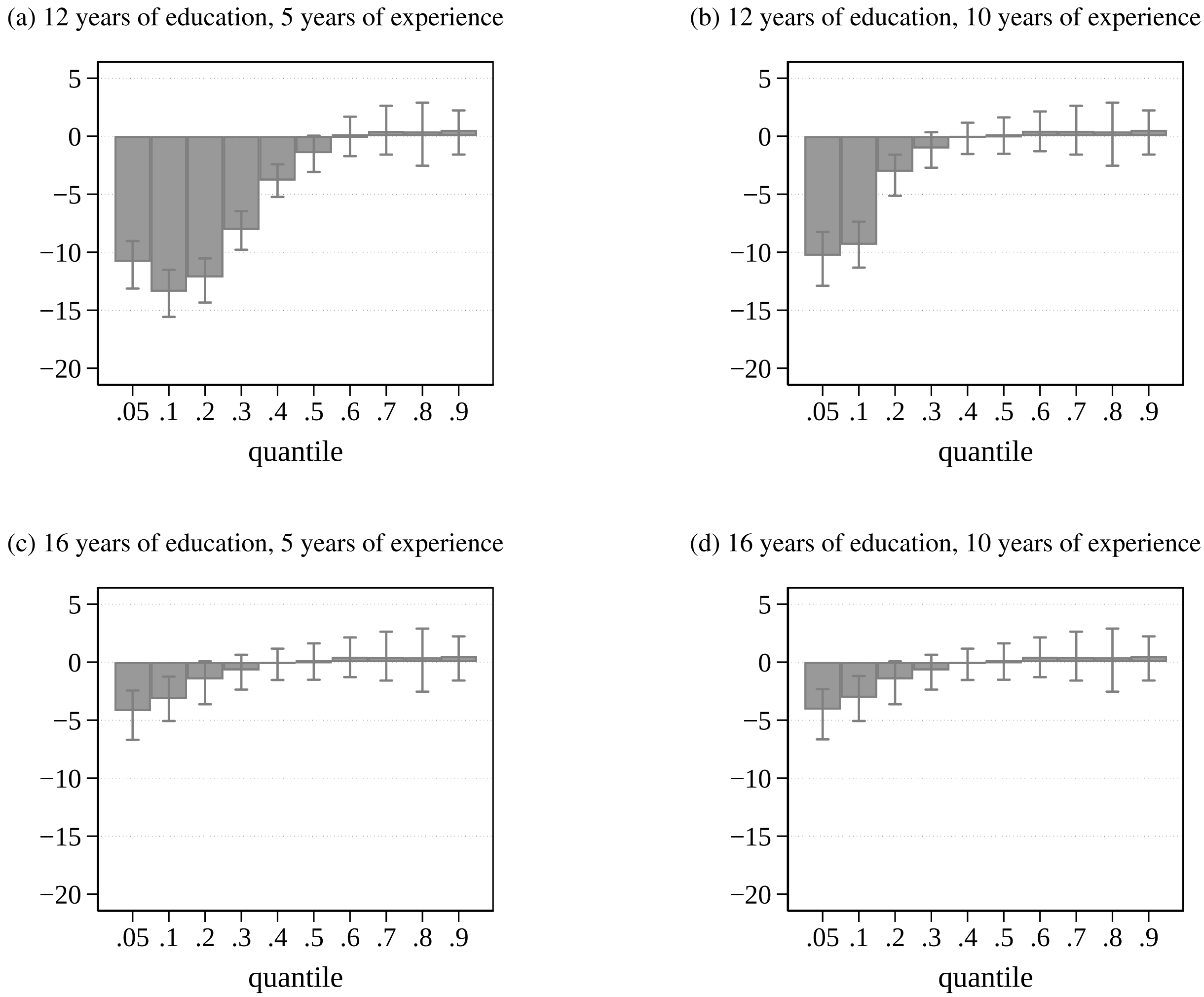


differential at the 0.1th quantile is at least as high as the increase in the median for all groups. Our results indicate that the minimum wage is another factor in accounting for the patterns of changes in the experience wage differential.

Gender wage differential We measure the gender wage differential by comparing male workers and female workers, holding education and experience constant. The four panels in Figure 11 show the national means of changes in the gender wage differential due to increases in the real value of the minimum wage for the years 1989 to 2012 by education and experience.

The minimum wage contributes to a reduction in the gender wage differential in the lower quantiles. The contribution of the minimum wage to a reduction in the gender wage differential is greater for less-

Figure 11: Contribution to the gender wage differential (males versus females)



Notes: The error bar represents the 95 percent confidence interval.

educated, less-experienced workers than more-educated, more-experienced workers. For each group of workers, the contribution of the minimum wage is greatest at the 0.05th quantile and gradually declines in absolute value to zero by the 0.2th to 0.5th quantiles. For workers with 12 years of education and 5 years of experience, however, it is slightly greater at the 0.1th quantile than the 0.05th quantile. The reason is that, at the 0.05th quantile in this group, both male and female workers are affected by a rise in the real value of the minimum wage. For workers with 16 years of education, however, the contribution of the minimum wage is only modest across quantiles.

