CENTER *for* RETIREMENT RESEARCH *at* BOSTON COLLEGE

THE MINIMUM WAGE AND ANNUAL EARNINGS INEQUALITY

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Abstract

This paper provides an empirical analysis of the impact of the minimum wage on annual earnings inequality in the United States over the last three and a half decades. We focus on men between the ages of 25 and 61, and use administrative Social Security earnings records from 1981-2015 from the U.S. Social Security Administration to measure annual earnings.

The paper found that:

- Increases in the minimum wage reduce inequality below about the 12th percentile of the annual earnings distribution.
- The increases are slightly larger than the impacts of the minimum wage on the bottom part of the hourly wage distribution, as measured in the CPS Outgoing Rotation Groups.
- But they are not statistically larger, given the precision of the estimation, and they are larger than the impacts on annual earnings in the March CPS, consistent with measurement error in CPS annual earnings.

The policy implications of the findings are:

- A typical increase in the minimum wage implies a 13.2 percent increase in annual earnings for minimum-wage workers at the bottom of the annual earnings distribution.
- This results in a 1.85 percent reduction in inequality in the bottom tail of the annual earnings distribution.
- The minimum wage is an important policy tool to decrease annual earnings inequality.

1. Introduction

Changing inequality in annual earnings and income in America has captured the attention of economists, policy makers, and the popular press (Piketty and Saez, 2003; Kopczuk et al., 2010). An important, but sometimes controversial, policy to combat growing inequality in the lower half of the income distribution is the minimum wage. While increasing the minimum wage can raise the hourly wages of low-skill workers as a tool of redistribution, it also can result in reductions in employment and hours worked. To ultimately reduce inequality and poverty, increases in the minimum wage must raise hourly wages by more than any reduction in employment and hours worked, and, hence, translate into increases in annual earnings. Although there is a large empirical literature focused on the separate impacts of the minimum wage on employment and the distribution of hourly wages, respectively (Brown, 1999; Katz and Autor, 1999; Autor et al., 2008; Lee, 1999; Neumark et al., 2014; Autor et al., 2016; among others), there has been surprisingly little analysis of the impact on the key redistributive outcome: annual earnings.

This paper provides an empirical analysis of the impact of the minimum wage on annual earnings inequality in the United States over the past three and a half decades. We focus on men between the ages of 25 and 61, a target population more mature than the young workers, who have been the focus of much of the minimum wage literature, yet are under the Social Security early entitlement age, so that retirement considerations are not necessarily paramount. We follow the minimum wage literature and use state-by-year variation in the real value of the minimum wage to identify estimated impacts on inequality. As a result, we exclude women from the analysis, in part because of many changes in labor-market policies during this time period that effectively varied by state and year and could be confounders (e.g., Medicaid and EITC expansions, and TANF reform).

In an important innovation over previous work, we use administrative earnings records from 1981-2015 from the U.S. Social Security Administration (SSA) to measure annual earnings. They provide broad workforce coverage and are free from measurement error from self-reporting, item non-response, and imputation in survey-based measures of annual earnings (Lillard et al., 1986; Lemieux, 2006; Autor et al., 2016; Bollinger et al., 2017). We complement these data with analyses on hourly wages, weekly earnings and annual earnings for 1981-2016, drawn from the *Current Population Survey* (CPS).

The first part of the paper uses state-by-year panel data on the real wage hourly distribution for 1981-2016 constructed from the CPS Outgoing Rotation Groups (ORG) to examine how changes in the effective minimum wage affect the distribution of hourly wages. The effective minimum wage for a worker is defined as the higher of the federal and the highest state minimum wage prevailing in the worker's state.[1] We follow the literature (Lee, 1999; Autor et al., 2016) and estimate how the bindingness of the minimum wage affects inequality in the hourly wage distribution. Our findings echo those of Autor et al. (2016) who focused on 1979-2012: increases in the minimum wage are associated with higher hourly wages up through the 10th percentile of the male hourly wage distribution.

The second part of the paper uses information from the CPS Outgoing Rotation Groups merged to the March Annual Social and Economic Supplement (ASEC) to examine where minimum-wage workers are located in the weekly and annual earnings distributions, and how that incidence changes with changes in the minimum wage. We focus on workers at or below the effective minimum wage. This group includes those working at the effective minimum wage, individuals working at lower-tier minimum wages, such as restaurant workers in some states, and those who have misreported (lower) their hourly wages in the CPS. The bulk of men with hourly wages at or below the effective minimum wage have weekly earnings at the 8th percentile or lower in the male weekly earnings distribution and, again, slightly higher in the annual earnings distribution.

The third part of the paper uses state-by-year panel data on real annual earnings for 1981-2015 constructed from Social Security earnings records, which are free from many forms of measurement error that might occur in the CPS. Increases in the minimum wage are associated with increases in annual earnings up through the 12th percentile of the earnings distribution for men. This suggests significant spillovers to workers with wages above the minimum, and, unlike in Autor et al. (2016), this finding cannot be explained alternatively by measurement error.

The last part of the paper uses a state-by-year-education-group panel for 1981-2016 constructed from the March CPS to examine how increases in the minimum wage affect the likelihood of having positive annual earnings, as well as annual hours. By decile of CPS annual

[1] Some states have tiered minimum wages. For those states, we select the highest tier minimum wage as the state's "minimum wage" for the calculation of the effective minimum wage.

earnings, there are no discernable effects on either outcome, although the estimates are not precise enough to draw firm conclusions.

The paper is organized as follows. Section 2 examines the impact of the minimum wage on the hourly wage distribution. Section 3 examines how the location of minimum wage workers in the weekly and annual earnings distributions changes with changes in the minimum wage. Section 4 introduces the Social Security earnings data and presents estimates of the impact of the minimum wage on annual earnings inequality. Section 5 examines responses for employment and annual hours. There is a brief conclusion.

2. Impact on Hourly Wage Inequality: Evidence from the CPS

Figure 1 shows the aggregate national time series of the real value of the minimum wage from 1981-2016.[2] The series was constructed using the monthly CPS Merged Outgoing Rotation Group (MORG) data from 1981-2016 from the NBER. For each state and month, the applicable nominal state and federal minimum wage rates were assigned to each ORG respondent. These minimum wages were then inflated into real 2016 dollars using the monthly all-items Consumer Price Index (CPI), and then the real wage data were weighted by the CPS sampling weight and collapsed into annual data. Therefore, the series in the figure represent the state-employment-weighted annual average national real minimum wage. The dashed line is the real federal minimum wage; the solid line is the "effective" minimum wage, defined as the higher of the state and federal minima.

From 1980-1986 the two series are essentially the same, as there was little state-by-time variation in the minimum wage that differed from the federal minimum. After 1986, there is some divergence between the series, as some states raised their minima above the federal level. The most striking aspect of the figure is the saw-toothed pattern of falling and rising real minimum wages, with real increases typically associated with increases in the federal nominal minimum wage, followed by real declines as inflation eroded the real value of the minimum wage.

Figure 2 plots the natural log of the real effective minimum wage (the solid line in Figure 1), measured on the right-hand vertical axis, versus one measure of inequality in the hourly wage

[2] We chose the starting year of our sample to be 1981, which is the first year for which we have earnings records for annual earnings above the maximum annual amount subject to Social Security payroll taxes.

distribution: the spread between the 5th and 50th percentiles of the real hourly wage distribution in each year from 1981-2016. The spread, the dashed line measured on the left-hand vertical axis, is the natural log of the difference between the 5th and 50th percentiles. The real hourly wage distribution in each year was constructed from the NBER monthly MORG datasets from 1981-2016. Specifically, for those ORG respondents who reported they were paid by the hour, the reported nominal hourly wage was used; otherwise, the nominal hourly wage was calculated as reported weekly earnings divided by reported hours worked in the previous week. The self-employed and those with imputed wage or hours data were excluded from the sample. The nominal hourly wages for each month were adjusted to real 2016 dollars using the monthly all-items Consumer Price Index (CPI), and then the real wage data were collapsed into annual data. The shaded periods in the figure denote recession years, according to the NBER business-cycle dating.

A higher value on the left-hand axis (i.e., a less negative spread) means there is less inequality in the hourly wage distribution. Therefore, if increases in the (log) real minimum wage reduce inequality, the solid and dashed lines should move roughly in tandem across time. Across all years, the sample correlation coefficient between the 5-50 spread and the minimum wage is 0.36. Figure 3 shows the same time-series pattern for inequality measured as the spread in the real hourly wage between the 10th and the 50th percentiles, slightly higher up the distribution of earners. The sample correlation coefficient between the 10-50 spread for women and the minimum wage is 0.20.

Overall, these figures suggest that increases in the minimum wage have decreased hourly wage inequality for men. A challenge, however, in interpreting these patterns as causal is that much of the variation in the minimum wage that identifies changes in the distribution of wages across years is purely time-series variation due to changes in the federal minimum wage. Omitted variables correlated with changes in wages in the lower half of the distribution and changes in the federal minimum wage, and trending over time, might explain these patterns equally well, leading to a fundamental identification problem.

