The Contribution of the Minimum Wage to U.S. Wage Inequality over Three Decades: A Reassessment*

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We reassess the effect of state and federal minimum wages on U.S. earnings inequality using two additional decades of data and far greater variation in minimum wages than was available to earlier studies. We argue that prior literature suffers from two sources of bias and propose an IV strategy to address both. We find that the minimum wage reduces inequality in the lower tail of the wage distribution (the 50/10 wage ratio), but the impacts are typically less than half as large as those reported elsewhere and are almost negligible for males. Nevertheless, the estimated effects extend to wage percentiles where the minimum is nominally non-binding, implying spillovers. However, we show that spillovers and measurement error (absent spillovers) have similar implications for the effect of the minimum on the shape of the lower tail of the measured wage distribution. With available precision, we cannot reject the hypothesis that estimated spillovers to non-binding percentiles are due to reporting artifacts. Accepting this null, the implied effect of the minimum wage on the actual wage distribution is smaller than the effect of the minimum wage on the measured wage distribution.

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Introduction

While economists have vigorously debated the effect of the minimum wage on employment levels for at least six decades (cf. Stigler, 1946), its contribution to the evolution of earnings inequality was largely ignored prior to the seminal contribution of DiNardo, Fortin and Lemieux (1996, DFL hereafter). Using kernel density techniques, DFL produced overwhelming visual evidence that the minimum wage substantially 'held up' the lower tail of the US earnings distribution in 1979, yielding a pronounced spike in hourly earnings at the nominal minimum value, particularly for females. By 1988, however, this spike had virtually disappeared. Simultaneously, the inequality of hourly earnings increased markedly in both the upper and lower halves of the male and female wage distributions: between 1979 and 1988, the 50/10 ('lower tail') log hourly earnings ratio expanded by 11 log points overall, and by 8 and 22 log points respectively among males and females (Table 1). To assess the causes of this rise, DFL constructed counterfactual wage distributions that potentially accounted for the impact of changing worker characteristics, labor demand, union penetration, and minimum wages on the shape of the wage distribution. Comparing counterfactual with observed wage densities, DFL concluded that the erosion of the federal minimum wage—which declined in real terms by 30 log points between 1979 and 1988—was the predominant cause of rising lower tail inequality between 1979 and 1988, explaining two-thirds of the growth of the 10/50 for both males and females.[1]

Though striking, a well-understood limitation of the DFL findings is that the estimated counterfactual wage distributions derive exclusively from reweighting of observed wage densities rather than from controlled comparisons. Thus, they are closer in spirit to simulation than to inference. Cognizant of this limitation, DFL highlight in their conclusion that the expansion of lower tail inequality during 1979 to 1988 was noticeably more pronounced in 'low-wage' than 'high-wage states,' consistent with the hypothesis that the falling federal minimum caused a differential increase in lower tail equality in states where the minimum wage was initially more binding. Building on this observation, Lee (1999) exploited cross-state

[1] DFL attribute 62 percent of the growth of the female 10/50 and 65 percent of the growth of the male 10/50 to the declining value of the minimum wage (Table III).

variation in the gap between state median wages and the applicable federal or state minimum wage (the 'effective minimum') to estimate what the share of the observed rise in wage inequality from 1979 through 1988 was due to the falling minimum rather than changes in underlying ('latent') wage inequality. Amplifying the findings of DFL, Lee concluded that *more than* the entire rise of the 50/10 earnings differential between 1979 and 1988 was due to the falling federal minimum wage; had the minimum been constant throughout this period, observed wage inequality would have fallen.[2]

There has been very little research on the impact of the minimum wage on wage inequality since these two very influential papers, even though the data they use is now over 20 years old. One possible reason for this is that while lower-tail wage inequality rose dramatically in the 1980s, it has not exhibited much of a trend since then (see Figure 2A). But this does not mean that the last 20 years contain no useful information; the extra years of data are very helpful both because they contain a number of years in which the federal minimum was raised and because they include a much larger number of cases where state minimum wages are above the federal minimum wage. This proves crucial in identifying the impact of minimum wages on wage inequality. Indeed, we show that there is insufficient cross-state variation in the minimum wage during the 1980s to reliably estimate the impact of the minimum wage on the shape of the wage distribution—thus, additional years of data are needed

The inclusion of twenty additional years of data also permits us to conduct a more thorough analysis of the identification strategy and principle findings of Lee's influential 1999 study. Central to Lee's identification strategy is the assumption that there is no correlation between mean state wage levels and latent state wage inequality (i.e., absent the minimum wage). Under this assumption there is no need to include state fixed effects in regression models when estimating the impact of the minimum wage on state wage inequality, and, following this logic, Lee's primary models exclude state effects. We present evidence that this assumption is strongly violated in the data, and consequently, that exclusion of state fixed effects leads Lee's

[2] Using cross-region rather than cross-state variation in the 'bindingness' of minimum wages, Teulings (2000 and 2003) reaches similar conclusions. See also Mishel, Bernstein and Allegretto (2006, chapter 3) for an assessment of the minimum wage's effect on wage inequality.

estimates of the impact of the minimum wage on wage inequality to be upward biased for the lower tail (10/50 inequality) and downward biased for the upper tail (90/50 inequality).

While the conventional response to this source of bias is to include state fixed effects or state trends, we show (as Lee also argued) that their inclusion worsens another source of bias endemic to a regression of measures of wage inequality on other distributional statistics such as the median: since transitory fluctuations in wages at different percentiles are only imperfectly correlated with one another, temporary upward (downward) fluctuations in a state's median wage this will generally lead to a temporary increase (decrease) in lower-tail inequality and a temporary decrease (increase) in upper-tail inequality. With state fixed effects or trends included in the regression model, these transitory fluctuations become a first-order issue, leading to an upward bias in the estimated impact of the minimum wage on both lower and upper tail wage inequality.[3] We propose a simple instrumental variables solution to both types of bias (i.e., stemming from transitory fluctuations and the failure of the state mean-variance orthogonality condition). We instrument for the effective minimum wage in each state—that is, the log gap between the state minimum and the state median—using only legislated variation in the state minimum and the average level of wages in a state. We find that this approach satisfies the intuitive falsification test proposed by Lee (1999)—specifically, it finds no impact of the minimum wage on the upper tail of the wage distribution.[4]

After addressing both sources of bias, we find that the impact of the minimum wage on inequality is substantially smaller than that found by Lee (1999), though still economically consequential. For example, conventional OLS estimates, comparable to those in Lee (1999), indicate that the falling real minimum wage accounted for almost the entirety of the observed increase in the 50/10 in the 1980s; had the minimum been at its real 1989 level in both 1979 and 1989, OLS models imply that 50/10 wage inequality would have risen by only 3 log points for females, and would have *fallen* for the male and pooled distributions. By contrast, 2SLS

[3] Recognizing this concern, Lee (1999) elected to use models without state fixed effects as his preferred specification and also took steps to reduce transitory fluctuations in the state median stemming from measurement error. We discuss his approach further below.

[4] Lee's own estimates for the female wage distribution satisfy this falsification test, while those for the male and pooled-gender wage distributions fail the test.

models find that, under the same counterfactual assumptions, female 50/10 inequality would have risen by 12-15 log points, male inequality would have risen slightly, and pooled gender inequality would have risen by around 7-8 log points. In most specifications, the decline in the real value of the minimum wage explains 30 to 50 percent of the rise in lower-tail wage inequality in the 1980s.

The finding that the impact of the minimum wage on wage inequality is only half as large as previously estimated also helps to explain another puzzle. Between 1979 and 2012, no more than thirteen percent of all hours worked by females, six percent of hours worked by males, and nine percent of hours worked in the aggregate were paid at or below the federal or applicable state minimum wage (see Figure 1 and Table 1, columns 4 and 8); indeed, only for females was the minimum wage directly binding at or above the 10th percentile.[5] This observation implies that any impact of the minimum wage on 50/10 male and pooled gender wage inequality must arise from a spillover effect, whereby the minimum wage raises the wages of workers earning above the minimum.[6] Such spillovers are a potentially important and little understood effect of minimum wage laws and, and Lee's estimates imply that these spillover effects are very large. Our estimates, while substantially smaller than those reported by Lee (1999), also imply important spillovers from the binding minimum wage to quantiles of the wage distribution where the minimum is not binding. Distinct from prior literature, we explore a novel interpretation of this result: measurement error. In particular, we assess whether the spillovers found in our samples, based on the Current Population Survey, may result from measurement errors in wage reporting rather than from true spillovers. This can occur if a fraction of minimum wage workers report their wages inaccurately, leading to a hump in the wage distribution centered on the minimum wage rather than (or in addition to) a spike at the minimum. After bounding the potential magnitude of these measurement errors, we are unable to reject the hypothesis that the apparent spillover from the minimum wage to higher

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[5] We define percentiles based on the distribution of paid hours, which weights the earnings distribution by hours worked.

[6] We assume no disemployment effects at the modest minimum wage levels mandated in the US, an assumption that is supported by a large recent literature (e.g., Card, Katz and Krueger, 1993; Card and Krueger, 2000; Neumark and Wascher, 2000).

(non-covered) percentiles is spurious. That is, while the spillovers *are* present in the data, they may not be present in the distribution of wages actually paid. These results do not rule out the possibility of true spillovers. But they underscore that spillovers estimated with conventional household survey data sources must be treated with caution since they cannot necessarily be distinguished from measurement artifacts with available precision.

The paper proceeds as follows. Section I discusses data and sources of identification. Section II presents the measurement framework and estimates a set of causal effects estimates models that, like Lee (1999), explicitly account for the bite of the minimum wage in estimating its effect on the wage distribution. We compare parameterized OLS and 2SLS models and document the pitfalls that arise in the OLS estimation. Section III uses point estimates from the main regression models to calculate counterfactual changes in wage inequality, holding the real minimum wage constant. Section IV analyzes the extent to which apparent spillovers may be due to measurement error. The final section concludes.

I. Change in the federal minimum wage and variation in state minimum wages

In July of 2007, the real value of the U.S. Federal minimum wage fell to its lowest point in over three decades, reflecting a nearly continuous decline from a 1979 high point, including two decade-long spans in which the minimum wage remained fixed in nominal terms—1981 through 1990, and 1997 through 2007. Perhaps responding to federal inaction, numerous states have over the past two decades legislated state minimum wages that exceed the federal level. At the end of the 1980s, 12 states' minimum wages exceeded the federal level; by 2008, this number had reached 31 (subsequently reduced to 26 by the 2009 federal minimum wage increase). Consequently, the real value of the minimum wage applicable to the average worker in 2007 was not much lower than in 1997, and was significantly higher than if states had not enacted their own minimum wages. Moreover, the post-2007 federal increases brought the minimum wage faced by the average worker up to a real level not seen since the mid-1980s. Appendix Table 1 illustrates the extent of state minimum wage variation between 1979 and 2012.

These differences in legislated minimum wages across states and over time are one of two sources of variation that we use to identify the impact of the minimum wage on the wage distribution. The second source of variation we use, following Lee (1999), is variation in the 'bindingness' of the minimum wage, stemming from the observation that a given legislated minimum wage should have a larger effect on the shape of the wage distribution in a state with a lower wage level. Table 1 provides examples. In each year, there is significant variation in the percentile of the state wage distribution where the state or federal minimum wage "binds." For instance, in 1979 the minimum wage bound at the 12th percentile of the female wage distribution for the median state, but it bound at the 5th percentile in Alaska and the 28th percentile in Mississippi. This variation in the bite or bindingness of the minimum wage was due mainly to cross-state differences in wage levels in 1979, since only Alaska had a state minimum wage that exceeded the federal minimum. In later years, particularly the current decade, this variation was also due to differences in the value of state minimum wages.

A. Sample and variable construction

Our analysis uses the percentiles of states' annual wage distributions as the primary outcomes of interest. We form these samples by pooling all individual responses from the Current Population Survey Merged Outgoing Rotation Group (CPS MORG) for each year. We use the reported hourly wage for those who report being paid by the hour, otherwise we calculate the hourly wage as weekly earnings divided by hours worked in the prior week. We limit the sample to individuals age 18 through 64, and we multiply top-coded values by 1.5. We exclude self-employed individuals and those with wages imputed by the BLS. To reduce the influence of outliers, we Winsorize the top two percentiles of the wage distribution in each state, year, sex grouping (male, female or pooled) by assigning the 97th percentile value to the 98th and 99th percentiles. Using these individual wage data, we calculate all percentiles of state wage distributions by sex for 1979-2012, weighting individual observations by their CPS sampling weight multiplied by their weekly hours worked.

Our primary analysis is performed at the state-year level, but minimum wages often change part way through the year. We address this issue by assigning the value of the minimum wage that was in effect for the longest time throughout the calendar year in a state and year. For those states and years in which more than one minimum wage was in effect for six months in the year, the maximum of the two is used. We have also tried assigning the maximum of the minimum wage within a year as the applicable minimum wage, and this leaves our conclusions unchanged.

II. Reduced form estimation of minimum wage effects on the wage distribution

A. General specification and OLS estimates

To begin, we consider our primary estimation equation and potential biases from straightforward OLS estimation of this model. The general model we estimate for the evolution of inequality at any point in the wage distribution (the difference between the log wage at the *p*th percentile and the log of the median) for state *s* in year *t* is of the form:

$$w_{st}(p) - w_{st}(50) =$$

$$\beta_1(p)[w_{st}^m - w_{st}(50)] + \beta_2(p)[w_{st}^m - w_{st}(50)]^2 + \sigma_{s0}(p) + \sigma_{s1}(p) \text{ x } time_t + \gamma_t^\sigma(p) + \varepsilon_{st}^\sigma(p) \tag{1}$$

In this equation, $w_{st}(p)$ represents the log real wage at percentile *p* in state *s* at time *t*; time-invariant state effects are represented by $\sigma_{s0}(p)$; state-specific trends are represented by $\sigma_{s1}(p)$; time effects represented by $\gamma_t^\sigma(p)$; and transitory effects represented by $\varepsilon_{st}^\sigma(p)$, which we assume to be independent of the state and year effects and trends.

In equation (1), w_{st}^m is the log minimum wage for that state/year. We follow Lee (1999) in defining the bindingness of the minimum wage to be the log difference between the minimum wage and the median (Lee refers to this as the effective minimum), and in modeling the impact of the minimum wage to be quadratic.[7] The quadratic term is important to capture the idea that a change in the minimum wage is likely to have more impact on the wage distribution

[7] Hence, in this formulation a "more binding minimum wage" is a minimum wage that is closer to the median, resulting in a higher (less negative) effective minimum wage.

where it is more binding.[8] By differentiating (1) we have that the predicted impact of a change in the minimum wage on a percentile is given by $\beta_1(p) + 2\beta_2(p)[w_{st}^m - w_{st}(50)]$.