The gender wage differential declined during the 1989–2012 period (Figure 12). Changes in the gender wage differential are typically attributed in the literature to changes in workforce composition

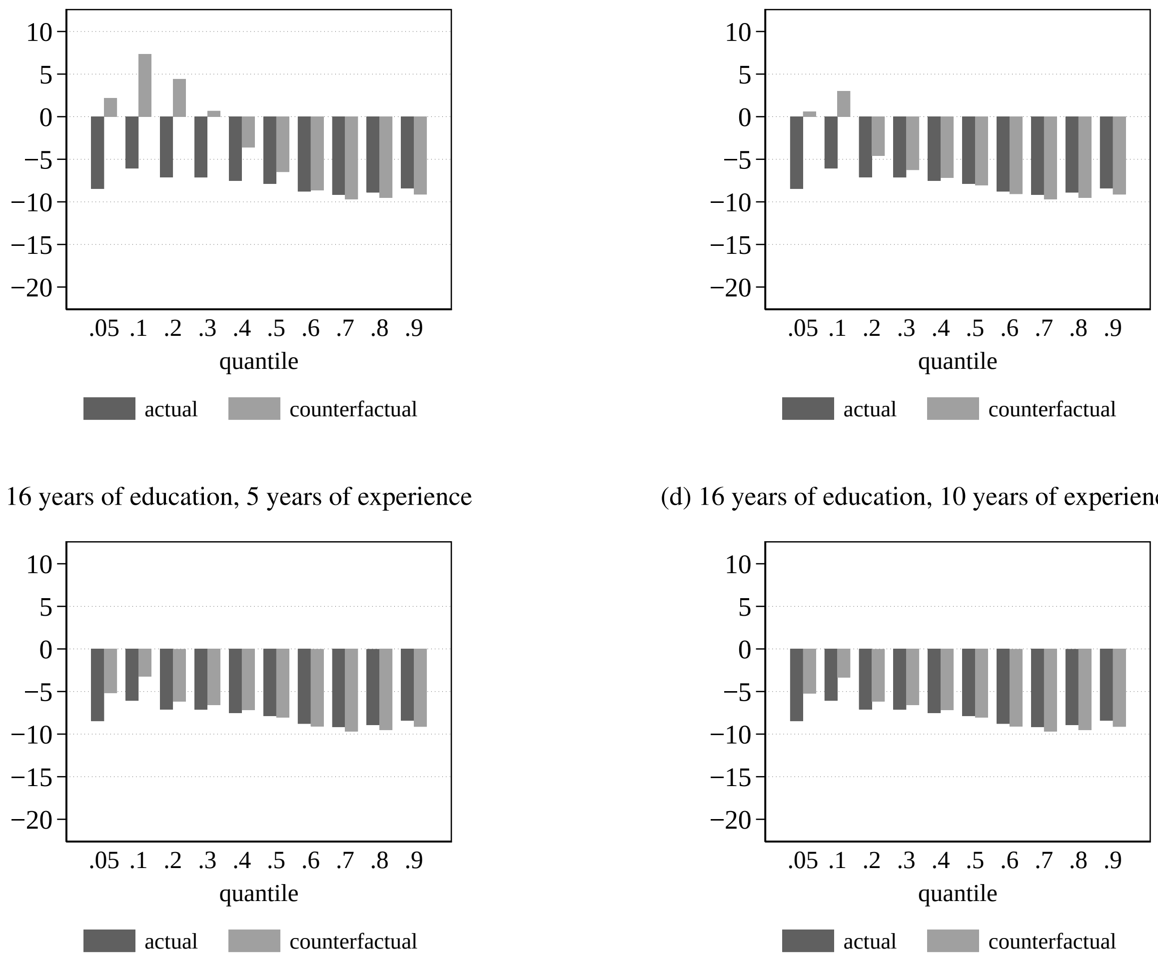
Figure 12: Changes in the gender wage differential (males versus females), 1989–2012

(a) 12 years of education, 5 years of experience

(b) 12 years of education, 10 years of experience

(c) 16 years of education, 5 years of experience

(d) 16 years of education, 10 years of experience



and gender discrimination (Blau and Kahn, 2017). Differently from the education and experience wage differentials, the magnitude of the change in the gender wage differential is almost uniform across quantiles. If there were no increase in the real value of the minimum wage, however, the gender wage differential would decline less in the lower quantiles. For workers with 12 years of education, the gender wage differential would not decline but could increase in the lower quantiles. Consequently, in the counterfactual case in which the real value of the minimum wage is kept constant, the decline in the gender wage differential is less in the lower quantiles than the higher quantiles for all groups. Our results indicate that the minimum wage is another factor in accounting for the patterns of changes in the gender wage differential.