To attempt to circumvent this and identify causal impacts on wage inequality, the analysis moves to a regression framework similar to that in Lee (1999) and Autor et al. (2016). In particular, let s and t index the state of residence and calendar year, respectively. We use the ORG data described above on real hourly wages for all months for each calendar year, weight the data using the CPS sampling weight, and collapse them to the state-by-year level to form a panel dataset.[3] Then we estimate the parameters of the following econometric specification:

$$(w_{st}^{p} - w_{st}^{50}) = \alpha + \beta_1^p (w_{st}^{MW} - w_{st}^{50}) + \beta_2^p (w_{st}^{MW} - w_{st}^{50})^2 + \psi_s + \tau_t + \psi_s \cdot t + u_{st}\,, \qquad (1)$$

where w_{st}^{p} represents the natural log of the hourly wage at percentile *p* of the wage distribution in state s in year t, and w^{50} represents the natural log of the median wage. The parameters ψ and τ represent state and calendar-year effects, respectively, and $\psi \cdot t$ is a state-specific linear time trend. The dependent variable $(w_{st}^{p} - w_{st}^{50})$ measures the percentage spread between the percentile *p* and median hourly wage (as was done in Figures 2 and 3, for $p = 5$ and 10, respectively). The focal explanatory variable is $(w_{st}^{MW} - w_{st}^{50})$, which is the difference between the log of the minimum wage and the log of the median wage. The term $(w_{st}^{MW} - w_{st}^{50})$ enters as a quadratic to reflect the fact that changes in the minimum wage should have a non-linear impact in states with lower median earnings, where the minimum wage binds at a higher percentile of the hourly wage distribution. The marginal effect of an increase in the minimum wage on the percentile *p*/median earnings inequality is $\beta_1^p + 2\beta_2^p (w_{st}^{MW} - w_{st}^{50})$. Because w_{st}^{50} appears on both the left- and right-hand sides of (1), we follow Autor et al. (2016) and estimate the parameters via instrumental variable estimation. The three instruments are: (i) the log of the minimum wage, w_{st}^{MW}; (ii) the square of the log of the minimum wage, $(w_{st}^{MW})^2$; and the interaction of the log minimum wage and the average log median wage for the state for 1981-2016, $w_{st}^{MW} \times \overline{w}_{s}^{50}$. Column 1 of Table 1 gives descriptive statistics for selected variables from this CPS sample, with standard deviations in parentheses.

Table 2 shows the IV estimates of the marginal effect of an increase in the minimum wage on the percentile *p*/median hourly wage inequality, i.e., $\hat{\beta}_1^p + 2\hat{\beta}_2^p (\overline{w_{st}^{MW} - w_{st}^{50}})$, where the $\hat{\beta}$'s are from the IV estimation of (1), and $(\overline{w_{st}^{MW} - w_{st}^{50}})$ is the sample mean spread of the (log)

[3] Autor et al. (2016) weighted their hourly wages by hours when they formed their state-year panel. We did not do this, because we want our hourly wages to be on the same basis as the annual earnings we construct below, the latter of which are not weighted by hours.

real minimum wage and the (log) median hourly wage.[4] Each table cell is an estimated marginal effect from a separate IV regression, so the table results reflect five IV regressions, one each for selected percentiles of the hourly wage distribution (i.e., $p = 5, 10, 20, 30, 40$). For example, the estimate in column 1, row 1 says that if the real minimum wage doubles, the spread between the 5th and 50th percentiles of the female hourly wage distribution falls by 8.8 percent. With a heteroscedasticity-robust standard error clustered at the state level of 0.030, shown in parentheses, this effect is significantly different from zero at conventional levels of significance. Hence, increases in the minimum wage reduce hourly wage inequality at the very bottom of the wage distribution. Based on the estimated marginal effects and standard errors, the minimum wage also reduces hourly wage inequality up through the 10th percentile for men. These are essentially the same results as those of Autor et al. (2016), who studied the 1979-2012 period.

Figure 4 expands on Table 2 and shows the estimated marginal effects and 95 percent confidence intervals from (1) for each percentile of the hourly wage distribution below the median. There are statistically significant impacts up through the 10th percentile; between the 10th and 20th percentiles, the impacts are economically small and not statistically significant at the 5 percent level.

The bottom panel of Table 2 replicates the specification check of Autor et al. (2016). In particular, changes in the minimum wage would not be expected to affect wages high in the hourly wage distribution. The final two rows of the table show estimated marginal effects from (1) for the 75th and 90th percentiles of the hourly wage distribution, respectively. These estimates are economically small and not statistically different than zero.

3. The Location of Minimum-Wage Workers in the Earnings Distribution

One of the key takeaways from Figure 4 is that the minimum wage has impacts only toward the bottom of the hourly wage distribution. In fact, Autor et al. (2016) calculated for 1979-2012 that 2-6 percent of aggregate hours for men were worked at or below the minimum wage. An important consideration then in moving from hourly wage inequality to earnings inequality is how far up the earnings distribution are minimum-wage workers located. If hourly wages and hours are strongly positively correlated, then minimum-wage workers will be

[4] Estimates and standard errors for all of the parameters in (1) are available upon request.

concentrated at the very bottom of both the hourly wage and the earnings distributions. Alternatively, if hourly wages and hours are inversely correlated, then minimum-wage workers will be located further up the earnings distribution.

To examine where minimum-wage workers are located in the earnings distribution, Figure 5 uses ORG data and illustrates how the percentage of minimum-wage workers changes in the *weekly earnings* distribution when the real minimum wage changes. The vertical axis shows the national average percentage of earners with hourly wages less than or equal to the effective minimum wage; the horizontal axis shows the percentile of the national weekly earnings distribution. Two years are depicted, 1995 and 1998. For each year, the national weekly earnings distribution was binned into percentiles, and then within each centile bin the percentage of workers with an hourly wage at or below the minimum was calculated. The dashed line in Figure 5 is for 1995, a year for which the real value of the minimum wage was at a trough in Figure 1. About 30 percent of the workers in the first five centiles of the weekly earnings distribution held minimum-wage jobs (i.e., reported earning on an hourly basis at or below the effective minimum wage in their state for that year). For the 5th-15th centiles of the weekly earnings distribution, about 6 percent of workers held minimum-wage jobs. In contrast, the solid line in the figure is for 1998, which was year in which the real value of the minimum wage was at a peak, primarily because of an increase in the nominal federal minimum wage in September, 1997, to $5.15 per hour. For the 15th percentile and below of the weekly earnings distribution, the percentage of workers at or below the minimum rises by as much as 5-15 percentage points; beyond the 15th percentile, the increase in the minimum wage does not change the density of minimum-wage workers. Overall, this figure illustrates that while the bulk of minimum-wage workers are at the bottom of the weekly earnings distribution, increases in the minimum wage between 1995 and 1998 still might be expected to have impacts as far up as the 15th percentile of the weekly earnings distribution for men. Figure 6 shows a similar pattern for the increase in the minimum wage between 2006 and 2013.

Figures 7 and 8 extend these illustrations to the *annual earnings* distribution. Again, if hourly wages and hours—in this case, annual hours, the product of weekly hours and weeks worked—are strongly positively correlated, then minimum-wage workers will be concentrated at the very bottom of both the hourly wage and the annual earnings distributions. If hourly wages and hours are inversely correlated, then minimum-wage workers will be located further up the annual earnings distribution.

To examine where minimum-wage workers are located in the annual earnings distribution for women, Figure 7 uses data for 1996 as the trough and 1998 as the peak, based on hourly wages and annual earnings for CPS respondents in the IPUMS 1997 March ASEC supplement (Flood et al., 2017).[5] The March supplement asks about annual earnings in the prior calendar year (i.e., 1996). We merged this data to information on the hourly wage data gathered for the same respondents who were in the outgoing rotation groups in the March, April, May, and June 1996 CPS. That is, the May-June 1996 information measures whether the individual was in a minimum-wage job (for those months) in 1996, and the March 1997 information measures annual earnings in 1996. The resulting sample for 1996 is smaller than that in Figure 5 for the weekly earnings calculation based on the full MORG. Hence, in Figure 7 the national annual earnings distribution in 1996 was binned into ventiles (rather than centiles). Then within each ventile bin, the percentage of workers with an hourly wage at or below the minimum was calculated.

In the figure, the vertical axis shows the national average percentage of earners with hourly wages less than or equal to the effective minimum wage; the horizontal axis shows the ventile of the national annual earnings distribution. For 1996, minimum-wage workers comprise a small share of earners, even in the bottom two ventiles (i.e., 10th percentile) of the annual earnings distribution. When the minimum wage rises in 1998, there are increases in the share who are minimum-wage earners in the (roughly) 4th-6th ventiles of the annual earnings distribution, but, even then, the overall share of earners working at or below the minimum wage in that range is small. Figure 8 paints a similar picture for 2006 (trough) and 2012 (peak): the share of annual earners working at or below the minimum wage rises up through the 7th ventile when the minimum wage rises, but the overall share of earners affected is low, from about 2.5 percent in the 7th ventile to almost 15 percent in the 1st ventile.

More generally, Figure 9 shows the percent of earners with hourly wages at or below the minimum wage pooled across all years. The share of earners directly affected by the minimum

[5] Due to the CPS redesign, we cannot use 1995 as the trough year, as in Figure 5 for weekly earnings, because respondents in the 1996 March CPS ASEC supplement cannot be linked to outgoing rotation groups in the 1995 IPUMS data. So, for the purposes of illustration, we used 1996 as the trough year in Figure 7.

wage drops rapidly through the first few ventiles of the annual earnings distribution. It suggests that changes in the minimum wage plausibly could affect annual earnings up through, say, the 25th percentile of the annual earnings distribution. To estimate this directly, Figure 10 plots the estimated impact of the minimum wage on the share of earners at or below the minimum based on the following time-series specification:

$$s_t^v = \alpha^v + \beta^v \ln(w_t^{MW}) + \gamma^v D_t^{Recession} + \lambda_t^v + u_t \ , \tag{3}$$

where the dependent variable, *s*, is the share earners in ventile *v* that earn at or below the minimum wage; $D^{Recession}$ is an indicator variable for whether the year is a recession year, based on the NBER business-cycle dating; λ is a linear time trend; and *u* is the error term. The focal explanatory variable is the natural log of the minimum wage. The parameter β measures the (semi-) elasticity of the share of earners at or below the minimum wage to the minimum wage, and indicates how many workers are affected when the minimum wage rises. The parameters in (3) are estimated separately for each ventile of the annual earnings distribution up through the median (e.g., $v = 1,...,10$).[6] Figure 10 plots $\beta^v \times 100$ for each ventile and the associated 95 percent confidence interval.

For example, for the first ventile of the annual earnings distribution, the share of earners working at or below the minimum wage increases by 30 percentage points when the minimum wage doubles. These elasticity estimates are positive and statistically different than zero up through the 4th ventile of the annual earnings distributions. Typically, however, the minimum wage does not double. From Table 1, a one-standard-deviation change in the minimum wage is 0.092 log points. The estimates in Figure 10 then would suggest that for a one-standard-deviation increase in the minimum wage, the share of earners at or below the minimum wage would rise roughly 3-5 percentage points in the decile of the annual earnings distribution, with even smaller effects in the second decile. Therefore, in the absence of substantial spillovers in the earnings distribution, a very small share of annual earners in this range of the distribution would be affected directly by typical changes in the minimum wage.