First, consider what happens if we estimate equation (1) by OLS excluding the state fixed effects and trends (which is the preferred specification from Lee 1999).[9] Column 1 of Tables 2A, and 2B reports estimates of this specification. We report the marginal effects of the effective minimum for selected percentiles when estimated at the weighted average of the effective minimum over all states and all years between 1979 and 2012. Figures 3A, 3C, and 3E provide a graphical representation of these estimated marginal effects for all percentiles. Similar to Lee, we find large significant effects of the minimum wage on the lower percentiles of the wage distribution that extend throughout *all* percentiles below the median for the male, female and pooled wage distributions. Also note that, with the exception of the male estimates, the upper tail 'effects' are small and insignificantly different from zero, which might be considered a necessary condition for the results to be credible estimates of the impact of the minimum wage on wage inequality at any point in the distribution.

B. Potential biases, and the need for state fixed effects / state time trends

Next, we consider possible causes of bias in estimates of (1). It is helpful to consider the following general model for the median log wage for state *s* in year *t*:

$$w_{st}(50) = \mu_{s0} + \mu_{s1} \text{x}\, time_t + \gamma_t^{\mu} + \varepsilon_{st}^{\mu} \quad (1)$$

That is, the median wage for the state is a function of a state effect, μ_{s1}, a state trend, μ_{s1}, a common year effect, γ_t^{μ}, and a transitory effect, ε_{st}^{μ}.

The existence, extent, and direction of bias depend on the covariance of the effective minimum wage terms with the errors in the equation. One natural assumption—which we

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[8] Since the log wage distribution has greater mass towards its center than at its tail, a 1 log point rise in the minimum wage affects a larger fraction of wages when the minimum lies at the 40th percentile of the distribution than when it lies at the 1st percentile.

[9] We include time effects in all of our estimation, as does Lee 1999. We estimate the model separately for each p (from 1 to 99), and impose no restrictions on the coefficients or error structure across equations.

maintain through the course of our estimation—is that $cov\left(w_{st}^m - w_{st}(50), w_{st}(50)\right) < 0$, that is, even after allowing for the fact that they may have a state minimum higher than the federal minimum, the bindingness of the minimum wage is lower in high wage states. Under this assumption, the possible sources of bias in estimates of equation (1) arise from the potential correlation between the residuals in the first and second equations. We consider two sources of this bias. The first is that $cov\left(\varepsilon_{st}^{\mu}, \varepsilon_{st}^{\sigma}(p)\right)$ may not be zero—that is, transitory fluctuations in state wage medians may be correlated with the gap between the state wage median and other wage percentiles. The second is that, because there are no state effects in our initial estimates of equation (1), $(\sigma_{s0}(p), \sigma_{s1}(p))$ may be correlated with (μ_{s0}, μ_{s1})—that is, that there may be a non-zero correlation between the state fixed effects and trends in the underlying level of inequality on the one hand and the state fixed effects and trends in the median on the other.

We begin by considering the first form of bias—stemming from transitory fluctuations—and assume for the moment that the latter correlations are zero, effectively imposing that in the absence of the minimum wage, high median wage states would not have systematic different levels of inequality from low median wage states. Under these assumptions, the only potential source of bias comes from the correlation between the transitory components in equations (1) and (2), that is, $cov\left(\varepsilon_{st}^{\mu}, \varepsilon_{st}^{\sigma}(p)\right)$. This covariance need not be zero. In fact, one might naturally expect that transitory shocks to the median do not translate one-for-one to other percentiles. If, plausibly, the effects dissipate as one moves further from the median, this would generate bias due to the non-zero correlation between shocks to the median wage and measured inequality throughout the distribution. Another possible source of such a correlation is sampling variation, which leads to a form of division bias (Borjas, 1980) since the measured median is included on the left- and right-hand sides of (1).[10] Either form of bias implies that we

[10] As discussed in footnote 3, Lee (1999) recognizes the potential bias stemming from sampling variation and attempts to address it by using two different measures of central tendency in the dependent and independent variables: the median of the dependent variable on the left-hand side, and the trimmed mean on the right (that is, the mean after excluding the bottom and top 30 percentiles). Although this procedure does reduce the correlation, it does not eliminate it. See the derivation in section A of the Appendix that, if the latent log wage distribution is normal, the correlation between the trimmed mean and the median will be about 0.93—i.e. not unity, but very high. Nevertheless, we have run simulations that suggest sampling variation with division bias is not a significant

would expect that $cov(\varepsilon_{st}^{\mu}, \varepsilon_{st}^{\sigma}(p)) < 0$ and that this covariance would attenuate as one considers percentiles further from the median. In this case the estimated minimum wage effects will be biased *upwards* (in magnitude) in both lower and upper tails.[11] The fact that there appears to be no relationship between the effective minimum wage and inequality in the upper tail (as in figures 3A and 3E) seemingly suggests that this bias is small (at least for the female and pooled samples).

However, this conclusion is predicated on the assumption proposed by Lee that the second form of bias is not meaningfully important, that is $(\sigma_{s0}(p), \sigma_{s1}(p))$ are uncorrelated with (μ_{s0}, μ_{s1}). The assumption that state log wage levels and latent state log wage inequality are uncorrelated can be tested if one has a measure of inequality that is unlikely to be affected by the level of the minimum wage. For this purpose we use 60/40 inequality (that is, the difference in the log of the 60th and 40th percentiles), which serves as a valid proxy measure of states' underlying (or 'latent') wage inequality under the assumption that the minimum wage has no effect on the 40th through 60th percentiles. We believe that this assumption is reasonable, given that the minimum wage never binds very far above the 10th percentile of the wage distribution over our sample period. To assess whether in practice average state latent inequality or trends in latent inequality are associated with average state wage levels or trends in state wage levels (using the log of the median as a measure of a state's wage level), we run state-level regressions of a state's average 60/40 inequality, or estimates of a state's trend in 60/40 inequality, on the state's average median wages and/or the trend in its median wages.

Table 3 reports these results, estimated separately for the female, male, and pooled distributions. The left-hand panel presents coefficient estimates from regressions of a state's average 60/40 inequality on its average real median wage (column 1), the trend in its log

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source of bias with our larger sample sizes (using data from 1979 through 2012), though it *does* impart significant upward bias for the shorter sample period used by Lee (results from these simulations are available upon request).

[11] Since the state median enters with a negative side of both sides of equation (1), transitory variation in the median will impart a positive bias to estimates of β_1. Moreover, if $cov(\varepsilon_{st}^{\mu}, \varepsilon_{st}^{\sigma}(p))$ attenuates at more distant percentiles from the median, as hypothesized, then the upward bias in impact estimates will be larger when estimating the impact of the minimum wage on very high and low wage percentiles (e.g., p10, p90) than when estimating intermediate percentiles (e.g., p30, p70).

median wage (column 2), and the mean and trend (column 3).[12] In all cases, there is a positive relationship between the state-level median and state-level 60/40 inequality: states with higher medians have greater inequality (though we note that the relationship is statistically insignificant for males). The right-hand panel presents coefficient estimates from regressions of the *trend* in a state's 60/40 inequality on its 60/40, log median wage, and the trend in the median wage. Again, in almost all instances there is a positive and statistically significant relationship between the trend in a state's inequality and its average 'latent' inequality (measured by the 60/40), average median wage, and the trend in its median. Figure 4 depicts these regressions visually. In the top panel, for each of the three samples, the cross-state relationship between the average log(p60)-log(p40) is plotted against the average log(p50). In the bottom panel, the cross-state relationship between the trends in the two measures is plotted. In all cases but panel E, there is a strong, positive visual relationship between the two—and, as table 3 demonstrates, even for the male sample there is, in fact, a statistically significant positive relationship between the trends in the log(p60)-log(p40) and log(p50).

The finding of a positive correlation between underlying inequality and the state median implies there is likely to be omitted variable bias from the exclusion of state fixed effects and trends—specifically, a further *upward* bias to the estimated minimum wage effect in the lower tail and, simultaneously, a *downward* bias in the upper tail. To see why, note that higher wage states have lower (more negative) effective minimum wages (defined as the log gap between the legislated minimum and the state median), and the results from table 3 imply that these states also have higher levels of latent inequality; thus they will have a more negative value of the left-hand side variable in our main estimating equation (1) for percentiles below the median, and a more positive value for percentiles above the median. Since the state median enters the right-hand side expression for the effective minimum wage with a negative sign, estimates of the relationship between the effective minimum and wage inequality will be *upward-biased* in the lower tail and *downward-biased* in the upper tail.

[12] We estimate the trend in the log(60)-log(40) or log median wage by regressing the variable, for each state, on a linear time trend. We use the coefficient from the time trend as a regressor in the regressions reported in Table 3.

Combined with our discussion above on potential biases stemming from the correlation between the transitory error components on both sides of equation (1) (leading to an *upward* bias on the coefficient on the effective minimum wage in both lower and upper tails), we infer that these two sources of bias reinforce each other in the lower tail, likely leading to an *overestimate* of the impact of the minimum wage on lower tail inequality. Simultaneously, they have countervailing effects on the upper tail. Thus our finding in the first column of Table 2 of a relatively weak relationship between the effective minimum wage and upper tail inequality (for the female and pooled samples) may arise because these two countervailing sources of bias largely offset one another for upper tail estimates. But since these biases are reinforcing in the lower tail of the distribution, the absence of an upper tail correlation is not sufficient evidence for the absence of lower tail bias.

If this reasoning is correct we would expect to find that including state fixed effects and trends—which alleviates the second form of bias stemming from the correlation between state medians and state latent inequality—would *reduce* the estimated impact of the minimum wage in the lower tail but *increase* it in the upper tail. Indeed, column 2 of Tables 2A and 2B, and Figures 3B, 3D, and 3E show that this is precisely what happens.[13] In all three samples, the estimated effect of the minimum wage in the lower tail falls quite substantially (though remains significantly different from zero) and for the female and pooled distributions there now appears a large positive relationship between the effective minimum wage and *upper tail* inequality (for the male distribution, the large positive relationship remains, similar to the base specification). This is consistent with bias now only coming from the transitory shocks (or from division bias), which we have argued is likely to be positive for both the lower and upper tails.[14] In the next sub-section, we address this second form of bias.

C. Correcting for additional bias, and our preferred specification

[13] In the table and figures, we include both state fixed effects and time trends. Excluding time trends, but including state fixed effects, we still find a large and positive relationship between the effective minimum and upper-tail inequality in all samples. We also estimate a first-differenced version of the levels equation (column 3), which produces even larger estimates at the top of the distribution (column 3).

[14] Our results from these two specifications (with and without state fixed effects) are qualitatively similar to those reported by Lee (1999).

The inclusion of state fixed effects and state trends in (1) accounts for the correlations between state wage levels and state inequality levels and trends documented in Table 3, but it does not correct for the bias stemming from $cov\left(\varepsilon_{st}^{\mu}, \varepsilon_{st}^{\sigma}(p)\right) < 0$. As noted above, this covariance may be due to division bias (stemming from the inclusion of the median on the right and left sides of the estimating equation combined with sampling error in the median) or from transitory shocks to the median that do not translate one-for-one to other percentiles. In either case, the problem posed by these error covariances becomes more severe when state fixed effects are included, since more of the remaining variation is the result of transitory variation. Indeed, Lee (1999) emphasizes this econometric pitfall, documents that inclusion of state fixed effects appears to exacerbate the problematic correlation between the effective minimum and upper tail inequality, and accordingly prefers estimates that exclude state fixed effects. Our Table 3 results imply, however, that state effects and trends are non-optional. Hence, we require an estimator that permits inclusion of state effects while purging the error covariance between the dependent and independent variables.

We address this challenge by applying an IV approach that has a long history as a method for dealing with problems caused by measurement error or other transitory shocks (Durbin, 1954). We instrument the observed effective minimum and its square using an instrument set that consists of: 1) the log of the real statutory minimum wage, 2) the square of the log of the real minimum wage, and 3) the interaction between the log minimum wage and average log median real wage for the state over the sample period. In this IV specification, identification in (1) for the linear term in the effective minimum wage comes entirely from the variation in the statutory minimum wage, and identification for the quadratic term comes from the inclusion of the square of the log statutory minimum wage and the interaction term.[15] As there are always

[15] To see why the interaction is important to include, expand the square of the effective minimum wage, log(min)-log(p50), which yields three terms, one of which is the interaction of log(min) and log(p50). We have also tried replacing the square and interaction terms with the square of the predicted value for the effective minimum, where the predicted value is derived from a regression of the effective minimum on the log statutory minimum, state and time fixed effects, and state trends (similar to an approach suggested by Wooldridge, 2002; section 9.5.2). 2SLS results using this alternative instrument are virtually identical to the strategy outlined in the main text. In general, using the statutory minimum as an instrument is similar in spirit to the approach taken by Card, Katz and Krueger (1993) in their analysis of the employment effects of the minimum wage.

time effects included in our estimation, all the identifying variation in the statutory minimum therefore comes from the state-specific minimum wages, which we assume to be exogenous to state wage levels or inequality.[16] Our second instrument is the square of the predicted value for the effective minimum from the regression outlined above, and relies on the same identifying assumptions (exogeneity of the statutory minimum wage).

Columns (4) of Tables 2A and 2B report the estimates when we instrument the effective minimum in the way we have described. Compared to column (2) the estimated impacts of the minimum wage in the lower tail are reduced, especially above the 10th percentile. This is consistent with what we have argued is the most plausible direction of bias in the OLS estimate in column (2). And, for all three samples, the estimated effect in the upper tail is now small and insignificantly different from zero, again consistent with the IV strategy reducing bias in the predicted direction.[17]

Our primary results are from models estimated in levels. For robustness, we also estimate them in first differences. Column (5) shows the results from first-differenced regressions that include state and year fixed effects, instrumenting the endogenous differenced variables using differenced analogues to the instruments described above. [18] Figures 5A, 5C, and 5E show the results for all percentiles from the levels IV specifications; figures 5B, 5D, and 5F show results from the first-differenced IV specifications. Qualitatively, the first-differenced regressions are similar to the levels regressions, although they imply slightly larger effects of the minimum wage at the bottom of the wage distribution.