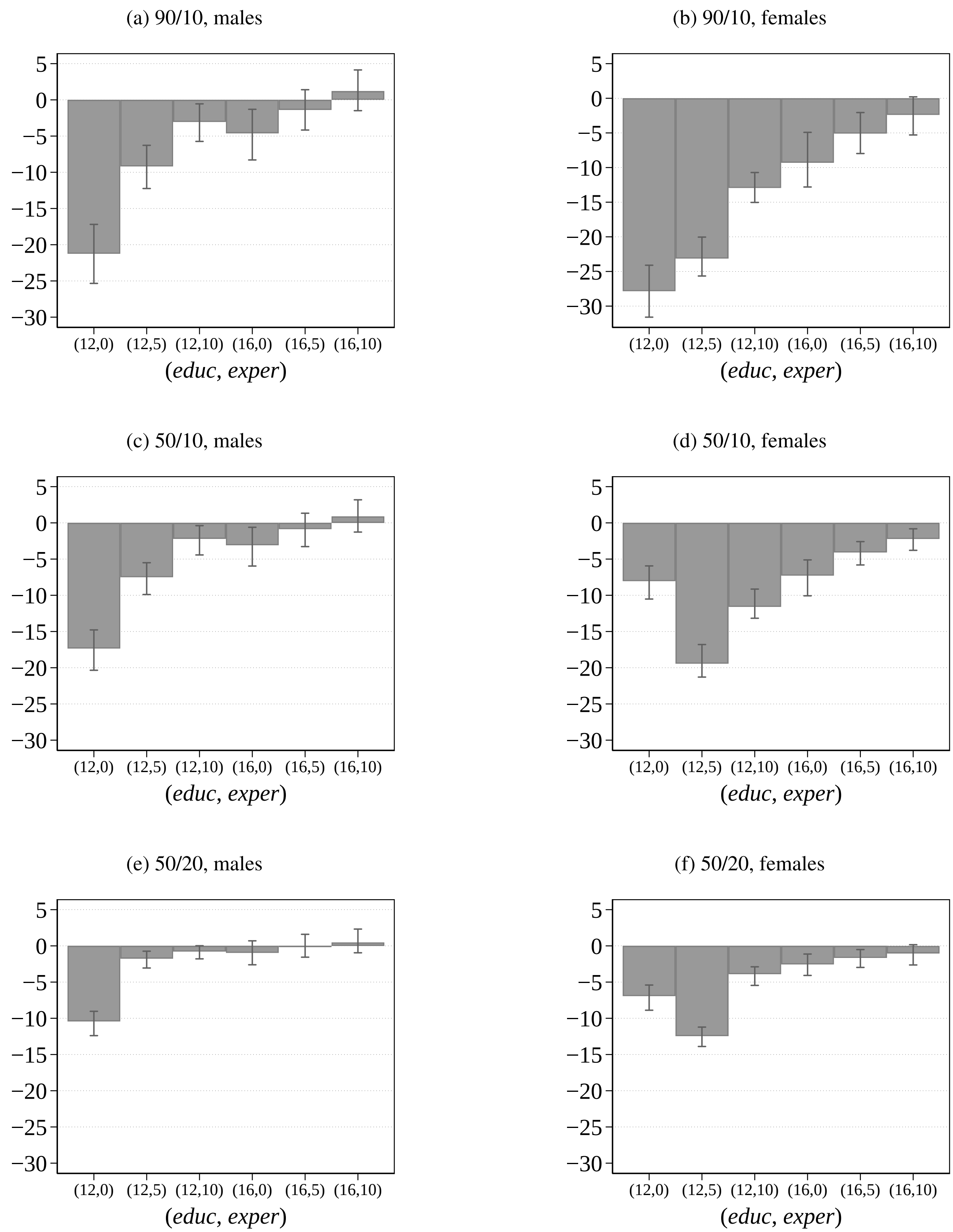
5.2.2 Within-group inequality

The four panels in Figure 13 show the national means of changes in the 90/10 and 50/10 within-group wage differentials due to increases in the real value of the minimum wage for the years 1989 to 2012 by education, experience, and gender.

The minimum wage contributes to a reduction in the 90/10 and 50/10 within-group wage differentials among workers with lower levels of education and experience. The contribution of the minimum wage is the same for changes in the 90/10 and 50/10 within-group wage differentials except for female workers with 12 years of education and no experience. The results reflect the fact that changes in the real value of the minimum wage have no effect at the median or higher quantiles for almost all groups. The minimum wage also contributes to a reduction in the 50/20 within-group wage differential, but only moderately for fewer groups. The contribution of the minimum wage to changes in within-group wage differentials is greater for less-educated, less-experienced, female workers than more-educated, more-experienced, male workers. For workers with 16 years of education and five or more years of experience, the contribution of the minimum wage is close to zero.