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[6] The cell sizes by state and year in the CPS were too small to estimate the parameters in (3) using state-by-year variation.

4. Impact on Inequality in Annual Earnings: Evidence from Administrative Data

To measure annual earnings inequality, we use SSA administrative earnings records. These series come from three sources. The first is SSA's Continuous Work History Sample (CWHS), which is a 1 percent sample of all Social Security numbers (SSNs) ever issued. The CWHS is created from several of SSA's administrative master files. The CWHS contains annual earnings covered by Social Security for all years since 1951 and earnings in both covered and non-covered employment for all years since 1978.[7] It also includes a limited set of demographics (date of birth, gender). It has two primary files: active and inactive. The active file contains SSNs that ever had any earnings from any employment (whether covered by Social Security or not). The inactive file contains SSNs for individuals who never worked (no earnings, covered or uncovered). The second is SSA's Numident file, which contains every SSN ever issued and includes place of birth. The third is the Longitudinal Employer-Employee Data (LEED), which cover the 1981-2015 calendar years. The LEED file differs from the basic CWHS file, in that the CWHS is person-based (one record per SSN; earnings are the sum of earnings from all jobs) and the LEED is job-based (one record per job per SSN per year). The LEED has earnings from each job a person held in a year and total earnings from all jobs. Importantly, the LEED also has state of residence and sector: private (non-agriculture); public (state and local, federal); military; agriculture; household workers; workers with self-reported tips. Self-employment income is recorded separately from wage and salary income. Throughout our analysis, we looked only at wage and salary income. For the empirical analysis below, we merge the CWHS, Numident, and LEED to form a 1 percent random sample from the universe of male U.S.-born civilian wage and salary earners for 1981-2015 that measures real annual earnings (deflated by the all-items CPI), state of residence, and sector. In all, there are 22,299,293 person-year observations in this sample.

To get the broadest coverage of earnings, we use Medicare-covered annual earnings. While some state and local public-sector workers are exempt from FICA taxation for Social Security (OASDI), the vast majority are covered under Medicare (HI) and pay the employee portion of the Medicare tax (1.45 percent) on Medicare-covered earnings, which, unlike Social Security-covered earnings, are not capped. Given the attention, for example, by Autor et al.

[7] The CWHS includes earnings in employment not covered by Social Security since 1978; however, the data for 1978-1980 have a higher rate of error than later years. Therefore, we include only earnings since 1981 in our study.

(2016) on measurement error in the CPS hourly wage data, the most important aspect of annual earnings based on administrative earnings records for our purposes is both their breadth of coverage and freedom from measurement error due to self-reporting and missing-value imputations in survey data, such as the CPS earnings (Lillard et al., 1986; Bollinger et al., 2017)

As a point of departure, Figure 10 plots the natural log of the real effective minimum wage (the solid line in Figure 1), measured on the right-hand vertical axis, versus the spread between the 5^{th} and 50^{th} percentiles of the real annual earnings distribution in each year from 1981-2013 based on annual earnings from administrative earnings records. The spread, the dashed line measured on the left-hand vertical axis, is the log difference of the 5^{th} and 50^{th} percentile annual earnings. A higher value on the left-hand axis (i.e., a less negative spread) means there is less inequality in the annual earnings distribution. Therefore, if increases in the (log) real minimum wage reduce inequality, the solid and dashed lines should move roughly in tandem across time. For men, there appears a negative correlation between the real minimum wage and $5^{th}/50^{th}$ annual earnings inequality, with inequality rising when the minimum wage is rising. The sample correlation coefficient between the series is -0.28. Figure 11 shows a similar pattern for the spread in real annual earnings between the 10^{th} and the 50^{th} percentiles, slightly higher up the distribution of earners. Overall, these time-series figures suggest equivocal impacts of the minimum wage for men.

To account for any time-series confounders, we next move to a regression framework similar to that in (1) for the hourly wage. In particular, we estimate a reduced-form econometric specification:

$$(y_{st}^{p} - y_{st}^{50}) = \alpha + \beta_1^{p}(w_{st}^{MW} - w_{st}^{50}) + \beta_2^{p}(w_{st}^{MW} - w_{st}^{50})^2 + \psi_s + \tau_t + \psi_s \cdot t + u_{st}\,, \qquad (2)$$

where y_{st}^{p} represents the natural log of annual earnings at percentile *p* of the annual earnings distribution in state s in year t, and y^{50} represents the log of median annual earnings. The dependent variable $(y_{st}^{p} - y_{st}^{50})$ measures the percentile *p*/median spread in log annual earnings. Since the key policy lever is the minimum hourly wage, the focal explanatory variable is $(w_{st}^{MW} - w_{st}^{50})$, the spread between the median and minimum wage rates, as in the analysis of hourly wages in (1). It enters (2) as a quadratic, so that $\beta_1^{p} + 2\beta_2^{p}(w_{st}^{MW} - w_{st}^{50})$ is the impact of an increase in the minimum *hourly wage* on the percentile *p*/median *annual earnings* inequality. It tells us how inequality in annual earnings changes when the minimum wage rises and becomes more binding. Since the median wage, w_{st}^{50}, on the right-hand side and the median annual earnings on the left-hand side in a state and year are likely correlated, we follow the same identification strategy as in (1) and estimate the parameters in (2) via instrumental variables, where there are three instruments: (i) the log of the minimum wage, w_{st}^{MW}; (ii) the square of the log of the minimum wage, $(w_{st}^{MW})^2$; and the interaction of the log minimum wage and the average log median wage for the state for 1981-2016, $w_{st}^{MW} \times \overline{w}_s^{50}$.

Table 3 shows the IV estimates of the marginal effect of an increase in the minimum wage on the percentile *p*/median annual earnings inequality in a state-year panel on real annual earnings for men from the administrative data in 1981-2015, i.e., $\hat{\beta}_1^p + 2\hat{\beta}_2^p(\overline{w_{st}^{MW} - w_{st}^{50}})$, where the $\hat{\beta}$'s are from the IV estimation of (2), and $(\overline{w_{st}^{MW} - w_{st}^{50}})$ is the sample mean spread of the (log) real minimum wage and the (log) median hourly wage. Column 1 shows estimates for the full sample of all male earners. Each table cell is an estimated marginal effect from a separate IV regression, so the top panel in column 1 results reflect nine IV regressions, one each for every fifth percentile below the median, from the 5th through the 45th, of the annual earnings distribution.

The marginal effects represent the elasticity of the inequality measure to the minimum wage. For example, the estimate in column 1, row 1 says that if the real minimum wage doubles, the spread between the 5th and 50th percentiles of the annual earnings distribution for all male earners falls by 19.9 percent. With a standard error of 0.092, shown in parentheses, this effect is significantly different from zero at conventional levels of significance.

Figure 13 shows the estimated impacts and 95 percent confidence interval for each percentile of the annual earnings distribution below the median. The estimated impacts are large and statistically different than zero (at close to the 5 percent significance level) up through the 12th percentile roughly. Hence, increases in the minimum wage reduce annual earnings inequality at the very bottom of the wage distribution for men. Qualitatively speaking, this is what was to be expected based on Figures 7-10, which illustrated the location of minimum-wage workers in the annual earnings distribution. Furthermore, although not statistically different than zero at the 5 percent level, the marginal effects are close to that much further up the earnings distribution.

However, the typical legislative change in the minimum wage is not a doubling of the minimum. From row 1 of column 2 in Table 1, the standard deviation of the log real minimum wage for this sample is 0.093. For example, multiplying the marginal effect for the 5^{th}/median spread by 0.093 (i.e., $0.199\times0.093=0.0185$) implies a 1.85 percent reduction in inequality for a typical change in the minimum wage (as measured by the standard deviation). In the first ventile of the annual earnings distribution in the CPS, 14 percent of workers earned at or below the minimum wage. Under the null hypothesis of no spillovers, a back-of-the-envelope calculation suggests this 1.85 percent reduction in inequality would imply a 13.2 percent increase in annual earnings for minimum-wage workers in this range of the earnings distribution (i.e., $0.0185/0.14=0.132$).

The remaining columns in Table 3 explore the robustness of these findings to alternative samples. The analysis of hourly wages in Table 2 was based on non-self-employed workers. To show roughly comparable results for annual earnings, Column 2 of Table 3 excludes person-year observations that had self-employment (Schedule C) income. This measure of self-employment is not fully comparable with that in Table 2, because the latter is based on self-reported employment status in the CPS, not the presence of Schedule C income. Column 3 excludes three broad classes of earners for whom true earnings might not be reported fully to SSA: agricultural workers, household workers, and those with self-reported tips. Column 4 further excludes public sector workers, for whom Medicare coverage might be less complete (than private sector workers). The estimated impacts for the various percentiles are similar in magnitude to those in the full sample of earners. Finally, column 5 is the most restrictive, excluding person-year observations from sectors with potentially less than full coverage, public sector workers, and those with self-employment income. Across these samples, the point estimates are very similar in magnitude, with some estimates more precise than others. Figures 14-17 show the full set of estimates and 95 percent confidence intervals for every percentile below the median for each of these respective samples. Overall, these estimates suggest that changes in the minimum wage have impacts up through (roughly) the 12^{th} percentile of the annual earnings distribution.

Finally, for the purposes of comparison, Table 4 shows an isomorphic set of estimates to those in Table 3, but based on a slightly longer state-year panel of annual earnings constructed from the March CPS data for 1981-2016. Figure 17 shows the complete set of estimates in the CPS data for every percentile below the median. The CPS estimates are slightly attenuated and less precise, as would be expected if CPS earnings are measured with error, but convey the same basic message.

5. Impact on the Extensive Margin: Evidence from the CPS

In summary, increases in the minimum wage raise both the hourly wage and annual earnings for earners at the bottom of those respective distributions for men. Unfortunately, the SSA administrative data have only state-of-residence information for individuals with earnings; SSA does not track state of residence for those out of the labor force (unless, of course, they are in current pay benefit status for OASDI benefits). Therefore, we turn to the CPS to explore equilibrium impacts on employment and hours.