Although our 2SLS estimates of the impact of the minimum wage on the lower tail are reduced, they are not trivial; they imply that the minimum wage has had a statistically significant impact, on average, up through about the 25th percentile for women, up through the

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[16] For our entire sample period (1979-2012), there is enough variation to estimate this, but for Lee's sample of 1979-1989 (with limited changes in federal and state minimum wages), there is little cross-state variation, and so our IV strategy will be much less useful for that restricted sample period, as described later in this section.

[17] For all 2SLS models, F-tests (not tabulated) indicate that the instruments are jointly highly significant and pass standard diagnostic tests for weak instruments (e.g., Stock, Wright and Yogo, 2002).

[18] The instruments for the first-differenced analogue are Δw_{st}^{m} and $\Delta(\widetilde{w_{st}^{m} - w(50)_{st}})^2$, where Δw_{st}^{m} represents the annual change in the log of the legislated minimum wage, and $\Delta(\widetilde{w_{st}^{m} - w(50)_{st}})^2$ represents the change in the square of the predicted value for the effective minimum wage.

10th percentile for men, and up through the 15th percentile or so for the pooled wage distribution. 2SLS estimates imply that a 10 log point increase in the effective minimum wage reduces 50/10 inequality by approximately 2 log points for women, by no more than 0.5 log points for men, and by roughly 1.5 log points for the pooled distribution. These estimates are less than half as large as those found by the baseline OLS specification.

D. Robustness to choice of time period

Our primary estimates are derived using data from 1979-2012, whereas the original work that explored rising inequality over the 1980s used data from 1979 through the late 1980s or early 1990s. As we have previously argued, an IV strategy is required due to the potential endogeneity of the effective minimum wage. However, our strategy—which relies on variation in statutory minimum wages across states and over time—does not perform well when limited to data only from the 1980s period. To demonstrate this, we estimate marginal effects by percentile, for the male and female pooled wage distribution, using our 2SLS estimation strategy (in levels and including state time trends, analogous to column 4 of Table 2) for each of three time periods: 1979-1989 (when there was little state-level variation in the minimum wage), 1979-1991 (incorporating an additional two years in which numerous states raised their minimum wage), and 1979-2012. Figure 6 shows the results of this exercise.

As seen in the top panel, our estimation strategy performs very poorly when using data only through 1989. The point estimates are enormous relative to both OLS estimates and 2SLS estimates that use additional years of data, and the confidence bands are extremely large (note that the scale in the figure runs from -25 to 25, many orders of magnitude larger than even the largest point estimates from Table 2). This lack of statistical significance is not surprising in light of the small number of policy changes in this period: between 1979 and 1985, only one state aside from Alaska adopted a minimum wage in excess of the federal minimum; the ten additional adoptions through 1989 all occurred between 1986 and 1989 (Table 1). Consequently, when calculating counterfactuals below, we apply marginal effects estimates obtained using additional years of data.

By extending the estimation window to 1991 (as was also done by Lee, 1999), we exploit the substantial federal minimum wage increase that took place between 1990 and 1991. This federal increase generated numerous cross-state contrasts since 9 states had by 1989 raised their minimums above the 1989 federal level and below the 1991 federal level (and an additional three raised their minimum to $4.25, which would be the level of the 1991 federal minimum wage). Adding these additional two years of data (panel B of Figure 6) reduces the standard errors around our estimates significantly, though the estimated marginal effects of changes in the effective minimum on a particular percentile are quite noisy across percentiles. Adding additional data (panel C) reduces the standard errors further and helps smooth out estimated marginal effects across percentiles.

Our interpretation of these findings is that, given the sort of variation required for our IV strategy to successfully identify minimum wage effects, it would have been impossible using data prior to 1991 to successfully estimate the effect of the minimum wage on the wage distribution using only a decade of data. It is only with subsequent data on comovements in state wage distributions and the minimum wage that more accurate estimates can be obtained. For this reason, our primary counterfactual estimates of changes in inequality (holding the minimum wage fixed at a particular level) rely on coefficient estimates from the full sample. However, we also discuss below the robustness of our findings to the choice of estimation sample.

III. Counterfactual estimates of changes in inequality

How much of the expansion in lower-tail wage inequality since 1979 was due to the declining minimum wage? Following Lee (1999), we present reduced form counterfactual estimates of the change in *latent* wage inequality absent the decline in the minimum wage—that is, the change in wage inequality that would have been observed had the minimum wage been held at a constant real benchmark. These reduced form counterfactual estimates do not distinguish between mechanical and spillover effects of the minimum wage, a topic that we analyze next. We consider counterfactual changes over two periods: 1979-1989 (which captures the large widening of lower-tail income inequality over the 1980s), and 1979-2012.

To estimate changes in latent wage inequality, Lee (1999) proposes the following simple procedure. For each observation in the dataset, calculate its rank in its respective state-year wage distribution. Then, adjust each wage by the quantity:

$$\Delta w_{st}(p) = \hat{\beta}_1(p)\left(\widetilde{m}_{s,\tau 0} - \widetilde{m}_{s,\tau 1}\right) + \hat{\beta}_2(p)\left(\widetilde{m}^2_{s,\tau 0} - \widetilde{m}^2_{s,\tau 1}\right) \tag{3}$$

where $\widetilde{m}_{s,\tau 1}$ is the observed end-of period effective minimum in state s in some year $\tau 1$, $\widetilde{m}_{s,\tau 0}$ is the corresponding beginning-of-period effective minimum in $\tau 0$, and $\hat{\beta}_1(p)$, $\hat{\beta}_2(p)$ are point estimates from the OLS and 2SLS estimates in Table 2 (columns 1, 4, or 5).[19] We pool these adjusted wage observations to form a counterfactual national wage distribution, and we compare changes in inequality in the simulated distribution to those in the observed distribution.[20]

The estimates in the top panel of Table 4 show that between 1979 and 1989, the female 50/10 log wage ratio increased by 25 log points. Applying the coefficient estimates on the effective minimum and its square obtained using the OLS model fit to the female wage data for 1979 through 2012 (first column in panel 1), we calculate that had the minimum wage been constant at its real 1989 level throughout this period, female 50/10 inequality would counterfactually have risen by only 2.5 log points. Applying the coefficient estimates for only the 1979-1991 period (second column in panel 1), female 50/10 inequality would have risen by 4 log points. Thus, consistent with Lee (1999), the OLS estimate implies that the decline in the real minimum wage can account for the bulk (22.5 of 25 log points) of the expansion of lower tail female wage inequality in this period.

The next two columns of the table present analogous counterfactuals estimated using 2SLS models estimated over 1979-2012 (either fixed effect or first difference) in place of OLS. These estimates find a substantially smaller role for the minimum wage. For females, the IV estimate

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[19] So, for example, taking $\tau_0 = 1979$ and $\tau_1 = 1989$, and subtracting Δw^p_{st} from each observed wage in 1979 would adjust the 1979 distribution to its counterfactual under the realized effective minima in 1989.

[20] Also distinct from Lee, we use states' observed median wages when calculating $\widetilde{m}$ rather than the national median deflated by the price index. This choice has no substantive effect on the results, but appears most consistent with the identifying assumptions.

implies that the minimum wage explains roughly one-third to one-half of the rise in female 50/10 inequality in this period (using the first-differenced specification, the minimum wage explains 9.2 log points of the 24.6 log point increase; using the levels specification, it explains 12.4 log points, or roughly half of the increase). These are non-trivial effects, of course, and they confirm, in accordance with the visual evidence in Figure 2, that the falling minimum wage contributed meaningfully to rising female lower-tail inequality during the 1980s and early 1990s.

The second and third rows of Table 4 calculate the effect of the minimum wage on male and pooled gender inequality. Here, the discrepancy between OLS and IV-based counterfactuals is substantially more pronounced. OLS estimates imply that the minimum wage *more than* explains the rise in male and pooled 50/10 inequality between 1979 and 1989. By contrast, 2SLS models indicate that the minimum wage makes a very modest contribution to the rise in male wage inequality and explains about one-third of the rise in pooled gender inequality.

Despite their substantial discrepancy with the OLS models, these estimates appear highly plausible. Figure 1 shows that the minimum wage was nominally *non-binding* for males throughout the sample period, with fewer than 6 percent of all male wages falling at or below the relevant minimum wage in any given year. For the pooled gender distribution, the minimum wage had somewhat more bite, with a bit more than 8 percent of all hours paid at or below the minimum in the first few years of the sample. But this is modest relative to its position in the female distribution, where 9 to 13 percent of wages were at or below the relevant minimum in the first five years of the sample. Consistent with these facts, 2SLS estimates indicate that the falling minimum wage generated a sizable increase in female wage inequality, a modest increase in pooled gender inequality, and a minimal increase in male wage inequality.

Panel B of Table 4 calculates counterfactual (minimum wage constant) changes in inequality over 1979-2012. In all cases, the contribution of the minimum wage to rising inequality is smaller when estimated using 2SLS in place of OLS models, and its impacts are substantial for females, modest for the pooled distribution, and negligible for males.

Figure 7 and the top panel of Figure 8 provide a visual comparison of observed and counterfactual changes in male, female and pooled-gender wage inequality during the critical period of 1979 through 1989, during which time the minimum wage remained nominally fixed while lower-tail inequality rose rapidly for all groups. As per Lee (1999), the OLS counterfactuals depicted in these plots suggest that the minimum wage explains essentially all (or more than all) of the rise in 50/10 inequality in the female, male and pooled-gender distributions during this period. The 2SLS counterfactuals place this contribution at a far more modest level. For example, the counterfactual series for males is indistinguishable from the observed series, implying that the minimum wage made almost no contribution to the rise in male inequality in this period. The lower panel of Figure 8, which plots observed and counterfactual wages change in the pooled gender distribution for the full sample period of 1979 through 2012 (again holding the minimum wage at its 1988 value), shows a similarly pronounced discrepancy between OLS and 2SLS models.[21]

To summarize, our estimates consistently find a considerably smaller role for the minimum wage in rise of U.S. inequality than prior work has suggested. While they do not reverse the view that the falling minimum wage contributed to the growth of lower tail inequality growth during the 1980s, they suggest a qualitatively and quantitatively large downward revision to the estimated magnitude of this contribution.

IV. The Limits of Inference: Distinguishing spillovers from measurement error

As highlighted in Figure 1, federal and state minimum wages were nominally non-binding at the 10th percentile of the wage distribution throughout most of the sample; in fact, there is only one three year interval (1979 to 1983), when more than ten percent of hours paid were at or below the minimum wage—and this was only the case for females. Yet our main estimates imply that the minimum wage modestly compressed both male and pooled-gender 50/10 wage

[21] As a robustness test, we have repeated these counterfactual calculations using coefficient estimates from years 1979 through 1991 (using the additional cross-state identification offered by the increases in the federal minimum wage over this period) rather than the full 1979-2012 sample period. The counterfactual estimates in this table are somewhat smaller but largely consistent with the full sample, both during the critical period of 1979 through 1989 and during other intervals.

inequality during the 1980s. This implies that the minimum wage had spillover effects onto percentiles above where it binds.

A mundane but nonetheless plausible explanation for this finding is measurement error. To see why, suppose that a subset of workers who are paid the minimum wage tend to report wage values that are modestly above or below the true minimum—that is, they report with error. Moreover, suppose that the central tendency of this reporting error moves in tandem with the minimum wage; when the minimum wage rises or falls, the measurement error cloud moves with it. Under these assumptions, the presence of measurement error may create the appearance of spillovers where none are present.

For example, consider a case where the minimum wage is set at the 5th percentile of the latent wage distribution and has no spillover effects. However, due to misreporting, the spike in the wage distribution at the true minimum wage is surrounded by a measurement error cloud that extends from the 1st through the 9th percentiles. If the legislated minimum wage were to rise to the 9th percentile and measurement error were to remain constant, the rise in the minimum wage would compress the *measured* wage distribution up to the 13th percentile (thus, reducing the measured 50/10 wage gap). This apparent spillover would be a feature of the data, but it would not be a feature of the true wage distribution.[22]

In this final section of the paper, we quantify the possible bias wrought by these measurement spillovers. Specifically, we ask whether we can reject the null hypothesis that the minimum wage only affects the earnings of those at or below the minimum (in which case, the apparent spillovers would be consistent with measurement error).[23] We use a simple measurement error model to test this hypothesis. Denote by p^* a percentile of the latent wage distribution (i.e. the percentile absent measurement error and without a minimum wage), and write the latent wage associated with it as $w^*(p^*)$.[24] Assuming that there are only direct effects

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[22] This argument holds in reverse for a decline in the minimum: a fall in the minimum from the 9th to the 6th percentile may reduce measured 50/10 wage inequality even if there is no impact on actual 50/10 wage inequality.

[23] Note that we are not testing whether an apparent spillover for a particular percentile, for a particular state/year, is attributable to measurement error—we are testing whether, on average, *all* of the observed spillovers could be attributable to measurement error.

[24] In the following discussion, it will be useful to distinguish between three distinct wage distributions: 1) the latent wage distribution, which is the wage distribution in the absence of a minimum wage and measurement error; 2)

of the minimum wage (i.e., no true spillovers and no disemployment effects), then the true wage at percentile p^* will be given by:

$$w(p^*) \equiv \max[w^m, w^*(p)], \tag{4}$$

where $w^*(p)$ is the true latent log wage percentile and w^m the log of the minimum wage. Denote by $\hat{p}(w^m)$ the true percentile at which the minimum wage binds. Then:

$$w^*\big(\hat{p}(w^m)\big) = w^m. \tag{5}$$

Now, allow for the possibility of measurement error, so that for a worker at true wage percentile p^*, we observe:

$$w_i = w(p^*) + \varepsilon_i, \tag{6}$$

where ε_i is an error term with density function $g(\varepsilon)$, which we assume to be independent of the true wage. The density of wages among workers whose true percentile is p^* is therefore given by $g\big(w - w(p^*)\big)$. The density of observed wages is simply the average of $g(\cdot)$ across true percentiles:

$$f(w) = \int_0^1 g\big(w - w(p^*)\big)dp^*. \tag{7}$$

And the cumulative density function for observed wages is given by:

$$F(w) = \int_{-\infty}^{w}\int_0^1 g\big(w - w(p^*)\big)dp^*dx. \tag{8}$$

This can be inverted to give an implicit equation for the wage at observed percentile p, $w(p)$:

$$p = \int_{-\infty}^{w(p)}\int_0^1 g\big(w - w(p^*)\big)dp^*dx. \tag{9}$$

By differentiating this expression with respect to the minimum wage, we obtain the following key result (with details given in Appendix B):

> Result 1: Under the null hypothesis of no actual spillovers and no disemployment, the elasticity of wages at an observed percentile with respect to the minimum wage is equal to the fraction of people at that observed percentile whose true wage is equal to the minimum.