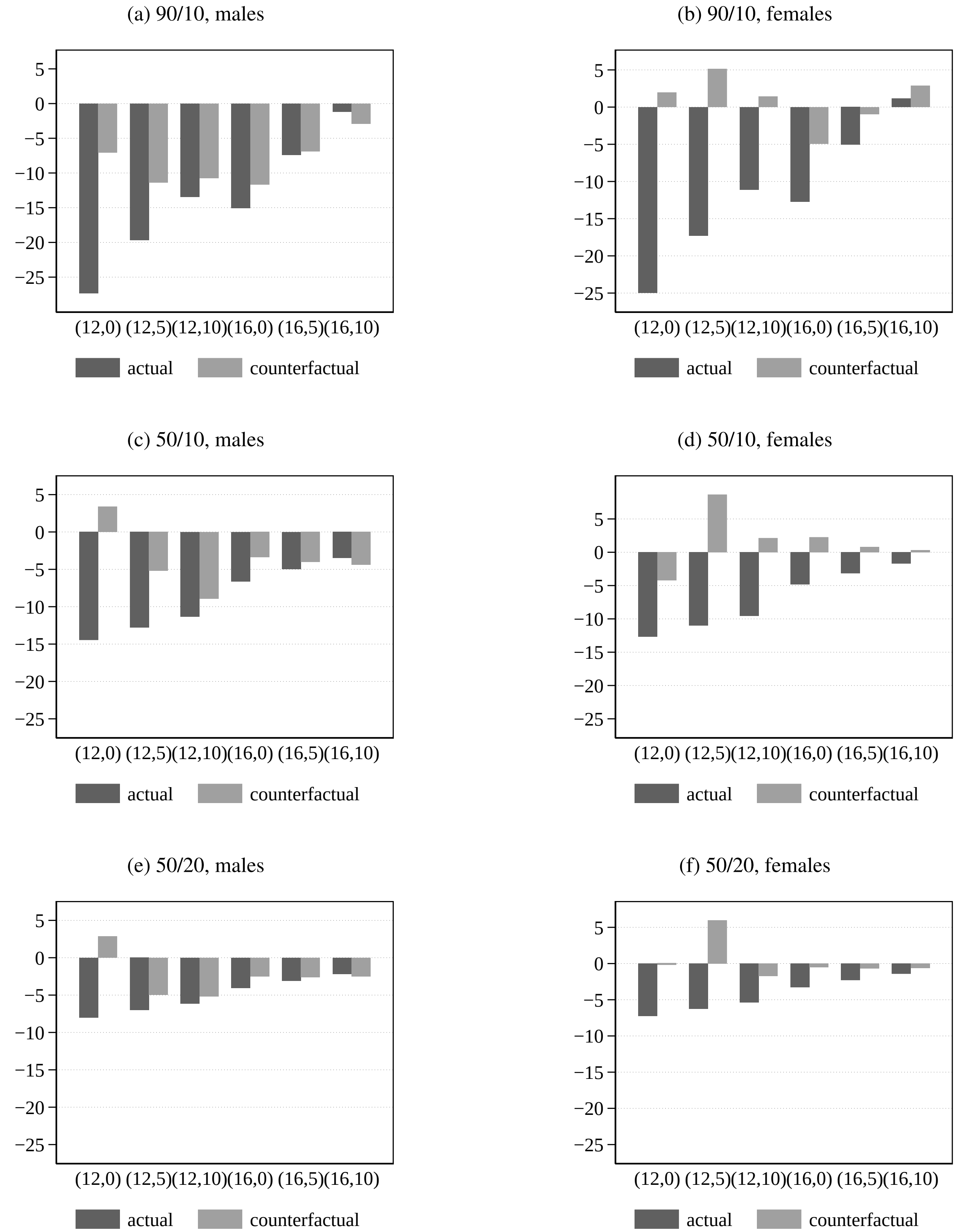
The 90/10, 50/10, and 50/20 within-group wage differentials declined during the 1989–2012 period (Figure 14). The 50/10 wage differential declined more than the 50/20 wage differential. The magnitude of the decline in within-group wage differentials is similar for male and female workers, but it is greater for less-educated, less-experienced workers than more-educated, more-experienced workers. If there were no increase in the minimum wage, however, the 50/10 and 50/20 wage differentials would change almost equally. Furthermore, within-group wage differentials would decline similarly for less-educated, less-experienced workers and more-educated, more-experienced workers, while they would decline less for male workers and would not decline but could increase for female workers. Our results indicate that the minimum wage accounts mostly for the patterns of changes in within-group wage differentials.

Figure 13: Contribution to the 90/10, 50/10, and 50/20 within-group differentials



Notes: The error bar represents the 95 percent confidence interval.

Figure 14: Changes in the 90/10, 50/10, and 50/20 within-group differentials, 1989–2012



6 Conclusion

We have examined the impact of the minimum wage on the wage structure and evaluated the contribution of the minimum wage to changes in between- and within-group inequality in the United States. In doing so, we have addressed the issues of heterogeneity, censoring, and missing wages by combining three quantile regression approaches.

We have shown that changes in the real value of the minimum wage over recent decades have affected the relationship of hourly wages with education, experience, and gender. In the literature, changes in between-group wage differentials are typically attributed to skill-biased technological change, compositional changes in the workforce, and changes related to gender discrimination. Our results indicate that changes in the real value of the minimum wage account in part for the patterns of changes in the education, experience, and gender wage differentials. If there were no increase in the real value of the minimum wage for the years 1989 to 2012, the education and experience wage differentials would increase more uniformly across quantiles, while the gender wage differential would decline less uniformly across quantiles. Therefore, when we interpret the patterns of changes in between-group wage differentials through the lens of economic models, there is a need to adjust the data taking into account the influence of the minimum wage.