In particular, we use the March CPS data to form a state-year panel and estimate the following reduced-form econometric specification:

$$f_{st}^{e} = \alpha + \beta_1^{e}(w_{st}^{MW} - w_{st}^{50}) + \beta_2^{e}(w_{st}^{MW} - w_{st}^{50})^2 + \psi_s + \tau_t + \psi_s \cdot t + u_{st}, \quad (3)$$

where f_{st}^{e} is the log share of individuals in state *s* and year *t* with educational attainment *e*, who report positive annual earnings, where, again, the focal explanatory variable is $(w_{st}^{MW} - w_{st}^{50})$ and enters as a quadratic. In (3), $\beta_1^{p} + 2\beta_2^{p}(w_{st}^{MW} - w_{st}^{50})$ is the impact of an increase in the minimum *hourly wage* on the share employed. Since the median wage, w_{st}^{50}, on the right-hand side and the fraction of earners on the left-hand side in a state and year are likely correlated, we follow the same identification strategy as in (1) and (2) above, and estimate the parameters in (3) for each educational group via instrumental variable estimation, where there are three instruments: (i) the log of the minimum wage, w_{st}^{MW}; (ii) the square of the log of the minimum wage, $(w_{st}^{MW})^2$; and the interaction of the log minimum wage and the average log median wage for the state for 1981-2016, $w_{st}^{MW} \times \overline{w}_{s}^{50}$.

Column 1 of Table 5 shows the IV estimates of the marginal effect of an increase in the minimum wage on the extensive margin, i.e., $\hat{\beta}_1^p + 2\hat{\beta}_2^p(\overline{w_{st}^{MW} - w_{st}^{50}})$, where the $\hat{\beta}$'s are from the IV estimation of (3), and $(\overline{w_{st}^{MW} - w_{st}^{50}})$ is the sample mean spread of the (log) real minimum wage and the (log) median hourly wage. Each table cell is an estimated marginal effect from a separate IV regression, so the Column 1 results reflect four IV regressions for the share employed, one each of four educational attainment groups (less than high school, high school, some college, and college graduate). Similarly, Column 2 shows estimates for four IV regressions for log annual hours, one each of four educational attainment groups. Across the eight specifications in the table, there is little systematic evidence of impacts on employment and hours, with many of the estimates imprecise enough to make any firm conclusions. Table 6 presents a parallel set of estimates for log annual hours by annual earnings decile. Again, the estimates are not precise enough to draw firm conclusions about impacts on hours, so that even though hourly wages and annual earnings appear to be rising in the bottom of those distributions, the impact on employment and annual hours remains an open question in this analysis.

6. Summary and Caveats

This paper provides an empirical analysis of the impact of the minimum wage on annual earnings inequality in the United States over the past three and a half decades. We focus on men between the ages of 25 and 61, and use administrative earnings records from 1981-2015 from the U.S. Social Security Administration to measure annual earnings. We find that increases in the minimum wage reduce inequality below about the 12th percentile of the annual earnings distribution. Unlike in Autor et al. (2016), the findings for earnings cannot be explained alternatively by measurement error. These increases are slightly larger than the impacts of the minimum wage on the bottom part of the hourly wage distribution, as measured in the CPS Outgoing Rotation Groups, but not statistically larger, given the precision of the estimation, and larger than impacts on annual earnings in the March CPS, consistent with measurement error in CPS annual earnings. Finally, we use data from the March CPS to examine impacts on annual hours and employment, but the estimates are not precise enough to draw any firm conclusions.

These conclusions are tempered by the following caveats. First, we do not provide a direct test for spillovers. Our estimates indicate that the minimum wage has statistically significant effects on annual earnings up through the 12^{th} percentile at the 5 percent level of statistical significance. If we weaken that standard by choosing a larger level of significance, our estimates suggest impacts much further up the annual earnings distribution based on the estimates shown in Figures 13-16, which could be associated with spillovers. Overall, limits to the precision of our estimates restrain our ability to say something more conclusive about whether changes in the minimum wage affect the earnings of workers with hourly wages above the minimum. Second, we focus on men, primarily because of worries that estimates for women are not identified. More work on women, who have been found to have larger hourly wage responses to the minimum wage than men, is clearly warranted. Finally, we have focused on the impact of the minimum wage on inequality in annual earnings. However, individual earnings are just one (albeit important) component of family income; changes in earnings by one family member may be offset by earnings of other members, as well as government and capital income (Congressional Budget Office, 2014; Gramlich, 1976; Dube, 2017). The SSA data are extremely rich but do not allow us to examine these broader impacts on family income and poverty.

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Table 1. Descriptive Statistics for Selected Variables and Samples (Standard Deviations in Parentheses)

Variable:	(1) CPS Hourly Wages	(2) SSA Annual Earnings	(3) CPS Annual Earnings
Log real minimum wage	2.019	2.017	2.019
	(0.094)	(0.093)	(0.094)
Log difference between real minimum wage and 50th percentiles	-1.036	-1.038	-1.036
	(0.139)	(0.139)	(0.139)
Log difference between 5th and 50th percentiles	-0.830	-2.417	-1.743
	(0.098)	(0.218)	(0.290)
Log difference between 10th and 50th percentiles	-0.664	-1.531	-1.138
	(0.085)	(0.156)	(0.163)
Log difference between 20th and 50th percentiles	-0.442	-0.785	-0.643
	(0.061)	(0.096)	(0.088)
Log difference between 30th and 50th percentiles	-0.275	-0.427	-0.373
	(0.041)	(0.055)	(0.059)
Log difference between 40th and 50th percentiles	-0.132	-0.190	-0.173
	(0.0245)	(0.025)	(0.037)
Square of log real minimum wage	4.085	4.077	4.085
	(0.383)	(0.377)	(0.383)
Log real minimum wage interacted with state average log median wage	43.319	43.299	43.319
	(6.430)	(6.379)	(6.430)
Years	1981-2016	1981-2015	1981-2016

Note: Authors' calculations.

Table 2. Instrumental Variable Estimates of the Marginal Effect of Log(Minimum Wage)-Log(Median Wage) and Inequality in Hourly Wages for Men, based on State-Year Panel from 1981-2016 CPS Merged Outgoing Rotation Group Data (Standard Errors in Parentheses)

	(1)
Dependent Variable: Log Difference in Hourly Wages between	Estimated Impact
5^{th} and 50^{th} percentiles	0.088**
	(0.030)
10^{th} and 50^{th} percentiles	0.046*
	(0.026)
20^{th} and 50^{th} percentiles	0.025
	(0.028)
30^{th} and 50^{th} percentiles	0.019
	(0.019)
40^{th} and 50^{th} percentiles	0.0008
	(0.015)
75^{th} and 50^{th} percentiles	0.006
	(0.014)
90^{th} and 50^{th} percentiles	-0.009
	(0.026)

Note: Each row represents a separate IV regression. Standard errors clustered at the state level shown in parentheses. The first-stage regression is identical for all rows, and the partial *F*-statistic on the instrument set in the first-stage is 350. The top panel of the table shows the estimated impacts in the bottom half of the hourly wage distribution (i.e., at the 5^{th}, 10^{th}, 20^{th}, 30^{th}, and 40^{th} percentiles). The bottom panel shows the estimated impacts for selected points in the upper tail of the hourly wage distribution and represents a falsification test. ** indicates $p<0.05$ for test of the null hypothesis that impact is zero versus the two-sided alternative; * $p<0.10$.

Table 3. Instrumental Variable Estimates for Men of the Marginal Effect of Log(Minimum Wage)-Log(Median Wage) on Inequality in Annual Earnings, based on State-Year Panel from 1981-2015 from Social Security Earnings Records (Standard Errors in Parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)
	Sample:					
Dependent Variable: Log Difference in Annual Earnings between	All Earners	Column (1) Excluding the 1980s	Column (1) Excluding Agriculture, Household, and Self-Reported Tips	Column (3) Excluding the Public Sector	Column (1) Excluding Those with Schedule C Income	Column (4) Excluding Those with Schedule C Income
5th and 50th percentiles	0.199**	0.164**	0.214**	0.174*	0.202**	0.178*
	(0.092)	(0.080)	(0.096)	(0.099)	(0.101)	(0.105)
10th and 50th percentiles	0.104**	0.111**	0.113*	0.090	0.117*	0.084
	(0.061)	(0.054)	(0.062)	(0.062)	(0.066)	(0.066)
15th and 50th percentiles	0.049	0.054	0.057	0.022	0.044	0.008
	(0.048)	(0.046)	(0.048)	(0.049)	(0.055)	(0.054)
20th and 50th percentiles	0.050	0.041	0.059	0.029	0.045	0.021
	(0.037)	(0.360)	(0.037)	(0.039)	(0.041)	(0.032)
25th and 50th percentiles	0.045	0.037	0.049	0.021	0.034	0.019
	(0.028)	(0.029)	(0.029)	(0.032)	(0.033)	(0.033)
30th and 50th percentiles	0.031	0.028	0.036*	0.018	0.030	0.012
	(0.021)	(0.023)	(0.022)	(0.023)	(0.022)	(0.026)
35th and 50th percentiles	0.013	0.010	0.016	0.005	0.009	0.004
	(0.016)	(0.018)	(0.017)	(0.019)	(0.017)	(0.020)
40th and 50th percentiles	0.003	0.001	0.007	-0.001	0.003	-0.004
	(0.011)	(0.013)	(0.012)	(0.013)	(0.011)	(0.013)
45th and 50th percentiles	0.006	0.004	0.010	-0.002	0.025	-0.001
	(0.008)	(0.009)	(0.008)	(0.007)	(0.016)	(0.007)
75th and 50th percentiles	0.019	0.019	0.022	0.006	0.025	0.013
	(0.016)	(0.013)	(0.016)	(0.015)	(0.016)	(0.016)
90th and 50th percentiles	-0.020	0.022	0.011	-0.011	0.015	-0.006
	(0.054)	(0.023)	(0.040)	(0.045)	(0.042)	(0.049)