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the true wage distribution, which is the wage distribution in the absence of measurement error but allowing for minimum wage effects; and 3) the observed wage distribution, which is the wage distribution allowing for measurement error and a minimum wage (i.e. what is measured from CPS data).

The intuition for this result is straightforward: if changes in the minimum wage only affect the wages of those directly affected, then the wage at an observed percentile can only change to the extent that some of those workers are truly paid the minimum wage. Thus, if the minimum wage rises by 10 percent, and 10 percent of workers at a given percentile are paid the minimum wage, the observed wage percentile at that percentile will rise by 1 percent.

This result has a simple corollary (proved in the Appendix C) that we use in the estimation below:

> <u>Result 2</u>: Under the null hypothesis of no true spillovers, the elasticity of the *overall* mean log wage with respect to the minimum wage is equal to the fraction of the wage distribution that is truly paid the minimum wage—that is, the size of the true spike.

This result follows from the fact that all individuals who are truly paid the minimum wage must appear *somewhere* in the observed wage distribution. And of course, changes at any point in the distribution also change the mean. Thus, if the true spike at the minimum wage comprises 10 percent of the mass of the true wage distribution, a 10 percent rise in the minimum will increase the *true and observed* mean wage by 1 percent. Note that no distributional assumptions about measurement error are needed for either Result 1 or Result 2, other than the assumption that the measurement error distribution is independent of wage levels.

The practical value of Result 2 is that we can readily estimate the effect of changes in the minimum wage on the mean using the methods developed above. Under the null hypothesis of no spillovers, Result 2 tells us that the effect of the minimum wage on the mean wage effect will be equal to the size of the 'true' spike. If the null hypothesis is false, however, we would expect the elasticity to *exceed* the size of the true spike since a subset of workers whose wages exceed the minimum wage will also have their wages increased by the minimum.

In practice, we estimate a version of equation (1), using as the dependent variable the average log real wage. On the right hand side, we include the effective minimum wage and its square as endogenous regressors (and instrument for them using the same instruments as in the earlier analysis), state and year fixed effects, state time trends, and the log of the median (to control for shocks to the wage level of the state that are unrelated to the minimum wage, assuming that any spillovers do not extend through the median). The dashed line in Figure 9 represent the marginal effect on the mean by year, taking the weighted average across all states for each year. Under the null hypothesis of no true spillovers, this estimate of the effect the minimum on the mean is an estimate of the size of the true spike. Under the alternative hypothesis that true spillovers are present, the marginal effect on the mean will exceed the size of the true spike. To distinguish these alternatives requires a second, independent estimate of the size of the true spike.

B. Estimating measurement error

We develop a second estimate of the magnitude of the true spike by directly estimating measurement error in wage reporting and then using this estimate to infer the size of the spike absent this error. We exploit the fact that under the assumption of full compliance with the minimum wage, all observations found below the minimum wage must be observations with measurement error.[25] Of course, wage observations below the minimum can only provide information on individuals with *negative* measurement error, since minimum wage earners with positive measurement error must have an observed wage above the minimum. Thus, a key identifying assumption is that that the measurement error is symmetric, that is $g(\varepsilon) = g(-\varepsilon)$.

In what follows, we use maximum likelihood to estimate the distribution of wages below the minimum and the fraction of workers at and above the minimum (for the sample of non-tipped workers as described in footnote 25). We assume that the 'true' wage distribution only has a mass point at the minimum wage so that $w^*(p^*)$ has a continuous derivative. We also assume that the measurement error distribution only has a mass point at zero so that there is a non-zero probability of observing the 'true' wage. (Without this assumption, we would be unable to rationalize the existence of a spike in the observed wage distribution at the minimum wage.) Denote the probability that the wage is correctly reported as γ. For those who report an

[25] There are surely some individuals who report sub-minimum wage wages and *actually* receive sub-minimum wages. One potentially large occupation class is tipped workers, who in many states can legally receive a sub-minimum hourly wage as long as tips push their total hourly income above the minimum. For instance, in 2009, about 55 percent of those who reported their primary occupation as waiter or waitress reported an hourly wage less than the applicable minimum wage for their state, and about 17 percent of all observed sub-minimum wages were from waiters and waitresses. If we treat the wages of these individuals as measurement error, we will clearly over-state the extent of misreporting. We circumvent this problem by conducting the measurement/spillover analysis on a sample that *excludes* employees in low-paying occupations that commonly receive tips or commission. These are: food service jobs, barbers and hairdressers, retail salespersons and telemarketers.

error-ridden wage, we will use, in a slight departure from previous notation, $g(\varepsilon)$ to denote the distribution of the error.

With these assumptions, the size of the spike in the *observed* wage distribution at the minimum wage, which we denote by $\tilde{p}$, is equal to the true spike times the probability that the wage is correctly reported:

$$\tilde{p} = \gamma\hat{p}. \tag{10}$$

Hence, using an estimate of γ, we can estimate the magnitude of the true spike as $\hat{p} \approx \tilde{p}/\tilde{\gamma}$.[26]

To estimate γ, we use observations on the fraction of workers paid strictly below the minimum, which we denote by Z. Assuming full compliance with the minimum wage statute, all of these subminimum wages will represent negative measurement error. We therefore have:

$$Z = (1-\gamma) \times \left[0.5\hat{p} + \int_{\hat{p}}^{1} G\big(w^m - w^*(p^*)\big)dp^*\right] \tag{11}$$

The symmetry assumption implies that half of those at the true spike who report wages with error will report wages below the minimum, and this is reflected as the first term in the bracketed expression ($0.5\hat{p}$). In addition, for workers paid above the minimum, some subset will report with sufficiently negative error that their reported wage will fall below the minimum, thus also contributing to the mass below the statutory minimum. This contributor to Z is captured by the second term in the bracketed expression.

C. Finding: Spillovers cannot be distinguished from measurement error

We assume that the latent log wage distribution is normal with mean μ and variance σ_w^2 and that the measurement error distribution is normal with mean 0 variance σ_ε^2. Our estimation proceeds in two steps. First, we use observations on the top part of the wage distribution—which we assume are unaffected by changes to the minimum wage—to estimate the median and variance of the observed latent wage distribution, allowing for variation across state and time. Equipped with these estimates, as well as the observed Z for each state and year, we

[26] One might wonder why none of the observed spike are 'errors', individuals whose are not paid the minimum but, by chance, have an error which makes them appeared to be paid the minimum. But, the assumption on the absence of mass points in the true wage distribution and the error distribution mean that this group is of measure zero so can be ignored.

estimate $(\sigma_\varepsilon^2,\ \gamma)$ by maximum likelihood. We assume that $(\sigma_\varepsilon^2,\ \gamma)$ vary over time but not across states (with further details found in Appendix D). As previously noted, we perform this analysis on a sample that excludes individuals from lower-paying occupations that tend to earn tips or commission.

Estimates of γ for males, females, and the pooled sample (not shown) generally find that the probability of correct reporting is around 80 percent, and mostly varies from between 70 to 90 percent over time (though is estimated to be around 65 to 70 percent in the early 1980s for females and the pooled distribution). We combine this estimate with the observed spike to get an estimate of the 'true' spike in each period, though this will be an estimate of the size of the true spike only for the estimation sample of workers in non-tipped occupations.

This leaves us in need of an estimate of the 'true' spike for the tipped occupations. Given the complexity of the state laws surrounding the minimum wage for tipped employees, we do not attempt to model these subminimum wages. Rather we simply note that the spike for tipped employees must be between zero and one, and we use this observation to bound the 'true' spike for the entire workforce. Because the fraction of workers in tipped occupations is small, these bounds are relatively narrow.

Figure 9 compares these bounds with the earlier estimates of the 'true' spike based on the elasticity of the mean with respect to the minimum in each year. Under the null hypothesis that the minimum wage has no true spillovers, the effect on the mean should equal the size of the 'true' spike. And indeed, the estimated mean effect lies within the bounds of the estimated 'true' spike in almost all years. We are accordingly unable to reject the hypothesis that the apparent effect of the minimum wage on percentiles above the minimum is a measurement error spillover rather than a true spillover.

If we tentatively accept this null, it has an important implication for our findings. Table 1 shows that there is only one short time period in our sample window (1979-1982) when more than 10 percent of the hourly wages were paid above the statutory minimum, and even then, this is just for the female distribution. For males and for the pooled-gender distribution, the minimum wage never covers more than 9 percent of the distribution.[27] Under the null hypothesis of no spillovers, we would have to conclude that the minimum wage had no effect on actual 50/10 inequality for the male and pooled-gender wage distributions throughout the sample period, and ceased having an effect on the actual female 50/10 after 1982. Thus, any changes in the actual (rather than the measured) 50/10 differential after 1983 could not be accounted for by the minimum wage.

Two points deserve emphasis. First, even accepting the null of no spillovers, our estimates for the effect of the minimum wage on *observed* wage inequality (both direct and spillover effects) in the prior sections are valid. However, observed and actual wage effects may differ systematically in a manner that overstates the role of the minimum wage. And clearly, spillovers from the legislated minimum to wages actually paid are of greater economic consequence than spillovers to wages that are (mis-)reported.

Second, our findings do not exclude the possibility of true spillovers—and indeed, we suspect these spillovers are present. Our results do, however, highlight that we do not have sufficient precision to distinguish actual spillovers from measurement error spillovers in currently available data. Better wage data, perhaps administrative payroll data, may be more conclusive.

V. Conclusion

This paper offers a reassessment of the impact of the minimum wage on the wage distribution by using a longer panel than was available to previous studies, incorporating many additional years of data and including significantly more variation in state minimum wages, and using an econometric approach that purges division bias and confounding correlations between state wage levels and wage variances that we find bias earlier estimates. Under our preferred model specification and estimation sample, we estimate that between 1979 and 1989, the

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[27] More precisely, the relevant comparison is the fraction of hours paid below the minimum in the true wage distribution (purged of measurement error) rather than the fraction in the error-ridden distribution. Given that the minimum lies in the left-hand tail of the distribution, that the assumed error distribution is additive, and that the statutory minimum is known without error, the fraction of hours below the minimum in the error-ridden distribution strictly overestimates the fraction of hours below the minimum in the true wage distribution.

decline in the real value of the minimum wage is responsible for 30 to 50 percent of the growth of lower tail inequality in the female, male, and pooled wage distributions (as measured by the differential between the log of the 50^{th} and 10^{th} percentiles). Similarly, calculations indicate that the declining minimum wage made a meaningful contribution to female inequality, a modest contribution to pooled gender inequality, and a negligible contribution to male lower tail inequality during the full sample period of 1979 – 2012. In net, these estimates indicate a substantially smaller role for the U.S. minimum in the rise of inequality than suggested by earlier work, which had attributed 85% to 110% of this rise to the falling minimum.

Despite these modest total effects, we estimate that the effect of the minimum wage extends further up the wage distribution than would be predicted if the minimum wage had a purely mechanical effect on wages (i.e. raising the wage of all who earned below it). One interpretation of these significant spillovers is that they represent a true wage effect for workers initially earning above the minimum. An alternative explanation is that wages for low-wage workers are mismeasured or misreported. If a significant share of minimum wage earners report wages in excess of the minimum wage, and this measurement error persists in response to changes in the minimum, then we would observe changes in percentiles above where the minimum wage directly binds in response to changes in the minimum wage. Our investigation of this hypothesis in Section IV is unable to reject the null hypothesis that all of the apparent effect of the minimum wage on percentiles above the minimum is the consequence of measurement error. Accepting this null, the implied effect of the minimum wage on the *actual* wage distribution is even smaller than the effect of the minimum wage on the *measured* wage distribution.

In net, our analysis suggests that there was a significant expansion in latent lower tail inequality over the 1980s, mirroring the expansion of inequality in the upper tail. While the minimum wage was certainly a contributing factor to widening lower tail inequality—particularly for females—it was not the primary one.

VI. Appendix

A. Correlation between the Trimmed Mean and the Median

Here, we derive the correlation coefficient between the median and a trimmed mean under the assumption that log wages are normally distributed and that we are drawing samples of size N from an underlying identical population. As in the main text, denote by $w(p)$ the log wage at percentile p.

A standard result (not dependent on a normality assumption) is that the covariance between wages at two percentiles is given by:

$$\text{cov}[w(p_1), w(p_2)] = \frac{p_1(1-p_1)}{Nf\big(w(p_1)\big)\cdot f\big(w(p_2)\big)},\ p_1 \leq\ p_2 \tag{A.1}$$

Where $f(\cdot)$ is the density function. If $p_1 = p_2$, this gives the variance of the wage at a particular percentile so that the variance of the median can be written as:

$$\text{var[w(0.5)]}=\frac{1}{4Nf[w(0.5)]^2} \tag{A.2}$$

The trimmed mean between the 30th and 70th percentiles can be written as:

$$\overline{w}^t = \frac{1}{0.4}\int_{0.3}^{0.7} w(p)dp \tag{A.3}$$

So that the covariance between the median and the trimmed mean can be written as:

$$\text{cov}\big[\overline{w}^t, w(0.5)\big] = \frac{1}{0.4}\int_{0.3}^{0.7}\text{cov}[w(p), w(0.5)]dp \tag{A.4}$$

The variance of the trimmed mean can be written as:

$$var\big(\overline{w}^t\big) = \frac{1}{0.4^2}\int_{0.3}^{0.7}\int_{0.3}^{0.7}\text{cov}[w(p), w(p')]dp\, dp' \tag{A.5}$$

The formulae in (A.2), (A.4) and (A.5) can be used to compute the correlation coefficient between the median and trimmed mean, which turns out to be about 0.93. Note that this correlation does not depend on the sample size N. If the distribution is normal with mean μ and variance σ^2 then the formula for the covariance in (A.1) can be written as:

$$\text{cov}[w(p_1), w(p_2)] = \frac{2\pi\sigma^2 p_1(1-p_2)}{Ne^{-\frac{1}{2}[\Phi^{-1}(\text{p}_1)]^2}e^{-\frac{1}{2}[\Phi^{-1}(\text{p}_2)]^2}},\ p_1 \leq\ p_2 \tag{A.6}$$

Where $\Phi^{-1}(\mathrm{p})$ is the inverse of the standard normal cumulative density function. The variance for the median is given by:

$$\mathrm{var}[\mathrm{w}(0.5)]=\frac{\pi\sigma^2}{2N} \tag{A.7}$$

Note that the correlation coefficient will not depend on either μ or σ^2.