We have further shown that the impact of the minimum wage is heterogeneous across quantiles of workers' productivity not attributable to their education, experience, or gender. In the literature, the sources of changes in within-group wage differentials are less conclusive than those of changes in between-group wage differentials. Our results indicate that changes in the real value of the minimum wage account mostly for the patterns of changes in within-group wage differentials for workers with 10 or less years of experience. In particular, the decline in the 50/10 and 50/20 within-group wage differential among female workers for the years 1989 to 2012 is attributed almost entirely to a rise in the real value of the minimum wage.

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A Appendix

A.1 Conceptual framework

We provide a simple conceptual framework to understand the role of the minimum wage for the determination of the wage structure. Our model is related to and builds on the model in Bound and Johnson (1992) and Katz and Autor (1999). The key idea of the model is that the actual wage can be decomposed into the competitive market wage and the wedge. The wedge, which can be referred to as the rent, is a deviation of the actual wage from the competitive market wage.

The actual wage, W_{ist}, for an individual i in state s and year t can be expressed as the product of the competitive market wage, W_t^c, in year t and the rent, R_{ist}, for an individual i in state s and year t.

$$W_{ist} = W_t^c R_{ist}$$

The log of the actual wage, w_{ist}, can be decomposed additively into the log of the competitive market wage, w_t^c, and the log of the rent, r_{ist}.

$$w_{ist} = w_t^c + r_{ist}$$

In general, the rent is determined by state-specific institutional and non-competitive factors, m_{st} and x_{st}, and individual-specific productivity factors, z_{ist}. Here, we consider the minimum wage to be a key institutional factor and allow for its interactive effect with individual productivity.

$$r_{ist} = f\left(m_{st}, x_{st}, z_{ist}\right) = e^{m_{st}\left(\beta_0 + z_{ist}'\beta_-\right)} e^{x_{st}'\gamma_0} e^{z_{ist}'\delta_{st}}$$

Given this functional form, the log wage equation can be derived as:

$$w_{ist} = m_{st}\left(\beta_0 + z_{ist}'\beta_-\right) + z_{ist}'\delta_{st} + x_{st}'\gamma_0,$$

where w_t^c is subsumed into x_{st}. The equation can be extended to allow for random coefficients.

$$w_{ist} = m_{st}\left(\beta_0 + z_{ist}'\beta_-(u)\right) + z_{ist}'\delta_{st}(u) + x_{st}'\gamma_0(u),$$

where u is uniformly distributed from zero to one, conditional on m_{st}, x_{st}, and z_{ist}. This random coefficients model is an alternative representation of the quantile regression model (1).

A.2 Estimation and imputation procedures

We describe the procedures for the censored quantile regression estimation and the quantile imputation. We implement the procedures for each state $s = 1, \ldots, 50$, each year $t = 1979, 1980, \ldots, 2012$, and each quantile $\tau = 0.04, 0.05, \ldots, 0.97$. In this section, we suppress the subscripts s and t for notational simplicity.

A.2.1 Censored quantile regression

The estimation proceeds in three steps (Chernozhukov and Hong, 2002). In the first and second steps, we select the sample to be used for estimation. In the third step, we estimate the quantile regression model using the selected sample.

Step 1. We estimate the probabilities of not being left- and right-censored for each individual. When we partition the support of z_i into $\mathscr{Z}_1, \ldots, \mathscr{Z}_H$, we can non-parametrically estimate the probabilities of not being left- and right-censored from the empirical probabilities: $\widehat{p}^L(z_i) := \sum_{h=1}^{H} \widehat{p}_h^L \{z_i \in \mathscr{Z}_h\}$ and $\widehat{p}^R(z_i) := \sum_{h=1}^{H} \widehat{p}_h^R \{z_i \in \mathscr{Z}_h\}$, respectively, where for each h

$$\widehat{p}_h^L(z_i) := \frac{\sum_{i=1}^{N} \mathbb{1}\{w_i > m, z_i \in \mathscr{Z}_h\}}{\sum_{i=1}^{N} \mathbb{1}\{z_i \in \mathscr{Z}_h\}} \qquad \text{and} \qquad \widehat{p}_h^R(z_i) := \frac{\sum_{i=1}^{N} \mathbb{1}\{w_i > c, z_i \in \mathscr{Z}_h\}}{\sum_{i=1}^{N} \mathbb{1}\{z_i \in \mathscr{Z}_h\}}.$$

We partition the support of z_i by years of education (0–12, 12+), years of experience (0–9, 10–19, 20–29, 30+), and gender. Using the empirical probabilities, we select the sample:

$$\mathscr{I}_1 := \left\{ i \in \{1, \ldots, N\} : 1 - \widehat{p}^L(z_i) + \eta^L < \tau < \widehat{p}^R(z_i) - \eta^R \right\},$$

where η^L and η^R are small positive constants to accommodate possible specification and estimation errors. Following Chernozhukov and Hong (2002), we set η^L and η^R at the 0.1th quantiles of the empirical probabilities of not being censored given $1 - \widehat{p}^L(z_i) < \tau$ and $\tau < \widehat{p}^R(z_i)$, respectively.