Note: Standard errors clustered at the state level shown in parentheses

Table 4. Instrumental Variable Estimates for Men of the Marginal Effect of Log(Minimum Wage)-Log(Median Wage) on Inequality in Annual Earnings, based on State-Year Panel from 1981-2016 from the March CPS (Standard Errors in Parentheses)

	(1)	(2)	(3)	(4)	(5)
	Sample:				
Dependent Variable: Log Difference in Annual Earnings between	All Earners	Column (1) Excluding the Self-Employed	Column (1) Excluding Agriculture, Household, and Selected Occupations with Tips	Column (3) Excluding the Public Sector	Column (4) Excluding the Self-Employed
5^{th} and 50^{th} percentiles	0.212*	0.161	0.191	0.293**	0.200*
	(0.130)	(0.117)	(0.134)	(0.131)	(0.120)
10^{th} and 50^{th} percentiles	0.071	0.085	0.071	0.107	0.067
	(0.085)	(0.084)	(0.082)	(0.088)	(0.080)
20^{th} and 50^{th} percentiles	0.034	0.031	0.046	0.034	0.024
	(0.047)	(0.039)	(0.039)	(0.045)	(0.046)
30^{th} and 50^{th} percentiles	0.026	0.031	0.020	0.009	-0.022
	(0.030)	(0.028)	(0.026)	(0.030)	(0.029)
40^{th} and 50^{th} percentiles	-0.011	0.023	-0.005	-0.013	-0.038*
	(0.021)	(0.019)	(0.017)	(0.022)	(0.023)
75^{th} and 50^{th} percentiles	0.014	0.020	0.027	0.014	0.003
	(0.026)	(0.028)	(0.028)	(0.032)	(0.035)
90^{th} and 50^{th} percentiles	-0.003	-0.022	0.001	-0.043	-0.027
	(0.043)	(0.048)	(0.046)	(0.042)	(0.047)

Note: Standard errors clustered at the state level shown in parentheses.

Table 5. Instrumental Variable Estimates for Men of the Marginal Effect of Log(Minimum Wage)-Log(Median Wage) on the Share of Men with Any Earnings and Annual Hours of Male Earners, by Educational Group, based on State-Year Panel from 1981-2016 March CPS Data (Standard Errors in Parentheses)

	(1)	(2)
Educational Group:	ln(Share with Any Earnings)	ln(Annual Hours)
High School Dropout	0.009	0.027
	(0.079)	(0.046)
High School	0.014	0.037**
	(0.024)	(0.018)
Some College	0.011	-0.016
	(0.021)	(0.019)
College Graduate	-0.016	0.004
	(0.015)	(0.014)

Note: Standard errors clustered at the state level shown in parentheses.

Table 6. Instrumental Variable Estimates for Men of the Marginal Effect of Log(Minimum Wage)-Log(Median Wage) on the Annual Hours of Individuals with Earnings, by Decile of CPS Annual Earnings, based on State-Year Panel from 1981-2016 March CPS Data (Standard Errors in Parentheses, Sample Mean with Earnings in Brackets)

Decile of Annual Earnings:	ln(Annual Hours)
1st	0.100
	(0.083)
2nd	-0.003
	(0.043)
3rd	0.045
	(0.041)
4th	0.033
	(0.028)
5th	0.007
	(0.029)

Note: Standard errors clustered at the state level shown in parentheses.

Figure 1. Annual Average Real Value of the Minimum Wage
in 2016 Dollars

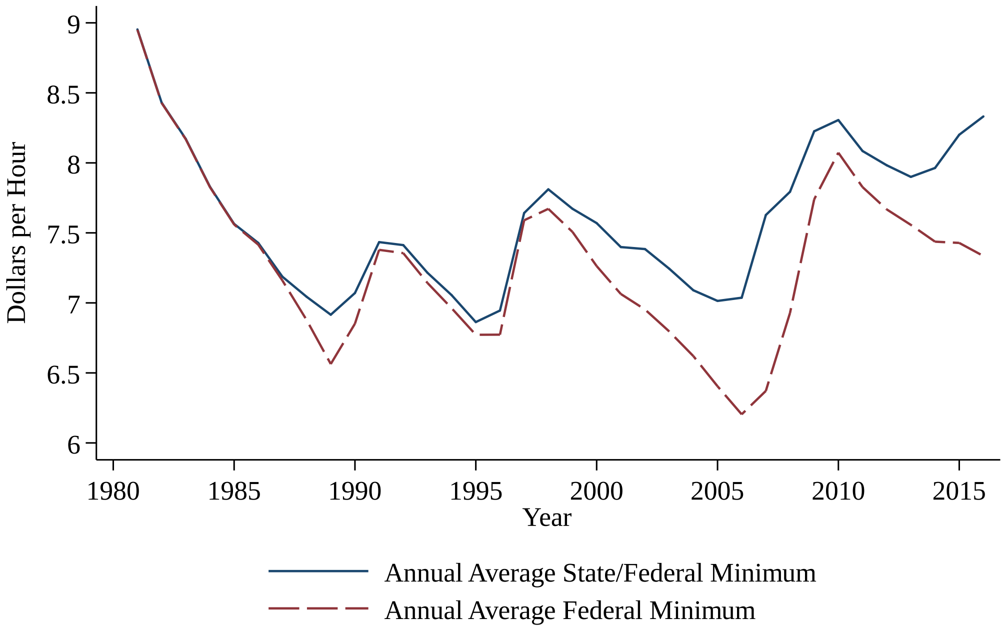
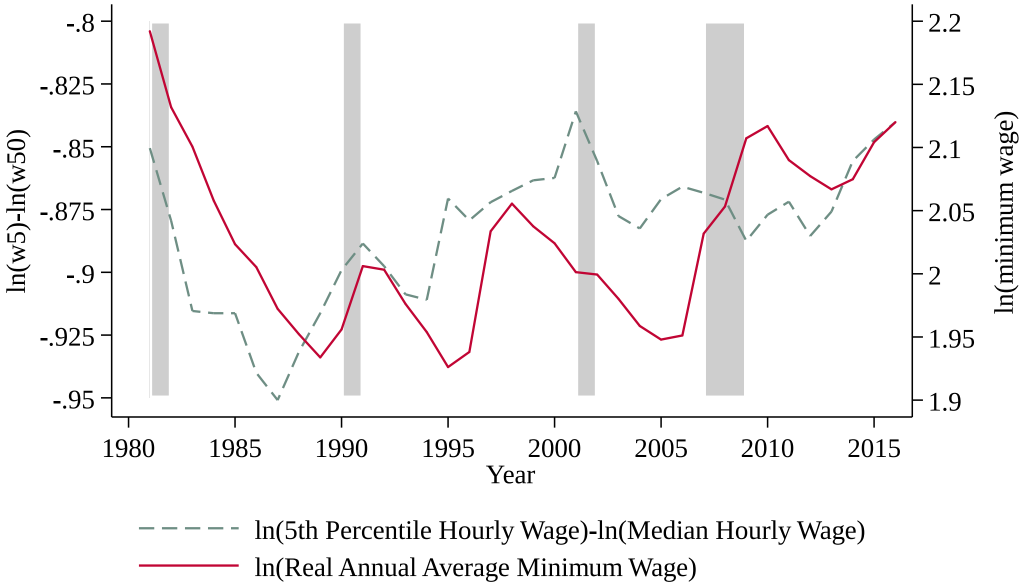
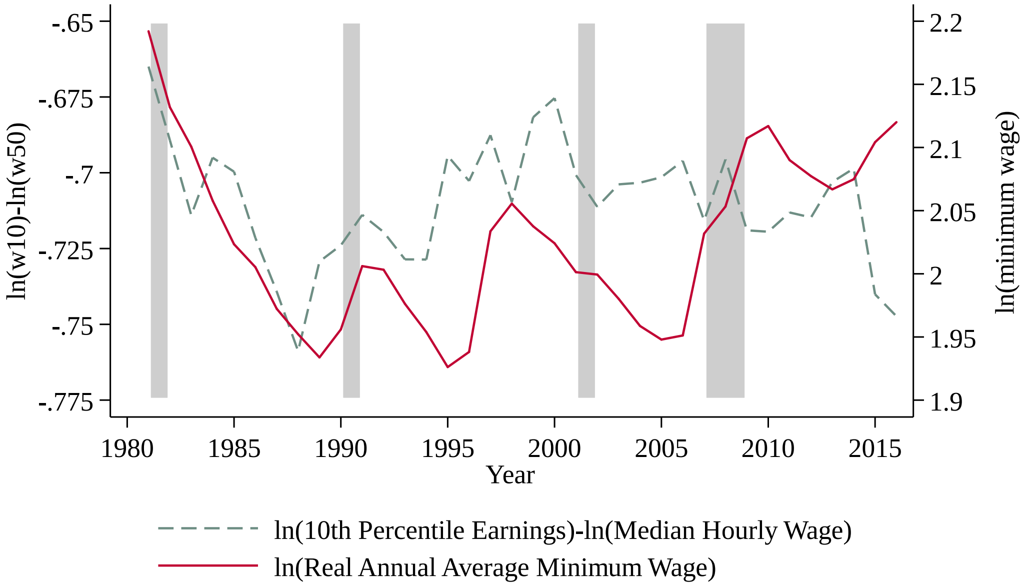


Figure 2. Log Minimum Wage and Log(5th Percentile)-Log(Median Hourly Wage)
Based on CPS Outgoing Rotation Groups for 1981-2016



Note: Shaded bands indicate recessions based on NBER business-cycle dating. Series' correlation is 0.36.

Figure 3. Log Minimum Wage and Log(10th Percentile)-Log(Median Hourly Wage)
Based on CPS Outgoing Rotation Groups for 1981-2016



Note: Shaded bands indicate recessions based on NBER business-cycle dating. Series' correlation is 0.20.