B. Proof of Result 1:

Differentiate (9) to give:

$$\left[\int_0^1 g[w(p)-w(p^*)]dp^*\right]\frac{\partial w(p)}{\partial w^m}+\int_{-\infty}^{w(p)}\int_0^1 \frac{\partial g[x-w(p^*)]}{\partial w^m}dp^* dx=0 \tag{A.8}$$

Now we have that:

$$\frac{\partial g[x-w(p^*)]}{\partial w^m}=-g[x-w(p^*)]\frac{\partial w(p^*)}{\partial w^m} \tag{A.9}$$

Which, from (4) is:

$$\frac{\partial g[x-w(p^*)]}{\partial w^m}=\begin{array}{rl} -g[x-w^m] & if \;\; p^*\leq \hat{p}(w^m) \\ 0 & if \;\; p^*>\hat{p}(w^m) \end{array} \tag{A.10}$$

Substituting (7) and (A.10) into (A.8) and re-arranging we have that:

$$\frac{\partial w(p)}{\partial w^m}=\frac{\hat{p}g[w(p)-w^m]}{f[w(p)]} \tag{A.11}$$

The numerator is the fraction of workers who are really paid the minimum wage but are observed with wage $w(p)$ because they have measurement error equal to $[w(p)-w^m]$. Hence the numerator divided by the denominator is the fraction of workers observed at wage $w(p)$ who are really paid the minimum wage.

C. Proof of Result 2

One implication of (A.11) is the following. Suppose we are interested in the effect of minimum wages on the mean log wage, $\overline{w}(p)$. We have that:

$$\frac{\partial \overline{w}}{\partial w^m} = \int_0^1 \frac{\partial w(p)}{\partial w^m} dp = \int_0^1 \frac{\hat{p} g[w(p) - w^m]}{f[w(p)]} dp \tag{A.12}$$

Change the variable of integration to $w(p)$. We will have:

$$dw = w'(p)dp = \frac{1}{f[w(p)]} dp \tag{A.13}$$

Hence (A.12) becomes:

$$\frac{\partial \overline{w}}{\partial w^m} = \hat{p} \int_{-\infty}^{\infty} g[w - w^m] dw = \hat{p} \tag{A.14}$$

That is, the elasticity of average log wages with respect to the log minimum is just the size of the true spike.

D. Estimation Procedure for the Measurement Error Model

Our assumption is that the true latent log wage is normally distributed according to:

$$w^{*} \sim N(\mu, \sigma_w^2) \tag{A.15}$$

To keep notation to a minimum we suppress variation across states and time, though this is incorporated into the estimation. The true wage is given by:

$$\text{w}=\max(w^{m}, w^{*}) \tag{A.16}$$

And the observed wage is given by:

$$v=w+D\varepsilon \tag{A.17}$$

Where D is a binary variable taking the value 0 if the true wage is observed and 1 if it is not. We assume that:

$$Pr(D=1)=1\text{-}\gamma \tag{A.18}$$

We assume that ε is normally distributed according to:

$$\varepsilon \sim N\left(0, \frac{1-\rho^2}{\rho^2}\sigma_w^2\right) \tag{A.19}$$

We choose to parameterize the variance of the error process as proportional to the variance of the true latent wage distribution as this will be convenient later. We later show that ρ is the correlation coefficient between the true latent wage and the observed latent wage when mis-reported—a lower value of ρ implies more measurement error so leads to a lower correlation between the true and observed wage. We assume that (w^{*}, D, ε) are all mutually independent.

Our estimation procedure uses maximum likelihood to estimate the parameters of the measurement error model. There are three types of entries in the likelihood function:

a. those with an observed wage equal to the minimum wage
b. those with an observed wage above the minimum wage
c. those with an observed wage below the minimum wage

Let us consider the contribution to the likelihood function for these three groups in turn.

a. Those Observed to be Paid the Minimum Wage

With the assumptions made above, the 'true' size of the spike is given by:

$$\hat{p} = \Phi\left(\frac{w^m - \mu}{\sigma_w}\right) \tag{A.20}$$

And the size of the observed 'spike' is given by:

$$\tilde{p} = \gamma\Phi\left(\frac{w^m - \mu}{\sigma_w}\right) \tag{A.21}$$

This is the contribution to the likelihood function for those paid the minimum wage.

b. *Those Observed to be Paid Below the Minimum Wage*

Now let us consider the contribution to the likelihood function for those who report being paid below paid the minimum wage. We need to work out the density function of actual observed wages *w,* where $w < w^m$. None of those who report their correct wages (i.e. have $D = 0$) will report a sub-minimum wage, so we need only consider those who mis-report their wage (i.e. those with $D = 1$). Some of these will have a true wage equal to the minimum and some will have a true wage above the minimum. Those who are truly paid the minimum will have measurement error equal to $(w - w^m)$ so, using (A.19) and (A.20) the contribution to the likelihood function will be:

$$(1-\gamma)\frac{\rho}{\sigma_w\sqrt{1-\rho^2}}\phi\left(\frac{\rho(w - w^m)}{\sigma_w\sqrt{1-\rho^2}}\right)\Phi\left(\frac{w^m - \mu}{\sigma_w}\right) \tag{A.22}$$

Now, consider those whose true wage is above the minimum but have a measurement error that pushes their observed wage below the minimum. For this group, their observed wage is below the minimum and their latent wage is above the minimum. The fraction of those who mis-report who are in this category is, with some abuse of the concept of probability:

$$\Pr(v = w, w^* > w^m) \tag{A.23}$$

Define:

$$v^* = w^* + \varepsilon \tag{A.24}$$

Which is what the observed wage would be if there was no minimum wage and they misreport i.e. $D = 1$.

From (A.15) and (A.17):

$$\begin{pmatrix} v^* \\ w^* \end{pmatrix} \sim N\left[\begin{pmatrix} \mu \\ \mu \end{pmatrix}, \begin{pmatrix} \sigma_w^2 + \sigma_\varepsilon^2 & \sigma_w^2 \\ \sigma_w^2 & \sigma_w^2 \end{pmatrix}\right] \tag{A.25}$$

$$\begin{pmatrix} v^* \\ w^* \end{pmatrix} \sim N\left[\begin{pmatrix} \mu \\ \mu \end{pmatrix}, \sigma_w^2 \begin{pmatrix} 1/\rho^2 & 1 \\ 1 & 1 \end{pmatrix}\right]$$

This implies the following:

$$\begin{pmatrix} v^* \\ w^* - \rho^2 v^* \end{pmatrix} \sim N\left[\begin{pmatrix} \mu \\ \mu(1-\rho^2) \end{pmatrix}, \sigma_w^2 \begin{pmatrix} 1/\rho^2 & 1 \\ 1 & 1-\rho^2 \end{pmatrix}\right] \tag{A.26}$$

Which is an orthogonalization that will be convenient.

Now for those paid above the minimum but whose wage is misreported, the true wage is w* and the observed wage is v*. So:

$$\begin{aligned} \Pr(v{=}w, w^* > w^m) &= \Pr(v^* = w, w^* > w^m) \\ &= \Pr(v^* = w, w^* - \rho^2 v^* > w^m - \rho^2 w) \\ &= \Pr(v^* = w)\Pr(w^* - \rho^2 v^* > w^m - \rho^2 w) \\ &= \frac{\rho}{\sigma_w}\phi\left(\frac{\rho(w-\mu)}{\sigma_w}\right)\left[1 - \Phi\left(\frac{[(w^m-\mu) - \rho^2(w-\mu)]}{\sigma_w\sqrt{1-\rho^2}}\right)\right] \end{aligned} \tag{A.27}$$

where the third line uses the independence of (A.26).

Putting together (A.22) and (A.27) the fraction of the population observed to be paid at a wage w below the minimum is given by:

$$\begin{aligned} L = (1-\gamma)\cdot & \\ &\left[\left[\frac{\rho}{\sigma_w\sqrt{1-\rho^2}}\phi\left(\frac{\rho(w-w^m)}{\sigma_w\sqrt{1-\rho^2}}\right)\right]\Phi\left(\frac{w^m-\mu}{\sigma_w}\right) + \right. \\ &\left.\frac{\rho}{\sigma_w}\phi\left(\frac{\rho(w-\mu)}{\sigma_w}\right)\left[1-\Phi\left(\frac{[(w^m-\mu)-\rho^2(w-\mu)]}{\sigma_w\sqrt{1-\rho^2}}\right)\right]\right] \end{aligned} \tag{A.28}$$

c. Those Observed to be Paid Above the Minimum Wage

Now let us consider the fraction observed above the minimum wage. These workers might be one of three types:

i. Those really paid the minimum wage who misreport a wage above the minimum

ii. Those really paid above the minimum wage who do not misreport

iii. Those really paid above the minimum wage, who *do* misreport, but *do not* report a sub-minimum wage.

For those who are truly paid the minimum wage and have a misreported wage, a half will be above, so the fraction of those who report a wage above the minimum is:

$$\frac{1}{2}(1-\gamma)\Phi\left(\frac{w^m-\mu}{\sigma_w}\right) \tag{A.29}$$

Those who do not misreport and truly have a wage above the minimum will be:

$$\gamma\left(1-\Phi\left(\frac{w^m-\mu}{\sigma_w}\right)\right) \tag{A.30}$$

Now, consider those whose true wage is above the minimum but who misreport. For this group we know their observed latent wage is above the minimum and that their true latent wage is above the minimum. The fraction who are in this category is:

$$\Pr(w^* > w^m, v^* > w^m) \tag{A.31}$$

Now:

$$\Pr(w^* > w^m, v^* > w^m) = 1 - \Pr(w^* < w^m) - \Pr(v^* < w^m) + \Pr(w^* < w^m, v^* < w^m)$$

$$=1-\Phi\left(\frac{w^m-\mu}{\sigma_w}\right)-\Phi\left(\frac{\rho(w^m-\mu)}{\sigma_w}\right)+\Phi\left(\frac{w^m-\mu}{\sigma_w},\frac{\rho(w^m-\mu)}{\sigma_w},\rho\right)$$

(A.32)

Where the final term is the cumulative density function of the bivariate normal distribution. Putting together (A.29), (A.30), and (A.32) the fraction of the population observed to be paid above the minimum is given by:

$$(1-\gamma)\cdot \left[\frac{1}{2}\Phi\left(\frac{w^m-\mu}{\sigma_w}\right)+1-\Phi\left(\frac{w^m-\mu}{\sigma_w}\right)-\Phi\left(\frac{\rho(w^m-\mu)}{\sigma_w}\right)+\Phi\left(\frac{w^m-\mu}{\sigma_w},\frac{\rho(w^m-\mu)}{\sigma_w},\rho\right)\right] +\gamma\left(1-\Phi\left(\frac{w^m-\mu}{\sigma_w}\right)\right) \tag{A.33}$$

This is the contribution to the likelihood function for those paid above the minimum.

There are three parameters in this model (σ_w, γ, ρ). These parameters may vary with state or time. In the paper we have already documented how the variance in observed wages varies across state and time so it is important to allow for this variation. Nevertheless, for ease of computation our estimates assume that (γ, ρ) only vary across time and are constant across states.

To estimate the parameters we use two steps.

Step 1:

We first use the information on the shape of the wage distribution above the median to obtain an estimate of the median and variance of the latent observed wage distribution for each state/year.[28] This assumes that the latent distribution above the median is unaffected by the minimum wage. It also assumes that latent observed wage distribution is normal, which is not consistent with our measurement error model (recall our model assumes that the latent observed wage distribution is a mixture of two normal, i.e. those who report their wage correctly and those who do not). This does not affect the estimate of the median but does

[28] To estimate this, we assume that the latent wage distribution for each state/year is log normal and can be summarized by its median and variance, so that $w_{st}^*(p) = \mu_{st} + \sigma_{st}F^{-1}(p)$, where μ_{st} is the log median and σ_{st} is the variance. We then assume that the minimum wage has no effect on the shape of the wage distribution above the median, so that upper-tail percentiles are estimates of the latent distribution. To estimate μ_{st} and σ_{st} , we pool the 50th through 75th log wage percentiles, regress the log value of the percentile on the inverse CDF of the standard normal distribution, and allowing the intercept (μ_{st}) and coefficient (σ_{st}) to vary by state and year (and including state-specific time trends in both the intercept and coefficient). Since we assume the wage distribution is unaffected by the minimum wage between the 50th and 75th percentiles, the distribution between the 50th and 75th percentiles, combined with our parametric assumptions, allows us to infer the shape of the wage distribution for lower percentiles. We have experimented with the percentiles used to estimate the latent wage distribution and the results are not very sensitive to the choices made.

affect the interpretation of the variance. Here we show how to map between this estimate of the variance and the parameters of our measurement error model.

Our measurement error model implies that the log wage at percentile p, w(p) satisfies the following equation:

$$\text{p}=\gamma\Phi\left(\frac{w(p)-\mu}{\sigma_w}\right)+(1-\gamma)\Phi\left(\frac{\rho(w(p)-\mu)}{\sigma_w}\right) \tag{A.34}$$

Differentiating this we obtain the following equation for w'(p):

$$1=\left[\gamma\left(\frac{1}{\sigma_w}\right)\phi\left(\frac{w(p)-\mu}{\sigma_w}\right)+(1-\gamma)\left(\frac{\rho}{\sigma_w}\right)\phi\left(\frac{\rho(w(p)-\mu)}{\sigma_w}\right)\right]w'(p) \tag{A.35}$$

Our estimated model which assumes a single normal distribution uses, instead, the equation:

$$1=\left(\frac{1}{\sigma}\right)\phi\left(\frac{w(p)-\mu}{\sigma}\right)w'(p) \tag{A.36}$$

And our estimation procedure provides an estimate of σ. Equating the two terms we have the following expression for the relationship between σ_w and σ:

$$\sigma_w=\sigma\frac{\left[\gamma\phi\left(\frac{w(p)-\mu}{\sigma_w}\right)+\rho(1-\gamma)\phi\left(\frac{\rho(w(p)-\mu)}{\sigma_w}\right)\right]}{\phi\left(\frac{w(p)-\mu}{\sigma}\right)} \tag{A.37}$$

If the values of the density functions are similar then one can approximate this relationship by:

$$\sigma_w=\sigma[\gamma+\rho(1-\gamma)] \tag{A.38}$$

This is an approximation, but simulation of the model for the parameters we estimate suggest it is a good approximation. This implies that we can write all elements of the likelihood function as functions of:

$$z_{st}=\left(\frac{w_{st}^m-\mu_{st}}{\sigma_{st}}\right) \tag{A.39}$$

That is, z_{st} is the standardized deviation of the minimum from the median using the estimate of the observed variance obtained as described above from step 1 of the estimation procedure.