Step 2. We estimate the quantile regression model using the selected sample $\mathscr{I}_1$. Using a set of estimated coefficients $\widetilde{\alpha}(\tau)$, we select the sample:

$$\mathscr{I}_2 := \left\{ i \in \{1, \ldots, N\} : m + \zeta^L < z_i' \widetilde{\alpha}(\tau) < c - \zeta^R \right\},$$

where ζ^L and ζ^R are small positive constants. Following Chernozhukov, Fernández-Val, and Kowalski (2015), we set η^L and η^R at the 0.03th quantiles of the positive fitted values of $z_i' \widetilde{\alpha}(\tau) - m$ and $c_i - z_i' \widetilde{\alpha}(\tau)$, respectively.

Step 3. We estimate the quantile regression model using the selected sample $\mathscr{I}_2$.

A.2.2 Quantile imputation

The imputation proceeds in two steps (Wei, 2017).

Step 1. We estimate the censored quantile regression model (5) using a sample of individuals for whom we can observe wages. We obtain a set of estimated coefficients $\{\widehat{\alpha}(\tau) : \tau \in \mathscr{T}^*\}$, where $\mathscr{T}^* := \{0.04, 0.05, \ldots, 0.49\}$.

Step 2. We draw a random variable, u_i^ℓ, from a uniform distribution over $\mathscr{T}^*$ independently 10 times for individuals for whom we cannot their wages. For each realization of u_i^ℓ, we predict their wages using the quantile regression model:

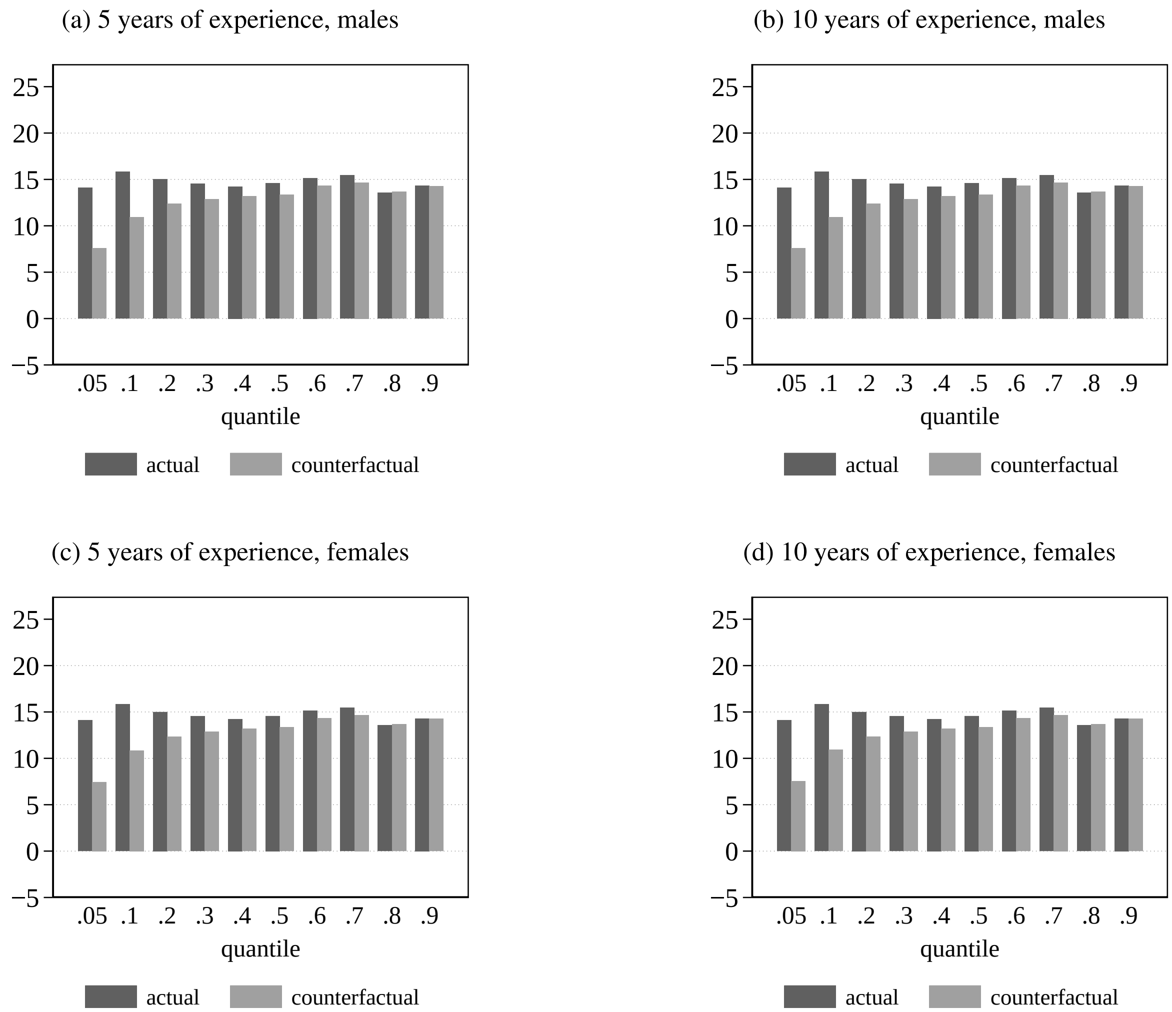
$$\widehat{w}_i^\ell := z_i' \widehat{\alpha}\left(u_i^\ell\right).$$