Figure 4. Estimated IV Impact of Log(Minimum)-Log(Median Wage) on Log(pth Percentile)-Log(Median Wage) by Percentile of Hourly Wage Distribution

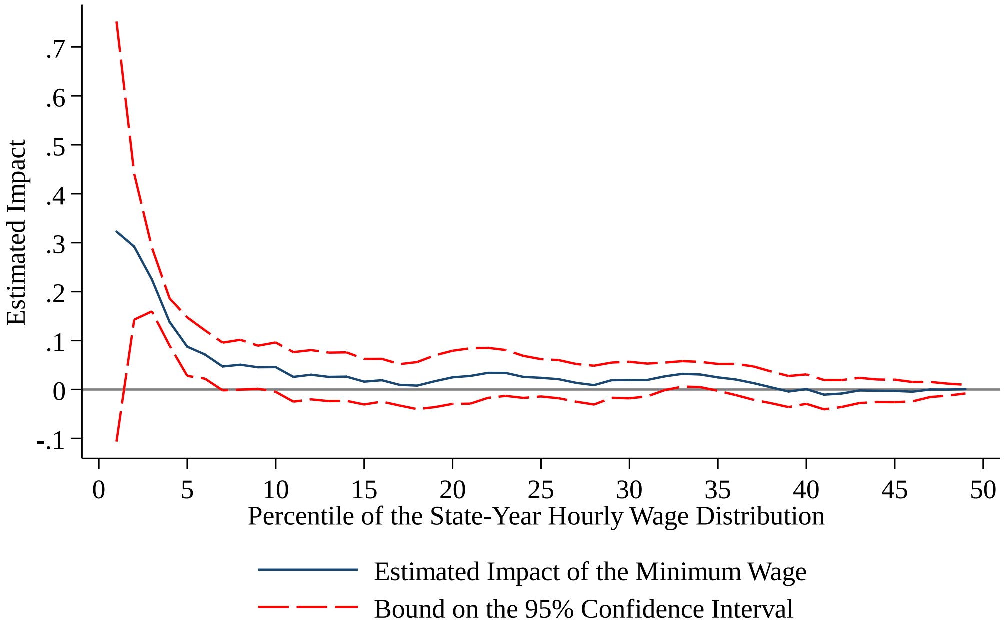


Figure 5. Percent of Earners with Hourly Wages Less Than or Equal to Minimum by Percentile of the CPS Weekly Earnings Distribution for 1995 and 1998

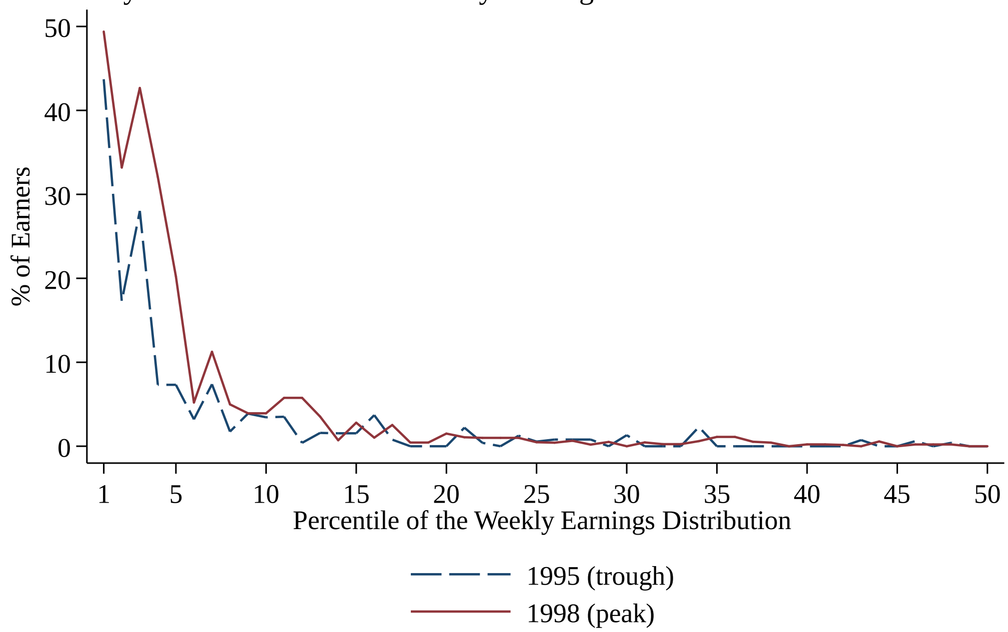


Figure 6. Percent of Earners with Hourly Wages Less Than or Equal to Minimum by Percentile of the CPS Weekly Earnings Distribution for 2006 and 2013

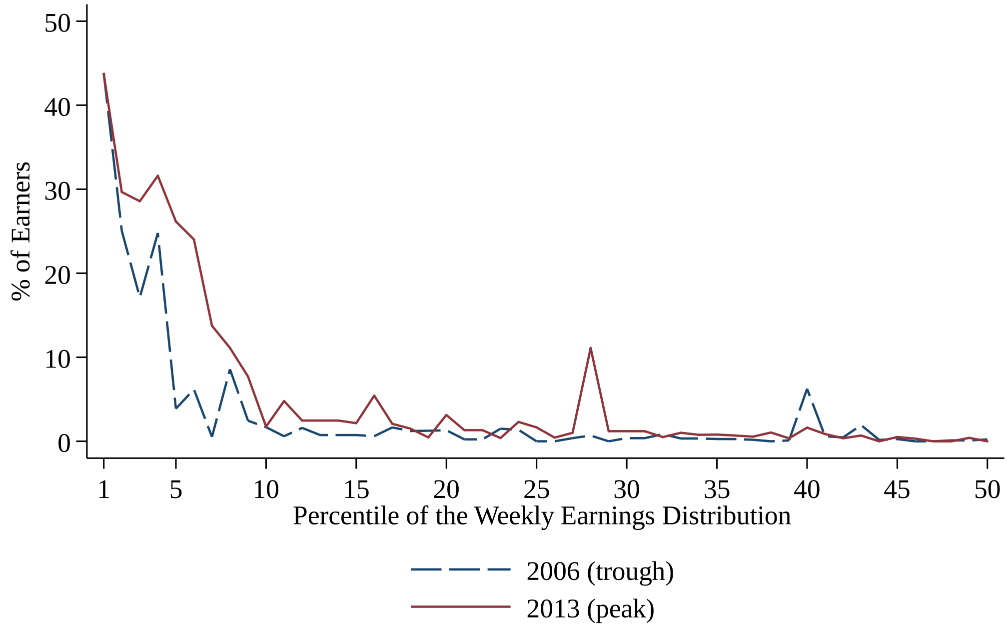


Figure 7. Percent of Earners with Hourly Wages At or Below the Minimum Wage by Ventile of the CPS Annual Earnings Distribution for 1996 and 1998

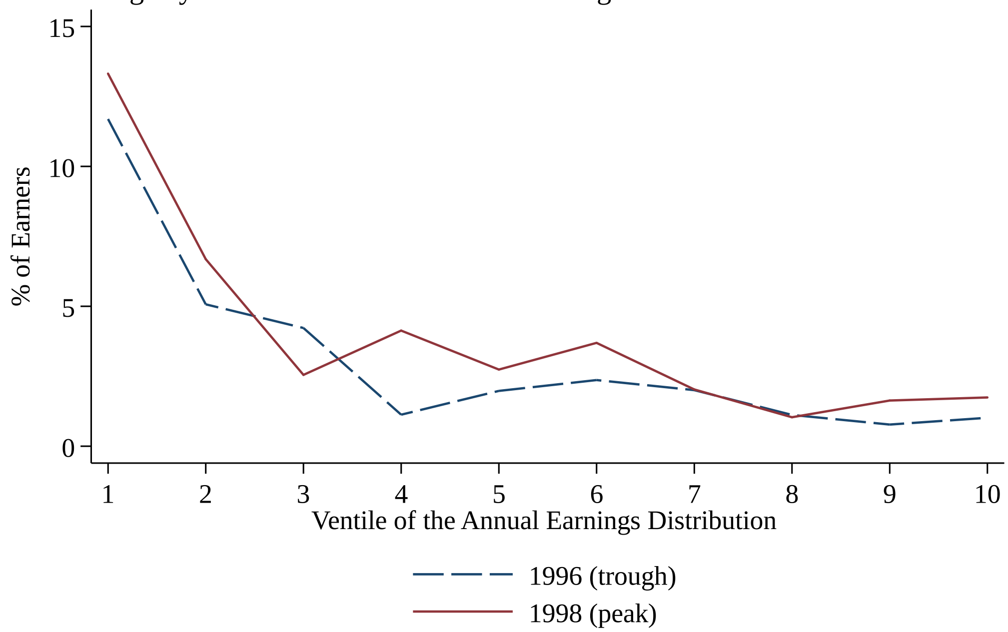


Figure 8. Percent of Earners with Hourly Wages At or Below the Minimum Wage by Ventile of the CPS Annual Earnings Distribution for 2006 and 2012

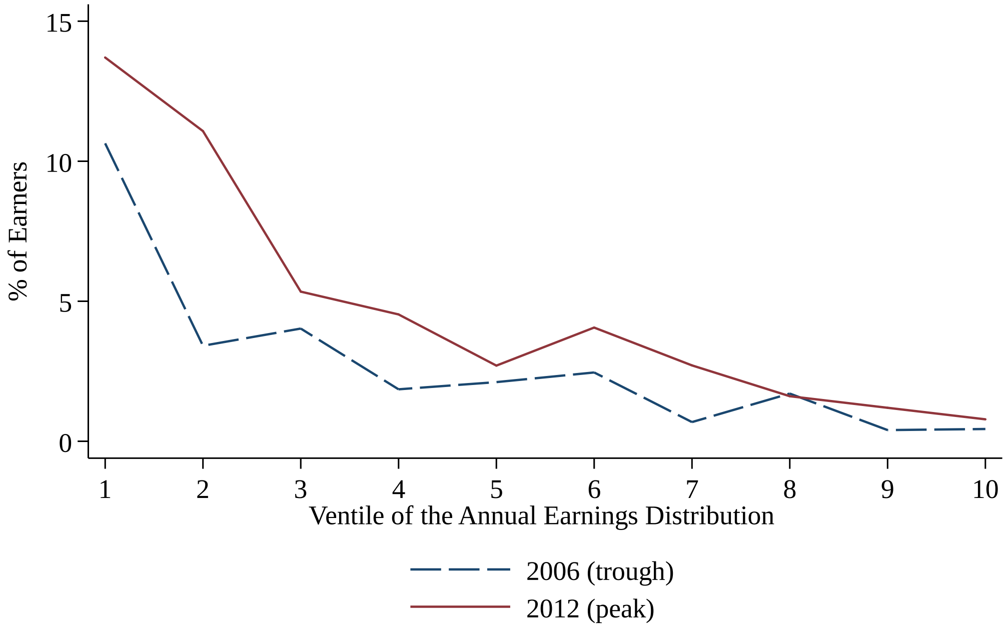


Figure 9. Percent of Earners with Hourly Wages At or Below the Minimum Wage
by Ventile of the Annual Earnings Distribution for All Years Pooled