Step 2:

In this step we estimate the parameters (ρ, γ) using maximum-likelihood. The elements of the likelihood function have been described above.

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Table 1a - Summary Statistics for Bindingness of State and Federal Minimum Wages

		A. Females				B. Males			
	# states w/higher min (1)	Min. binding pctile (2)	Max. binding pctile (3)	Share of hours at or below min (4)	Agg. log(10)-log(50) (5)	Min. binding pctile (6)	Max. binding pctile (7)	Share of hours at or below min (8)	Agg. log(10)-log(50) (9)
1979	1	5.0	28.0	0.13	-0.38	2.0	10.5	0.05	-0.64
1980	1	6.0	24.0	0.13	-0.40	2.5	10.0	0.06	-0.65
1981	1	5.0	24.0	0.13	-0.41	1.5	9.0	0.06	-0.68
1982	1	5.0	21.5	0.11	-0.48	2.0	8.0	0.05	-0.71
1983	1	3.5	17.5	0.10	-0.51	2.0	8.0	0.05	-0.73
1984	1	2.5	15.5	0.09	-0.54	1.5	7.5	0.04	-0.73
1985	2	2.0	14.5	0.08	-0.56	1.0	6.5	0.04	-0.74
1986	5	2.0	16.0	0.07	-0.59	1.0	6.5	0.03	-0.74
1987	6	2.0	14.0	0.06	-0.60	1.0	6.0	0.03	-0.73
1988	10	2.0	12.5	0.06	-0.60	1.0	6.0	0.03	-0.72
1989	12	1.0	12.5	0.05	-0.61	1.0	5.0	0.03	-0.72
1990	11	1.0	14.0	0.05	-0.58	0.5	6.0	0.03	-0.72
1991	4	1.5	18.5	0.07	-0.58	0.5	9.0	0.04	-0.71
1992	7	2.0	14.0	0.07	-0.58	1.0	6.5	0.04	-0.72
1993	7	2.5	11.0	0.06	-0.59	1.0	5.0	0.03	-0.73
1994	8	2.5	11.0	0.06	-0.61	1.0	4.5	0.03	-0.71
1995	9	2.0	9.5	0.05	-0.61	0.5	4.5	0.03	-0.71
1996	11	2.0	12.5	0.05	-0.61	1.0	7.0	0.03	-0.71
1997	10	2.5	14.5	0.06	-0.60	1.0	7.5	0.04	-0.69
1998	7	2.5	11.5	0.06	-0.58	1.0	7.0	0.04	-0.69
1999	10	2.5	11.0	0.05	-0.58	1.0	5.5	0.03	-0.69
2000	10	2.0	9.5	0.05	-0.59	1.0	6.0	0.03	-0.68
2001	10	2.0	8.5	0.05	-0.60	1.0	5.5	0.03	-0.69
2002	11	1.5	9.0	0.04	-0.60	1.0	6.0	0.03	-0.70
2003	11	1.5	9.0	0.04	-0.61	0.5	5.0	0.03	-0.69
2004	12	1.5	7.5	0.04	-0.63	1.0	5.0	0.03	-0.70
2005	15	1.5	8.5	0.04	-0.64	1.0	5.0	0.02	-0.71
2006	19	1.5	9.5	0.04	-0.64	0.5	6.0	0.02	-0.70
2007	30	1.5	10.0	0.05	-0.63	0.5	6.0	0.03	-0.70
2008	31	2.0	13.0	0.06	-0.64	1.0	6.5	0.04	-0.71
2009	26	2.5	10.5	0.06	-0.64	1.0	6.0	0.04	-0.74
2010	15	3.5	9.5	0.06	-0.64	2.0	6.5	0.04	-0.73
2011	19	3.0	10.5	0.06	-0.65	1.5	8.0	0.04	-0.72
2012	19	3.0	9.5	0.06	-0.66	1.5	7.0	0.04	-0.74

Notes: Column 1 displays the number of states with a minimum that exceeds the federal minimum for at least 6 months of the year. Columns 2 and 6, and 3 and 8 display estimates of the lowest and highest percentile at which the minimum wage binds across states (DC is excluded). The binding percentile is estimated as the highest percentile in the annual distribution of wages at which the minimum wage binds (rounded to the nearest half of a percentile), where the annual distribution includes only those months for which the minimum wage was equal to its modal value for the year. Columns 4 and 8 display the share of hours worked for wages at or below the minimum wage. Columns 5 and 9 display the weighted average value of the log(p10)-log(p50) for the male or female wage distributions across states.

Table 1b - Summary Statistics for Bindingness of State and Federal Minimum Wages

	C. Males and Females, Pooled				
	# states w/higher min.	Min. binding pctile	Max. binding pctile	Share of hours at or below min.	Avg. log(10)-log(50)
	(1)	(2)	(3)	(4)	(5)
1979	1	3.5	17.0	0.08	-0.58
1980	1	4.0	15.5	0.09	-0.59
1981	1	2.5	14.5	0.09	-0.60
1982	1	3.5	12.5	0.07	-0.63
1983	1	3.0	11.5	0.07	-0.65
1984	1	2.0	10.5	0.06	-0.67
1985	2	1.5	9.5	0.06	-0.69
1986	5	1.5	10.0	0.05	-0.70
1987	6	1.5	9.0	0.04	-0.70
1988	10	1.5	8.0	0.04	-0.69
1989	12	1.0	7.0	0.04	-0.68
1990	11	0.5	9.0	0.04	-0.67
1991	4	1.0	12.5	0.05	-0.67
1992	7	1.5	9.5	0.05	-0.67
1993	7	1.5	7.5	0.04	-0.68
1994	8	2.0	7.5	0.04	-0.69
1995	9	1.5	6.0	0.04	-0.68
1996	11	1.5	9.5	0.04	-0.67
1997	10	1.5	10.0	0.05	-0.66
1998	7	2.0	8.0	0.05	-0.65
1999	10	2.0	7.0	0.04	-0.65
2000	10	1.5	7.5	0.04	-0.65
2001	10	1.5	6.5	0.04	-0.66
2002	11	1.5	7.0	0.03	-0.66
2003	11	1.5	6.5	0.03	-0.66
2004	12	1.5	6.0	0.03	-0.68
2005	15	1.5	6.5	0.03	-0.68
2006	19	1.0	7.5	0.03	-0.68
2007	30	1.5	7.5	0.04	-0.68
2008	31	1.0	8.5	0.04	-0.69
2009	26	2.0	8.0	0.05	-0.71
2010	15	3.0	7.5	0.05	-0.70
2011	19	2.5	9.0	0.05	-0.69
2012	19	2.0	8.0	0.05	-0.71

See notes for Table 1a.

Table 2a: OLS and 2SLS relationship between log(p)-log(p50) and log(min. wage)-log(p50), for select percentiles of given wage distribution, 1979 - 2012

	(1)	(2)	(3)	(4)	(5)
			Females		
5	0.63	0.44	0.54	0.32	0.39
	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)
10	0.52	0.27	0.46	0.22	0.17
	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)
20	0.29	0.12	0.29	0.10	0.07
	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)
30	0.15	0.07	0.23	0.02	0.04
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
40	0.07	0.04	0.17	-0.01	0.03
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
75	-0.05	0.09	0.24	-0.03	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
90	-0.04	0.15	0.34	-0.02	0.04
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
			Males		
5	0.55	0.25	0.43	0.17	0.16
	(0.04)	(0.02)	(0.03)	(0.02)	(0.04)
10	0.38	0.12	0.34	0.04	0.05
	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)
20	0.21	0.06	0.24	0.01	0.02
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
30	0.09	0.05	0.19	0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
40	0.04	0.06	0.15	0.04	0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)
75	0.09	0.14	0.24	0.00	0.02
	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
90	0.14	0.16	0.30	0.02	0.03
	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)
OLS / 2SLS	OLS	OLS	OLS	2SLS	2SLS
Levels / First-Diff	Levels	Levels	FD	Levels	FD
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes
State trends	No	Yes	No	Yes	No

See Notes at bottom of Panel B

Table 2b: OLS and 2SLS relationship between log(p)-log(p50) and log(min. wage)-log(p50), for select percentiles of pooled wage distribution, 1979 - 2012

	(1)	(2)	(3)	(4)	(5)
			Males and Females Pooled		
5	0.62	0.35	0.45	0.29	0.29
	(0.03)	(0.02)	(0.04)	(0.03)	(0.06)
10	0.44	0.18	0.35	0.16	0.17
	(0.03)	(0.02)	(0.03)	(0.02)	(0.04)
20	0.26	0.09	0.23	0.07	0.04
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
30	0.14	0.06	0.20	0.03	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
40	0.06	0.05	0.16	0.03	0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
75	0.01	0.11	0.22	0.00	0.02
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
90	0.04	0.15	0.27	0.01	0.02
	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)
OLS / 2SLS	OLS	OLS	OLS	2SLS	2SLS
Levels / First-Diff	Levels	Levels	FD	Levels	FD
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes
State trends	No	Yes	No	Yes	No

Notes: N=1700 for levels estimation, N=1650 for first-differenced estimation. Sample period is 1979-2012. Estimates are the marginal effects of log(min. wage)-log(p50), evaluated at its hours-weighted average across states and years. Standard errors clustered at the state level are in parenthesis. Regressions are weighted by the sum of individuals' reported weekly hours worked multiplied by CPS sampling weights. For 2SLS specifications, the effective minimum and its square are instrumented by the log of the minimum, the square of the log minimum, and the log minimum interacted with the average real log median for the state over the sample. For the first-differenced specification, the instruments are first-differenced equivalents.

Table 3: Relationship between log(p60)-log(p40) and log(p50): OLS estimates

	A. Mean log(p60)-log(p40), 1979-2012			B. Trend log(p60)-log(p40), 1979-2012			
	(1)	(2)	(3)	(1)	(2)	(3)	(4)
				Females			
Mean log(p50), 1979-2012	0.123 (0.029)		0.139 (0.024)	0.005 (0.001)		0.005 (0.001)	
Trend log(p50), 1979-2012		-0.80 (1.55)	-2.44 (1.32)		0.161 (0.071)	0.107 (0.063)	
Mean log(p60)-log(p40), 1979-2012							0.029 (0.005)
				Males			
Mean log(p50), 1979-2012	0.060 (0.053)		0.062 (0.048)	0.009 (0.001)		0.009 (0.001)	
Trend log(p50), 1979-2012		-1.85 (1.68)	-1.93 (1.67)		0.038 (0.076)	0.026 (0.045)	
Mean log(p60)-log(p40), 1979-2012							0.020 (0.007)
				Males and Females Pooled			
Mean log(p60)-log(p40), 1979-2012	0.113 (0.039)		0.122 (0.033)	0.005 (0.002)		0.005 (0.002)	
Mean log(p50), 1979-2012		-2.01 (1.29)	-2.60 (1.13)		0.147 (0.058)	0.122 (0.055)	
Mean log(p60)-log(p40), 1979-2012							0.029 (0.007)

Notes: N=50 (one observation per state). Observations are wighted by the average hours worked per state. Robust standard errors are in parentheses. The dependent variable in panel A (left) is the mean log(p60)-log(p40) for the state, over the 1979-2012 period. The dependent variable in panel B (right) is the linear trend in the log(p60)-log(p40) for the state, over the 1979-2012 period.

Table 4: Actual and counterfactual changes in log(p50/10) between selected years: Changes in log points (100 x log change)

	Observed Change	OLS Counterfactuals Levels, No FE 1979-2012	OLS Counterfactuals Levels, No FE 1979-1991	2SLS Counterfactuals Levels FE 1979-2012	2SLS Counterfactuals First Diffs 1979-2012
			A. 1979 - 1989		
Females	24.6	2.5	4.0	12.2	15.4
Males	2.5	-6.6	-5.4	1.3	1.5
Pooled	11.8	-1.5	-0.2	7.0	8.2
			B. 1979 - 2012		
Females	28.5	6.0	7.1	15.7	18.8
Males	7.9	3.0	3.5	6.9	7.1
Pooled	11.4	0.7	1.8	7.1	8.1

Note: Estimates represent changes in actual and counterfactual log(p50)-log(p10) between 1979 and 1989, and 1979 and 2012, measured in log points (100 x log change). Counterfactual wage changes in panels A represents counterfactual changes in the 50/10 had the effective minimum wage in 1979 equalled the effective minimum wage in 1989 for each state. Counterfactual wage changes in Panel B represent changes had the effective minima in 1979 and 2012 equaled the effective minimum in 1989. OLS counterfactual estimates (using point estimates from the 1979-2012 period) are formed using coefficients from estimation reported in column 1 of Table 2. 2SLS counterfactuals (using point estimates from the 1979-2012 period) are formed using coefficients from estimation reported in columns 4 and 5 of Table 2. Counterfactuals using point estimates from the 1979-1991 period are formed using coefficients from analogous regressions for the shorter sample period.