If the predicted value is smaller than the minimum wage or greater than the top-coded value, it is replaced with the minimum wage or the top-coded value. We impute their wages by taking the mean of predicted values. We calculate their weights using hours worked imputed by fitting a fifth-order polynomial regression on wages.

A.3 Changes in between- and within-group wage differentials, 1979–1989

We provide the results on actual and counterfactual changes in between- and within-group wage differentials for the years 1979 to 1989 (Figures 15 to 18).

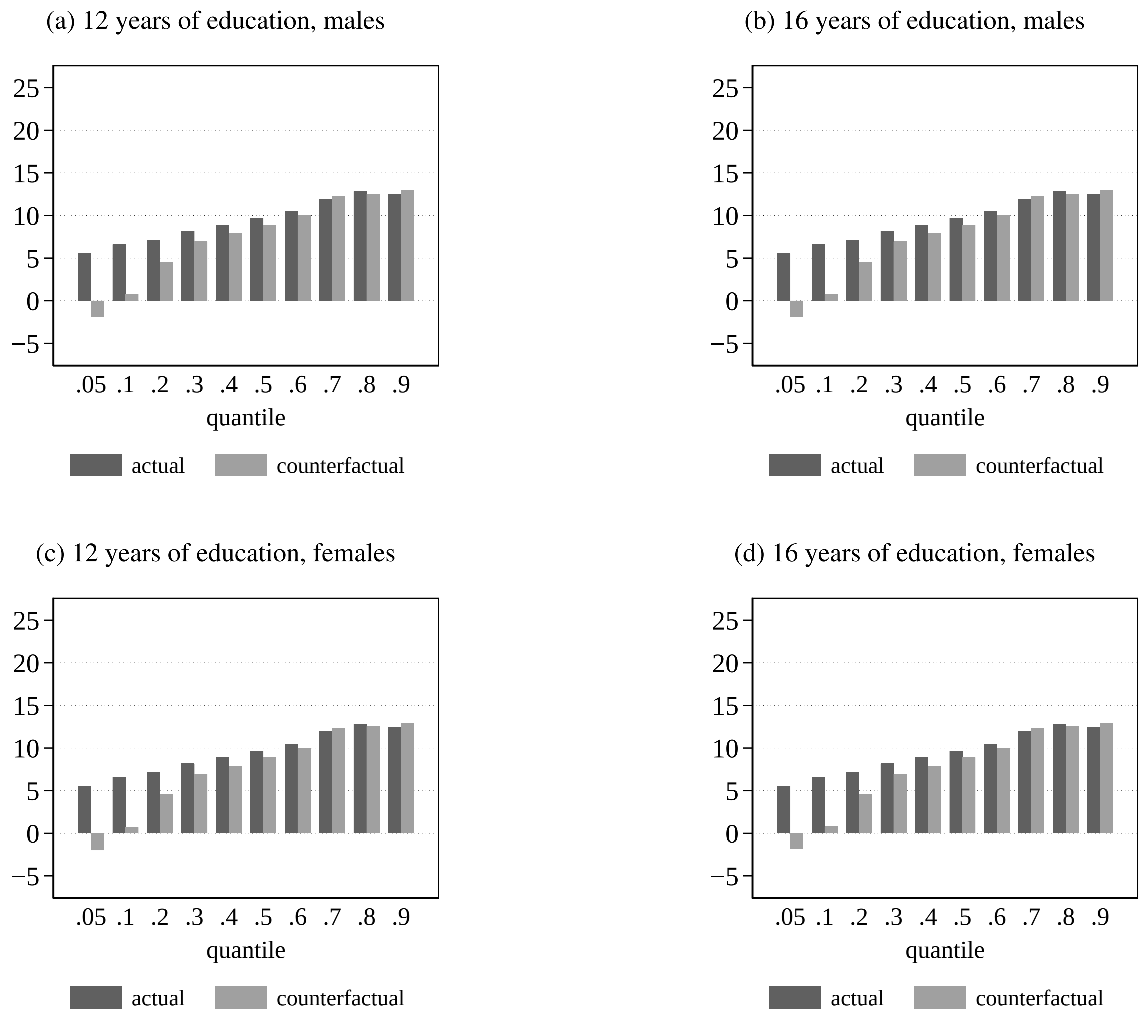
Figure 15: Changes in the educational wage differential (16 versus 12 years of education), 1979–1989



During the 1979–1989 period, the educational wage differentials increased almost uniformly across quantiles (Figures 15), as also shown by Buchinsky (1994) and Angrist, Chernozhukov, and Fernández-Val (2006). If there were no decrease in the real value of the minimum wage, however, the educational wage differentials would increase less uniformly across quantiles.