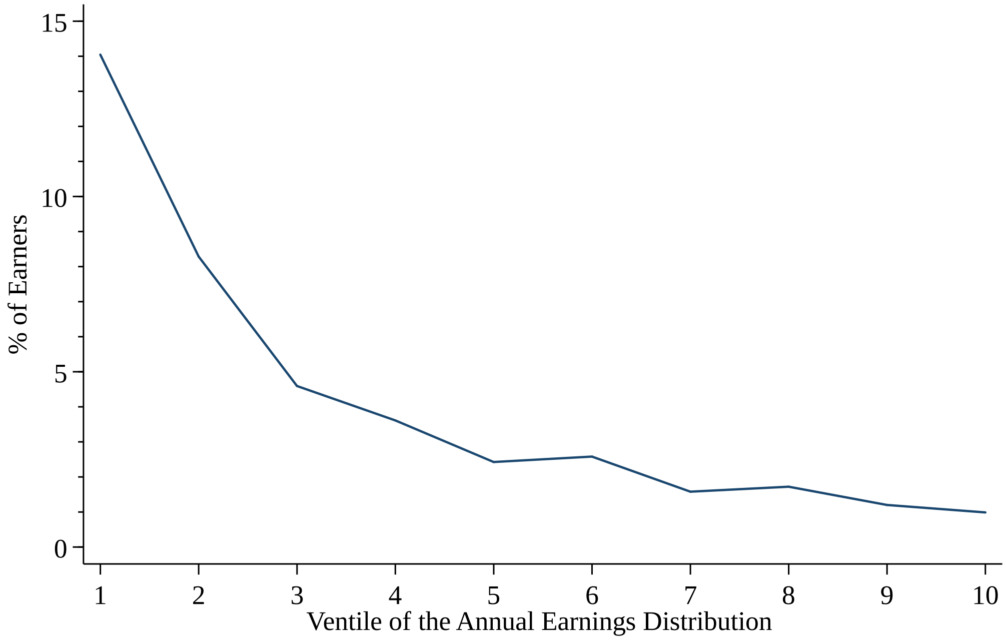


Figure 10. Impact of Minimum Wage on Percent of Men with Hourly Wages At or Below the Minimum Wage by Ventile of the Annual Earnings Distribution

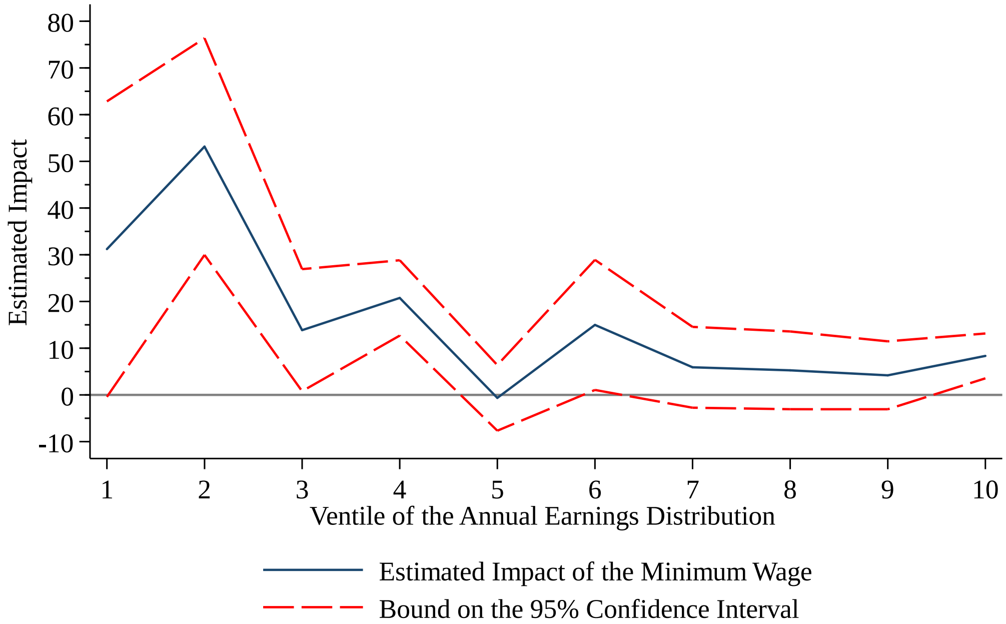
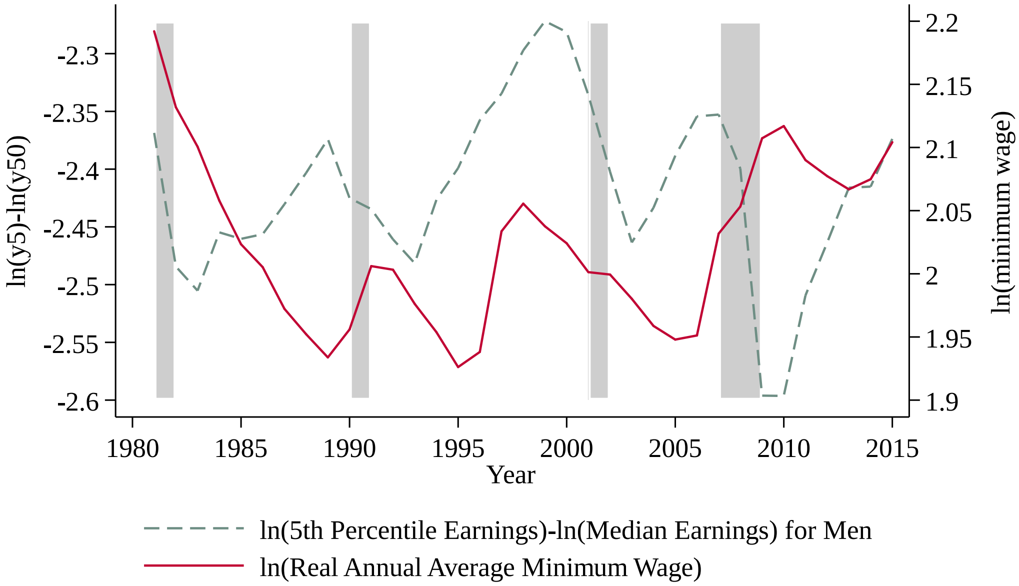
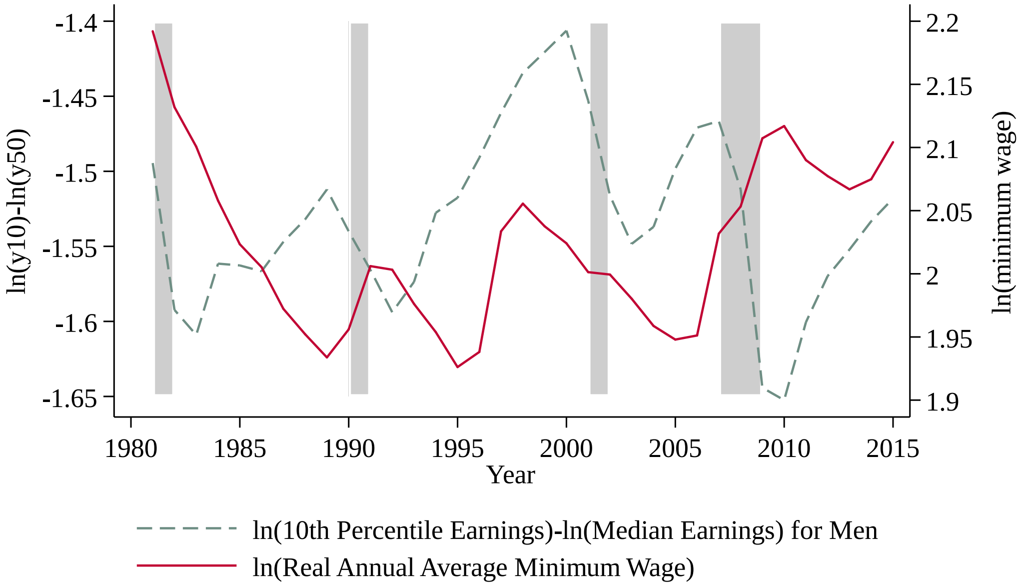


Figure 11. Log Minimum Wage and Log(5th Percentile)-Log(Median Earnings)
Based on Annual Social Security Administrative Earnings for 1981-2015



Note: Shaded bands indicate recessions based on NBER business-cycle dating. Series' correlation is -0.28.

Figure 12. Log Minimum Wage and Log(10th Percentile)-Log(Median Earnings) based on Social Security Administrative Earnings for 1981-2015



Note: Shaded bands indicate recessions based on NBER business-cycle dating. Series' correlation is -0.28.