Appendix Table 1 - Variation in State Minimum Wages

	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
Federal min. wage	2.90	3.10	3.35	3.35	3.35	3.35	3.35	3.35	3.35	3.35	3.35	3.80	4.25	4.25	4.25	4.25	4.25	4.25
Alabama																		
Alaska	3.40	3.60	3.85	3.85	3.85	3.85	3.85	3.85	3.85	3.85	3.85	4.30	4.75	4.75	4.75	4.75	4.75	4.75
Arizona																		
Arkansas																		
California											4.25	4.25						
Colorado																		
Connecticut										3.75	4.25	4.25	4.27	4.27	4.27	4.27	4.27	4.27
Delaware																		4.65
Florida																		
Georgia																		
Hawaii										3.85	3.85	3.85		4.75	5.25	5.25	5.25	5.25
Idaho																		
Illinois																		
Indiana																		
Iowa												3.85		4.65	4.65	4.65	4.65	4.65
Kansas																		
Kentucky																		
Louisiana																		
Maine							3.45	3.55	3.65	3.65	3.75	3.85						
Maryland																		
Massachusetts									3.65	3.70	3.75							4.75
Michigan																		
Minnesota										3.55	3.85	3.95						
Mississippi																		
Missouri																		
Montana																		
Nebraska																		
Nevada																		
New Hampshire									3.45	3.55	3.65							
New Jersey														5.05	5.05	5.05	5.05	5.05
New Mexico																		
New York																		
North Carolina																		
North Dakota																		
Ohio																		
Oklahoma																		
Oregon												4.25	4.75	4.75	4.75	4.75	4.75	4.75
Pennsylvania																		
Rhode island									3.60	3.83	4.13	4.25	4.45	4.45	4.45	4.45	4.45	4.45
South Carolina																		
South Dakota																		
Tennessee																		
Texas																		
Utah																		
Vermont									3.50	3.60	3.70	3.85					4.50	4.75
Virginia																		
Washington											3.85	3.85				4.90	4.90	4.90
West Virginia																		
Wisconsin																		
Wyoming																		

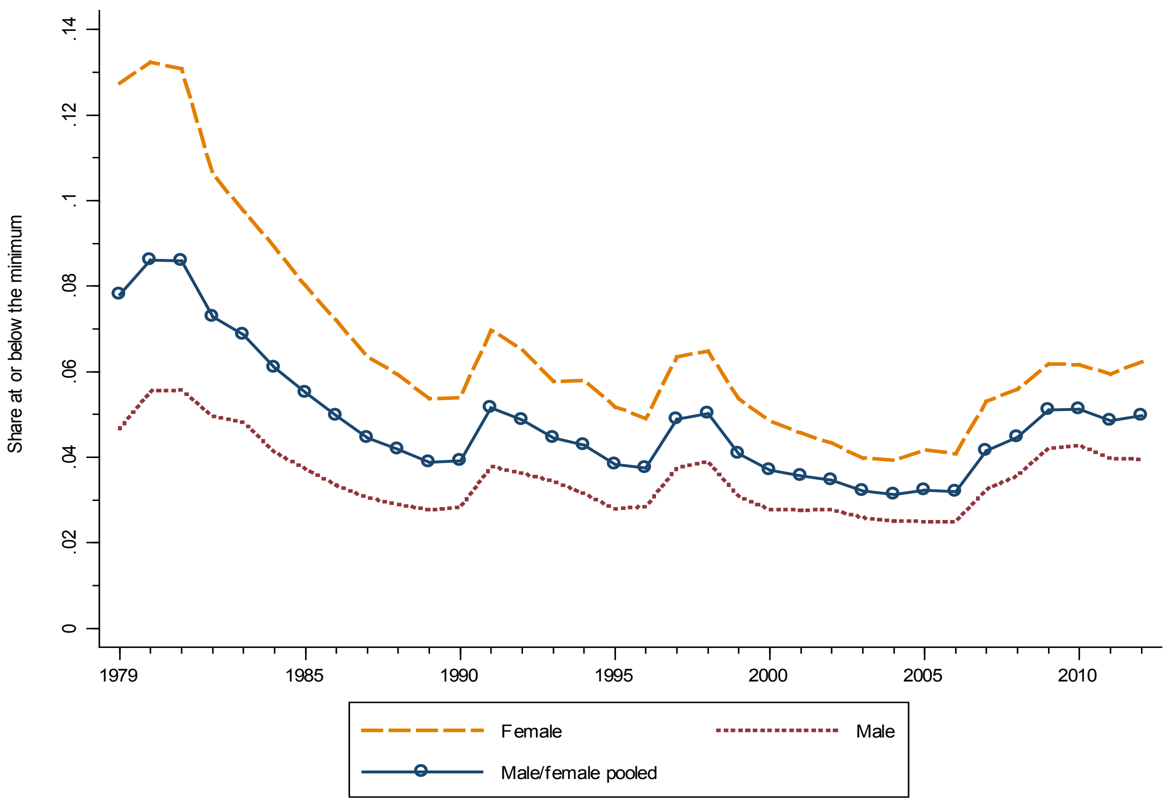
Note: Table indicates years in which each state had a state minimum wage that exceeded the federal minimum wage for at 6 months or more of the year.

Appendix Table 1 (cont) - Variation in State Minimum Wages

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Federal min. wage	4.75	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25
Alabama																
Alaska	5.25	5.65	5.65	5.65	5.65	5.65	7.15	7.15	7.15	7.15	7.15	7.15	7.15	7.75	7.75	7.75
Arizona											6.75	6.90	7.25		7.35	7.65
Arkansas											6.25	6.25				
California	5.00	5.75	5.75	5.75	6.25	6.75	6.75	6.75	6.75	6.75	7.50	8.00	8.00	8.00	8.00	8.00
Colorado											6.85	7.02	7.28		7.36	7.64
Connecticut	4.77	5.18	5.65	6.15	6.40	6.70	6.90	7.10	7.10	7.40	7.65	7.65	8.00	8.25	8.25	8.25
Delaware			5.65	5.65	6.15	6.15	6.15	6.15	6.15	6.15	6.65	7.15	7.15			
Florida									6.15	6.40	6.67	6.79	7.21		7.31	7.67
Georgia																
Hawaii	5.25	5.25	5.25	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.25	7.25	7.25			
Idaho																
Illinois								5.50	6.50	6.50	7.00	7.63	7.88	8.13	8.25	8.25
Indiana																
Iowa											6.20	7.25	7.25			
Kansas																
Kentucky																
Louisiana																
Maine						5.75	6.25	6.25	6.35	6.50	6.75	7.00	7.25	7.50	7.50	7.50
Maryland										6.15	6.15	6.15				
Massachusetts	5.25	5.25	5.25	6.00	6.75	6.75	6.75	6.75	6.75	6.75	7.50	8.00	8.00	8.00	8.00	8.00
Michigan											7.05	7.28	7.40	7.40	7.40	7.40
Minnesota										6.15	6.15	6.15				
Mississippi																
Missouri											6.50	6.65	7.05			
Montana											6.15	6.25	6.90		7.35	7.65
Nebraska																
Nevada											6.24	6.59	7.20	7.55	8.25	8.25
New Hampshire																
New Jersey	5.05									6.15	7.15	7.15	7.15			
New Mexico												6.50	7.50	7.50	7.50	7.50
New York									6.00	6.75	7.15	7.15	7.15			
North Carolina											6.15	6.15				
North Dakota																
Ohio											6.85	7.00	7.30	7.30	7.40	7.70
Oklahoma																
Oregon	5.50	6.00	6.50	6.50	6.50	6.50	6.90	7.05	7.25	7.50	7.80	7.95	8.40	8.40	8.50	8.80
Pennsylvania											6.70	7.15	7.15			
Rhode island	5.15			5.65	6.15	6.15	6.15	6.75	6.75	7.10	7.40	7.40	7.40	7.40	7.40	7.40
South Carolina																
South Dakota																
Tennessee																
Texas																
Utah																
Vermont	5.00	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.00	7.25	7.53	7.68	8.06	8.06	8.15	8.46
Virginia																
Washington	4.90		5.70	6.50	6.72	6.90	7.01	7.16	7.35	7.63	7.93	8.07	8.55	8.55	8.67	9.04
West Virginia											6.20	6.90	7.25			
Wisconsin									5.70	6.50	6.50	6.50				
Wyoming																

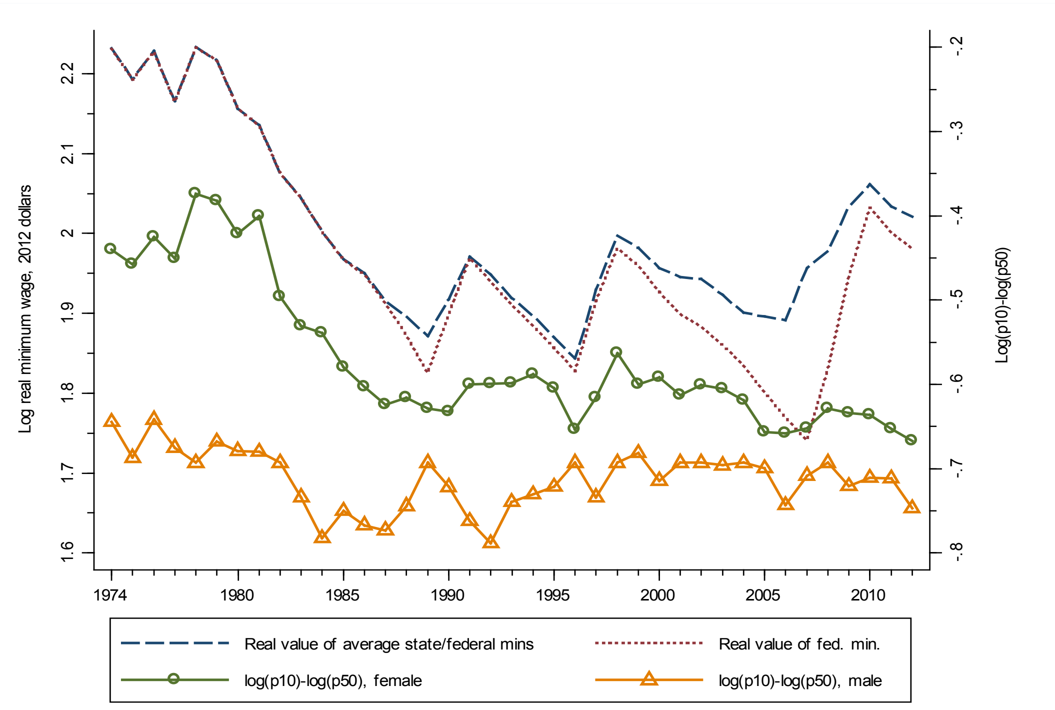
Note: Table indicates years in which each state had a state minimum wage that exceeded the federal minimum wage for at least 6 months or more of the year.

Figure 1: Share of hours at or below the minimum wage



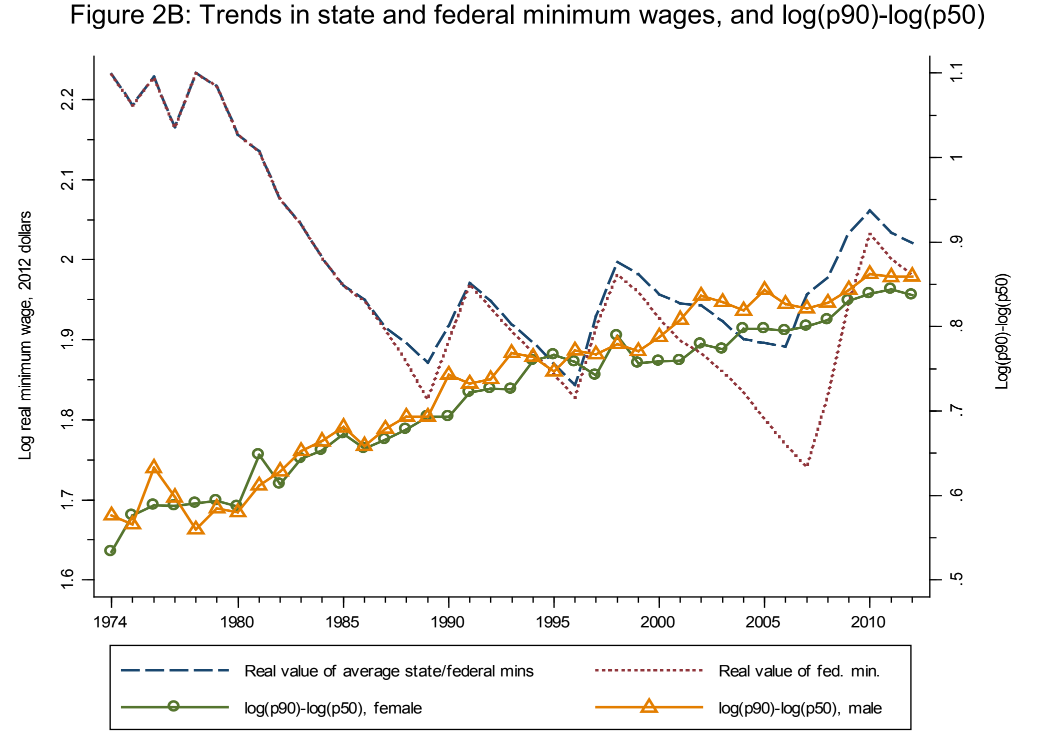
Note: Lines are estimates of the share of hours worked for reported wages equal to or less than the applicable state or federal minimum wage, and correspond with data from column 4 and 8 of Table 1A, and column 4 of Table 1B.

Figure 2A: Trends in state and federal minimum wages, and log(p10)-log(p50)



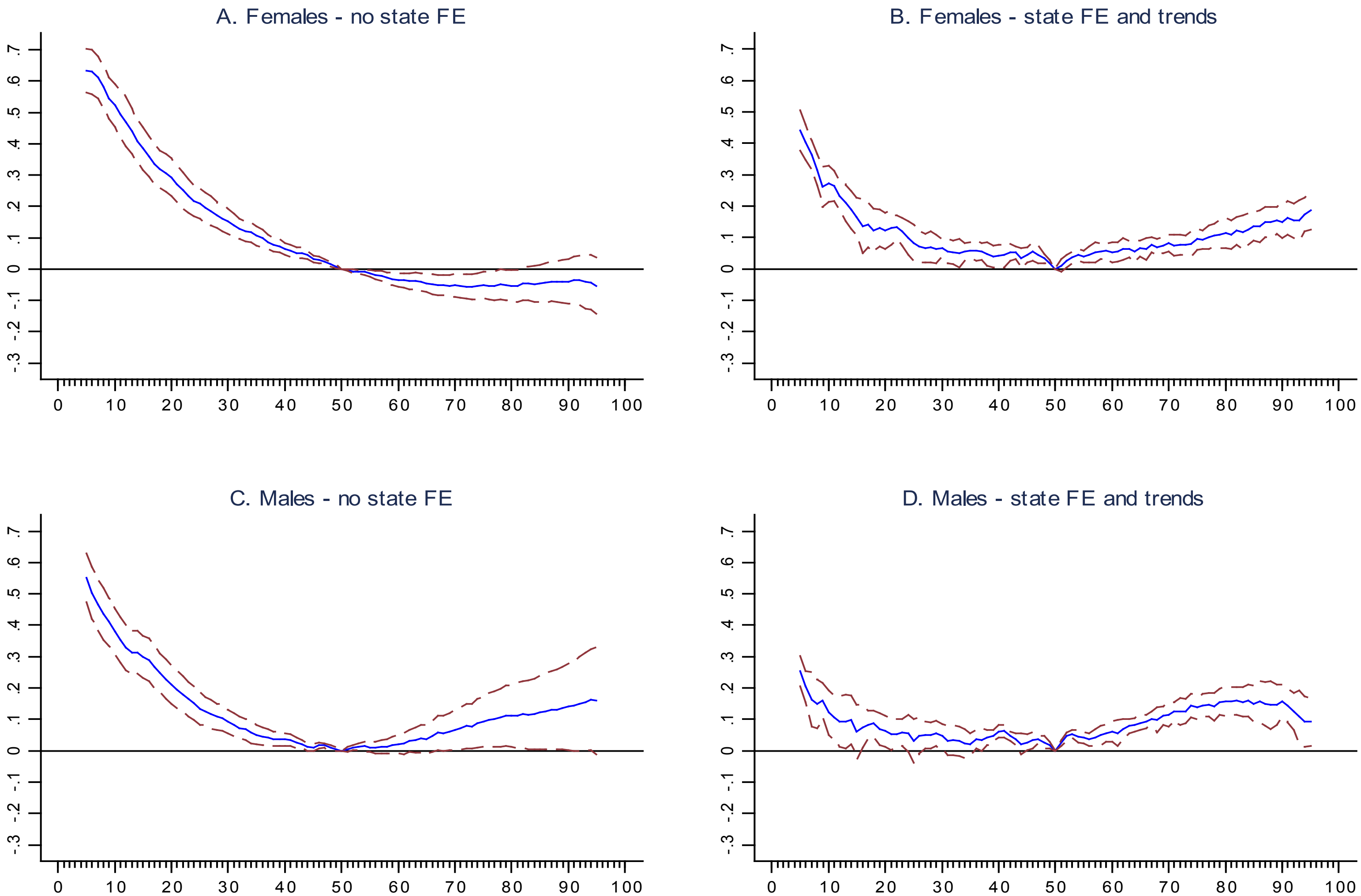
Note: Annual data on state and federal minimum wages and log percentiles. Minimum wages are in 2012 dollars.