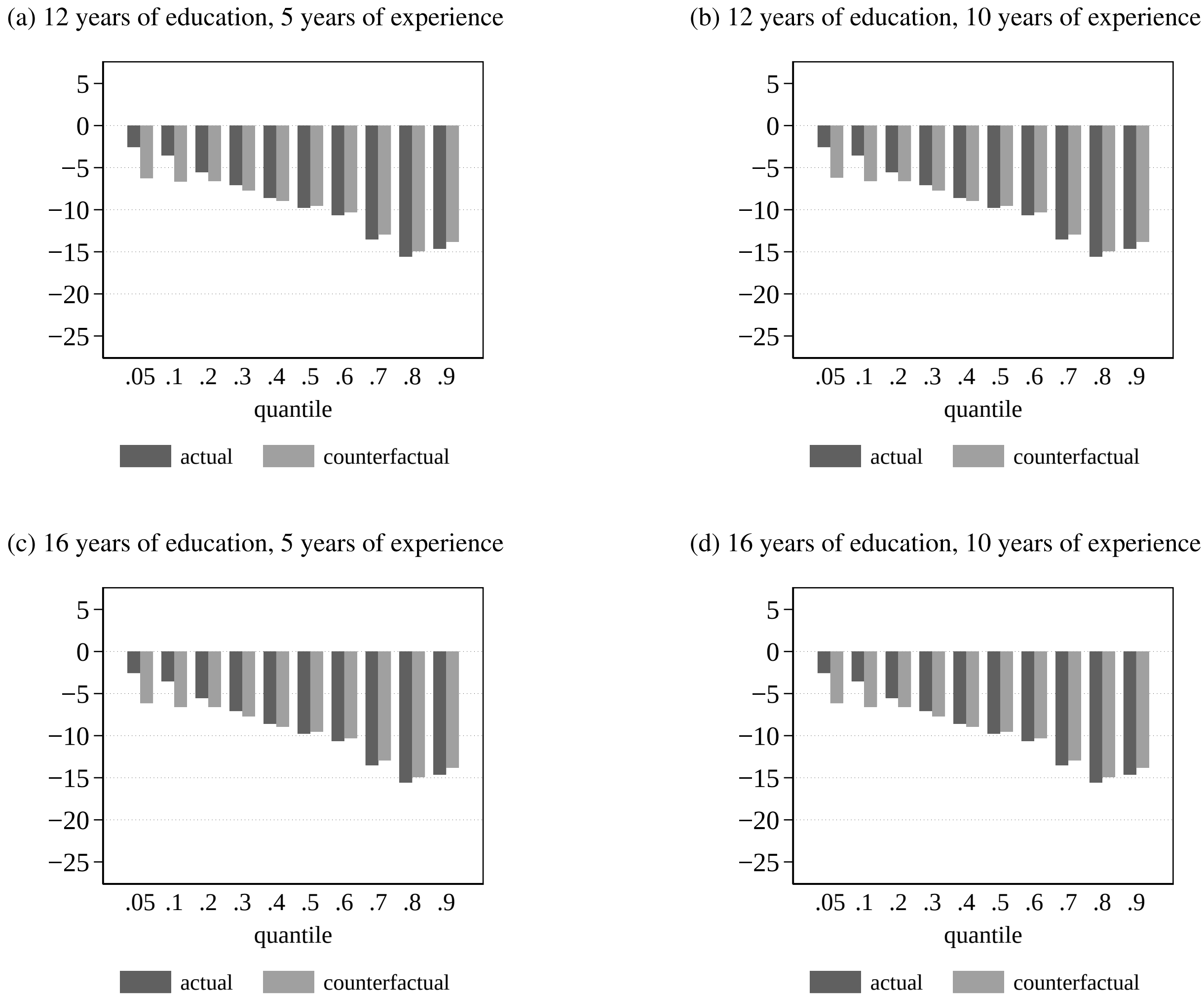
The experience wage differentials also increased roughly uniformly, although they increased slightly more in the higher quantiles than the lower quantiles (Figures 16). If there were no decrease in the real value of the minimum wage, however, the experience wage differentials would increase more differently across quantiles.

Figure 16: Changes in the experience wage differential (25 versus 5 years of experience), 1979–1989



The gender wage differential declined more in the higher quantiles than the lower quantiles. If there were no decrease in the real value of the minimum wage, however, the gender wage differential would decline more uniformly across quantiles.

Figure 17: Changes in the gender wage differential (males versus females), 1979–1989



The 90/10, 50/10, and 50/20 within-group wage differentials changed little for male workers and increased for female workers. For female workers, the magnitude of the increase in within-group wage differentials is similar for less-educated and more-educated workers but greater for more-experienced than less-experienced workers. If there were no decrease in the real value of the minimum wage, however, within-group wage differentials would increase much less especially for workers with 5 or less years of experience.

Figure 18: Changes in the 90/10, 50/10, and 50/20 within-group differentials, 1979–1989