Figure 13. Impact for All Earners of Log(Minimum)-Log(Median Wage)
on Log(pth Percentile)-Log(Median SSA Earnings) by Earnings Percentile

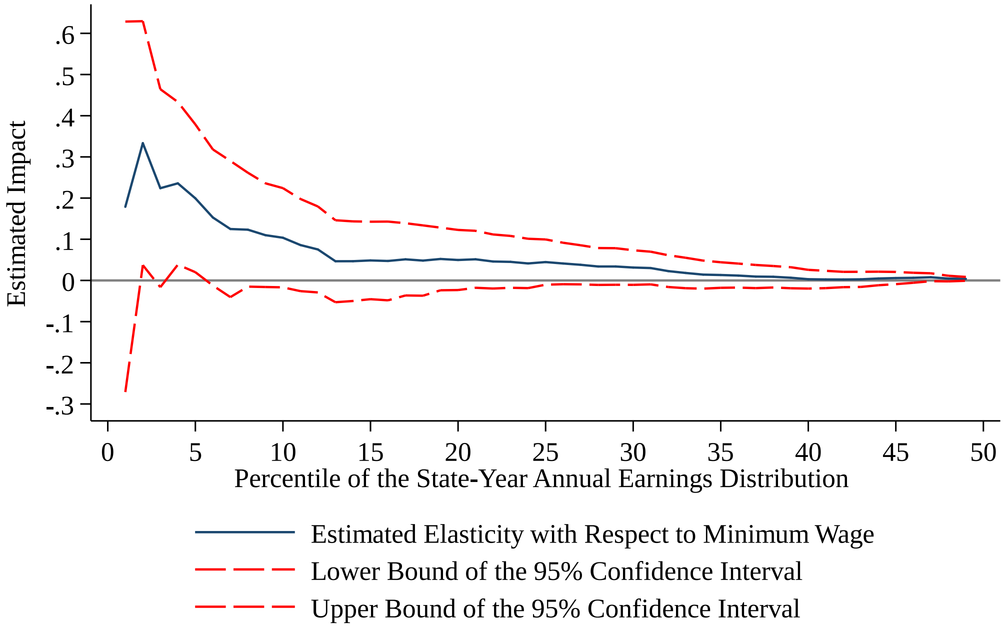


Figure 14. Impact of Log(Minimum)-Log(Median Wage) on Log(pth Percentile)-Log(Median SSA Earnings) by Earnings Percentile Excluding the 1980s

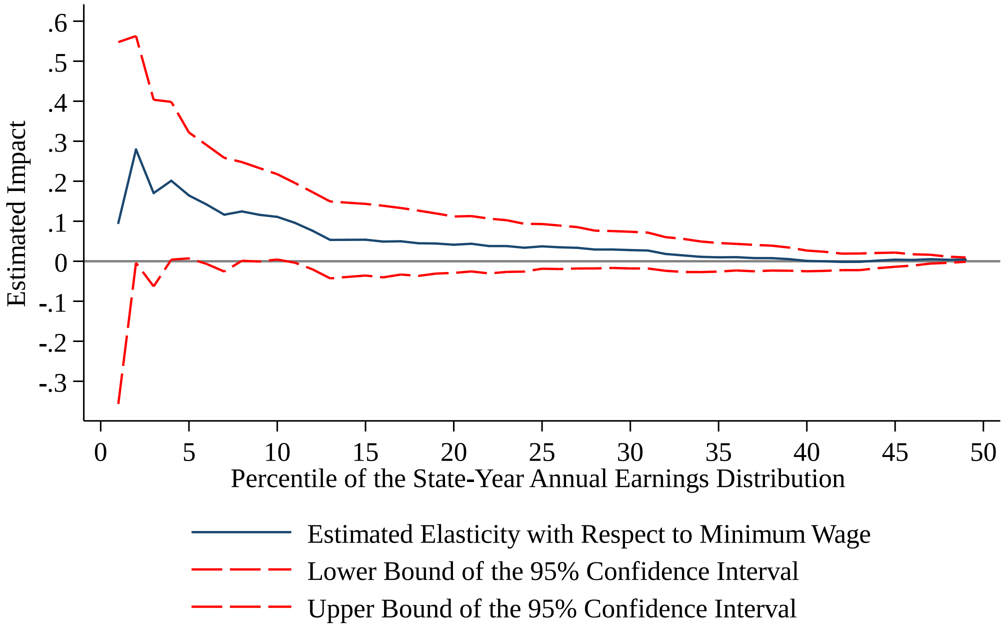


Figure 15. Impact for Earners in High-Coverage Sectors of Log(Minimum)-Log(Median Wage) on Log(pth Percentile)-Log(Median SSA Earnings)

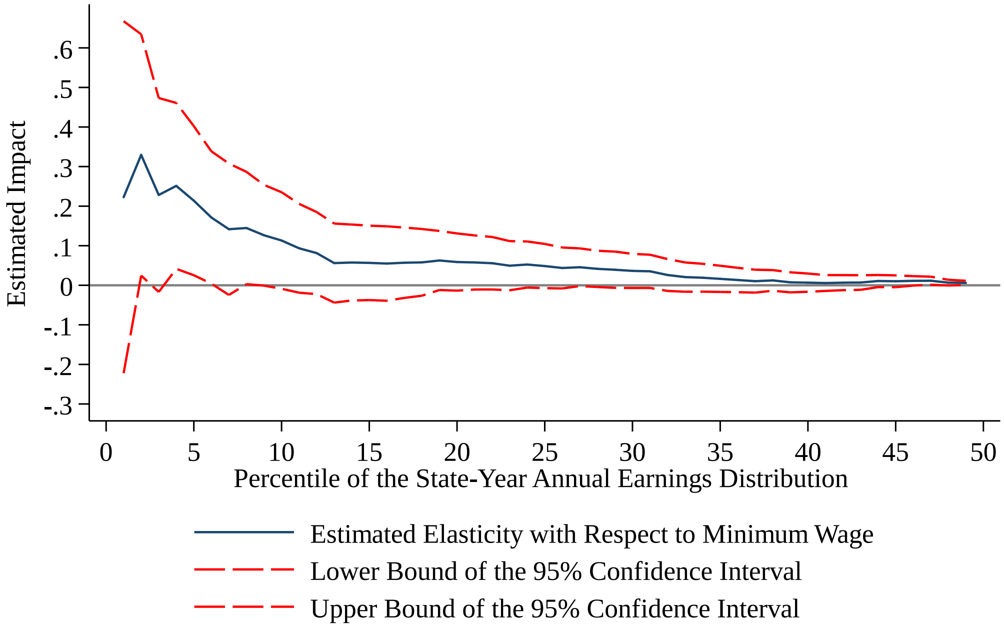


Figure 16. Impact for Earners in High-Coverage Private Sectors of Log(Minimum)-Log(Median Wage) on Log(pth Percentile)-Log(Median SSA Earnings)

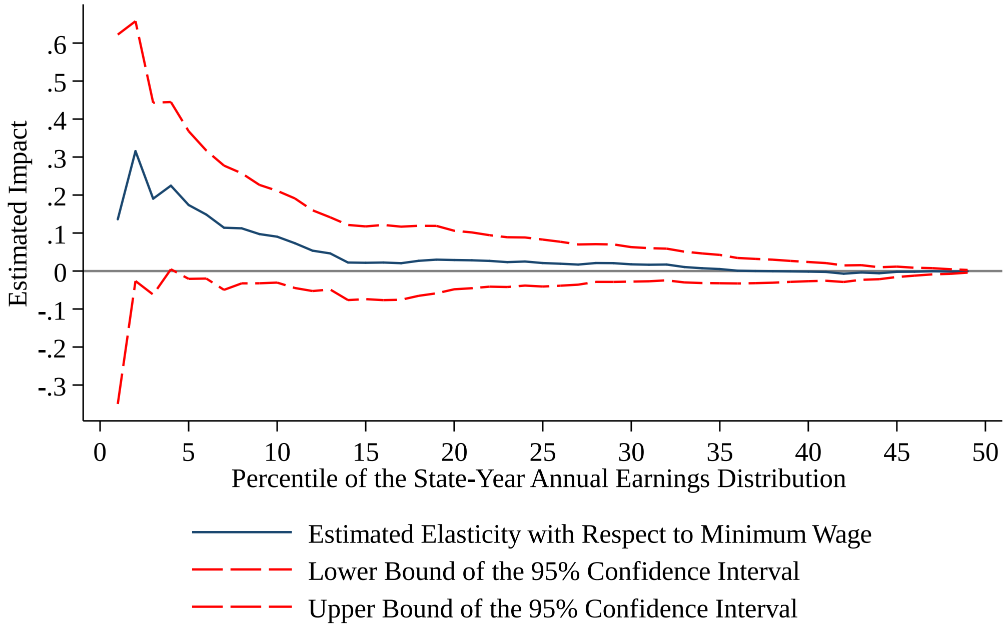
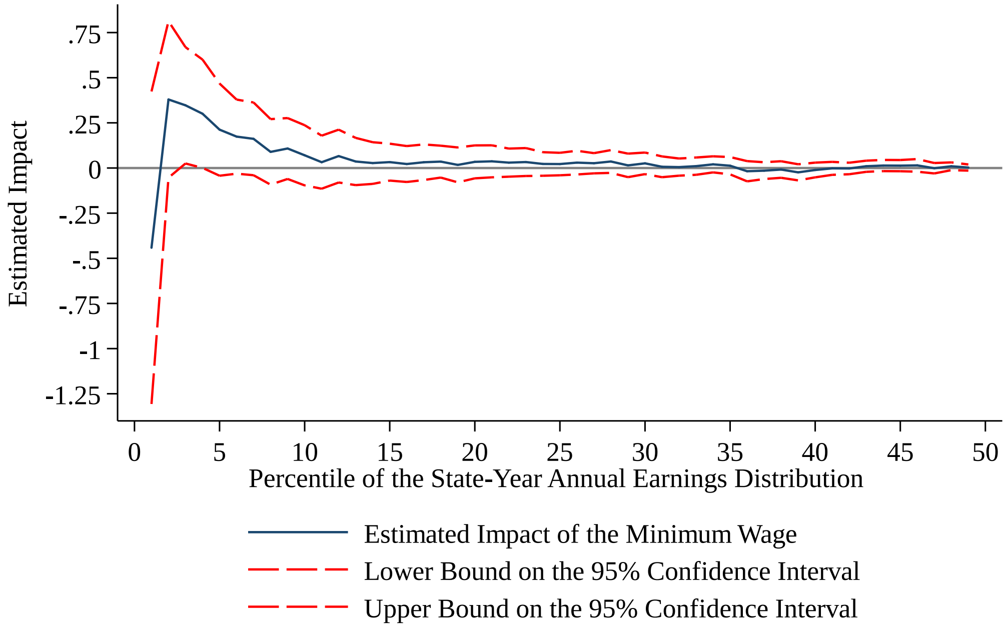


Figure 17. Impact for All Earners of Log(Minimum)-Log(Median Wage) on Log(pth Percentile)-Log(Median CPS Earnings) by Earnings Percentile



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