Figure 2B: Trends in state and federal minimum wages, and log(p90)-log(p50)



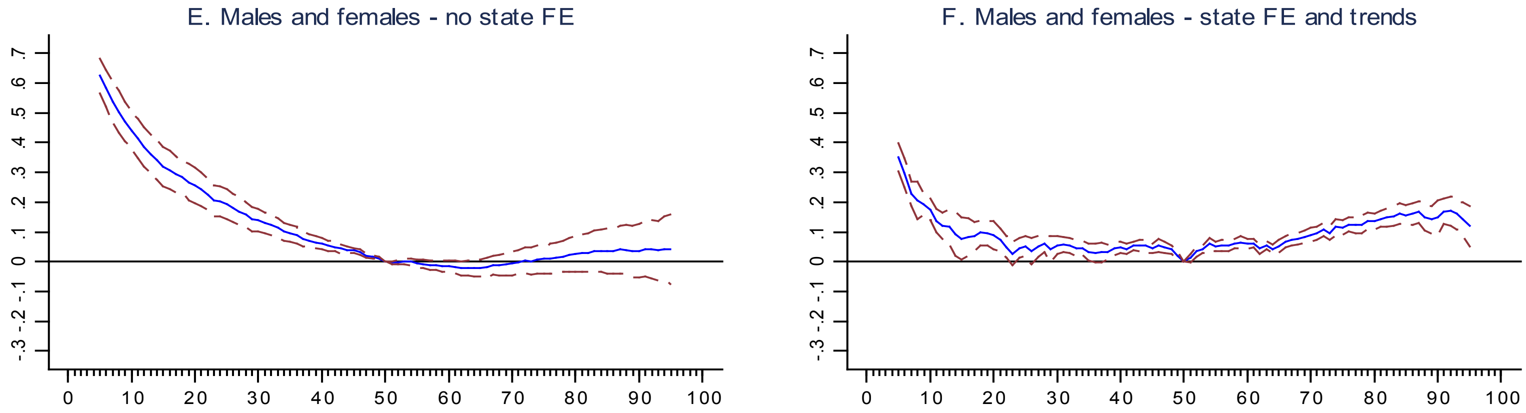
Note: Annual data on state and federal minimum wages and log percentiles. Minimum wages are in 2012 dollars.

Figure 3: OLS estimates of the relationship between log(p)-log(p50) and log(min)-log(p50) and its square, 1979-2012



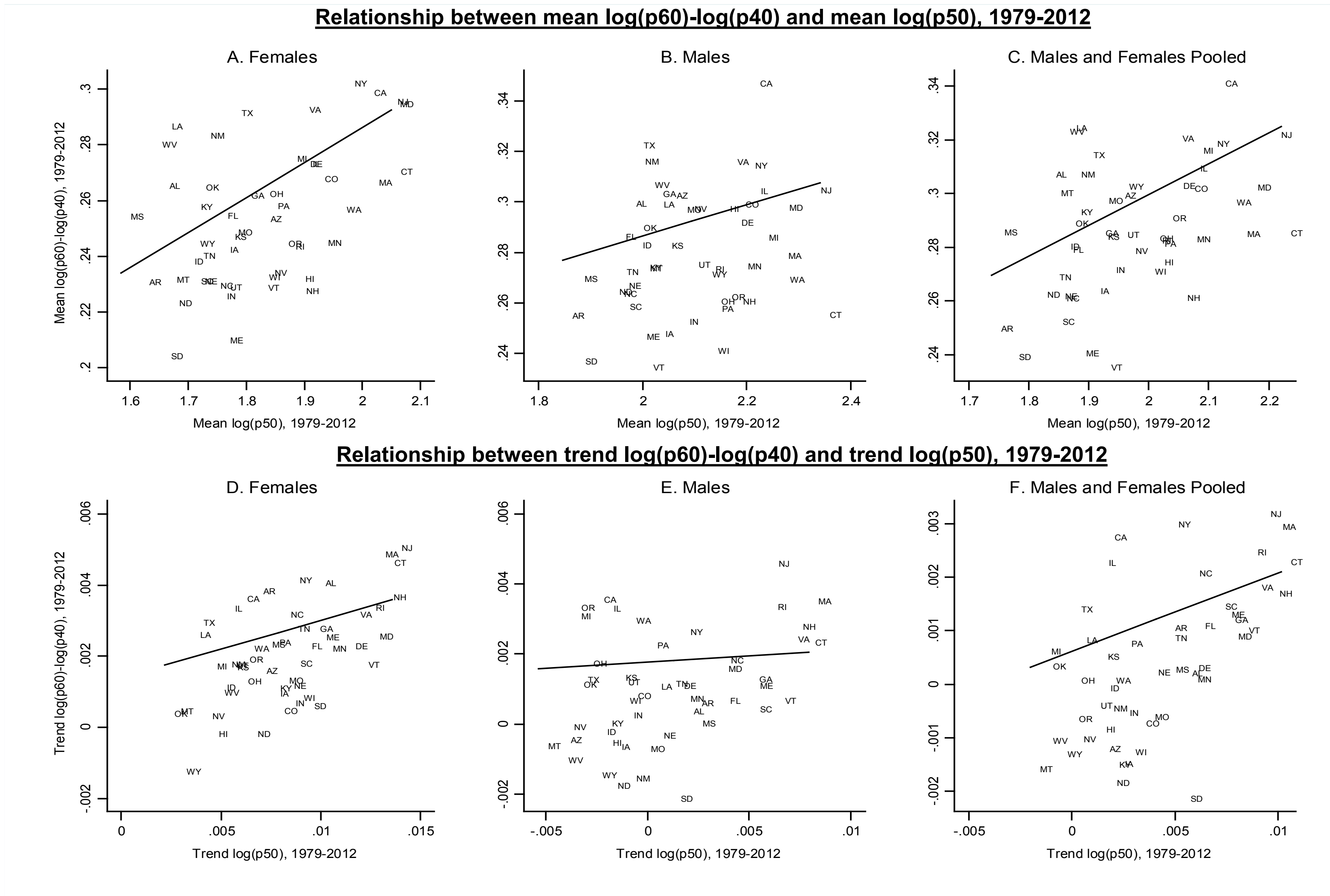
Note: Estimates are the marginal effects of log(min. wage)-log(p50), evaluated at the hours-weighted average of log(min. wage)-log(p50) across states and years. Observations are state-year observations. 95% confidence interval is represented by the dashed lines. Panels A and C correspond with column 1 of Table 2. Panels B and D correspond with column 2 of Table 2.

Figure 3 (cont.): OLS estimates of the relationship between log(p)-log(p50) and log(min)-log(p50) and its square, 1979-2012



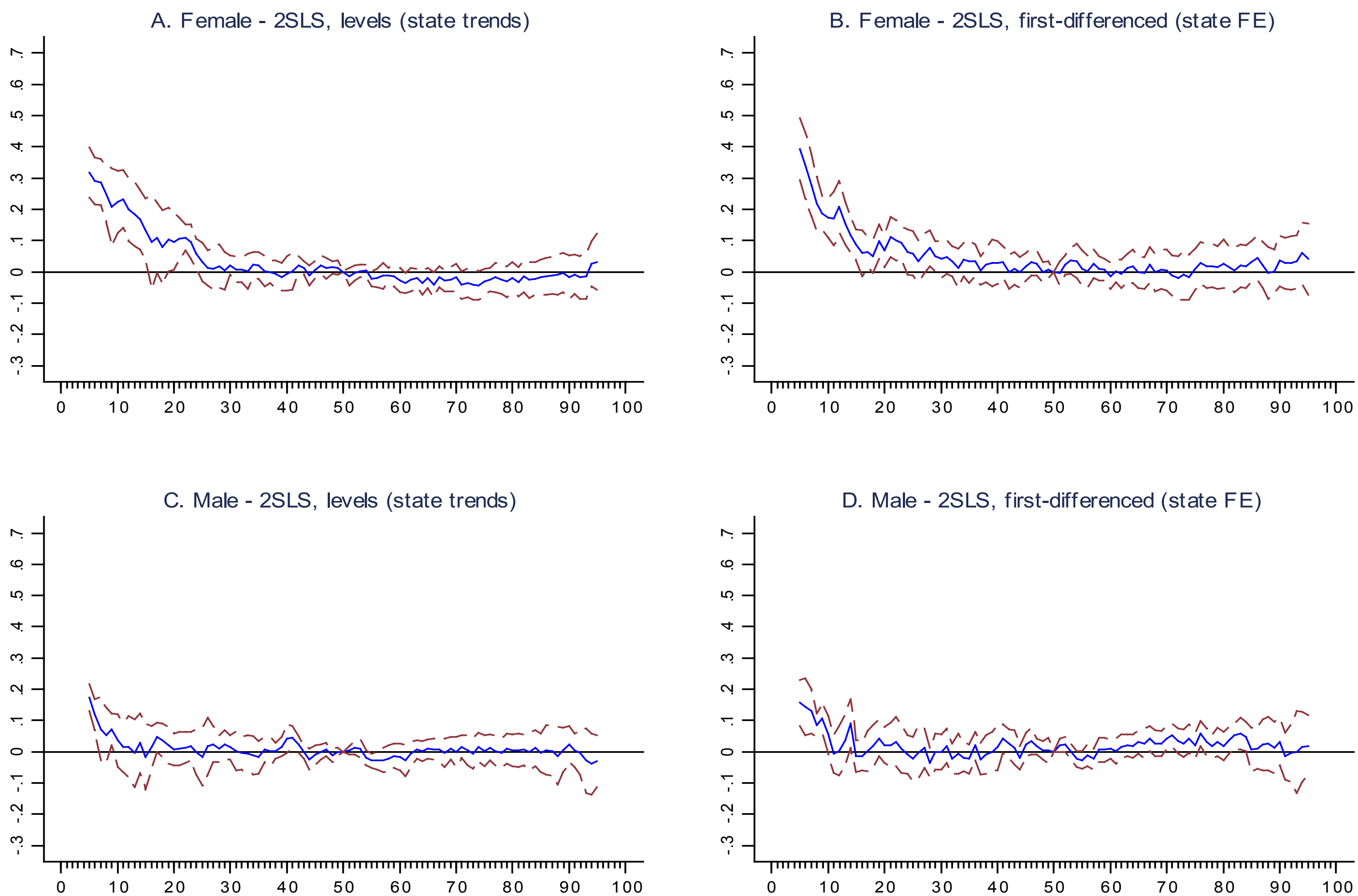
Note: Estimates are the marginal effects of log(min. wage)-log(p50), evaluated at the hours-weighted average of log(min. wage)-log(p50) across states and years. Observations are state-year observations. 95% confidence interval is represented by the dashed lines. Panel E corresponds with column 1 of Table 2. Panels F corresponds with column 2 of Table 2.

Figure 4 : OLS estimates of the relationship between mean (and trend) log(p60)-log(p40) and mean (and trend) log(p50), 1979-2012



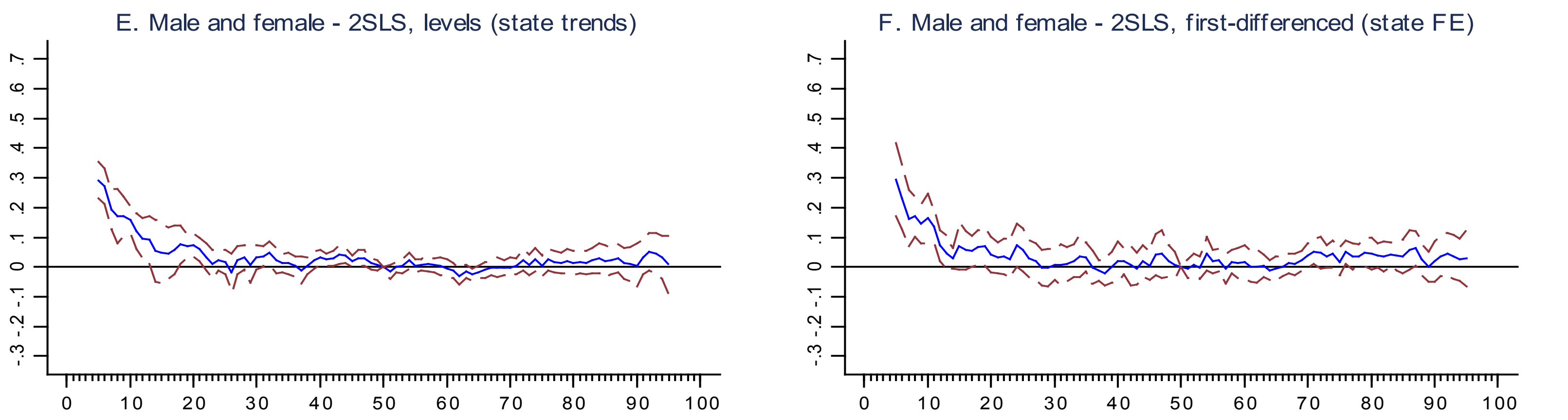
Note: Estimates correspond with regressions from Table 3. The top panel shows the cross-state relationship between the average log(p60)-log(p40) and log(p50) between 1979 and 2012. The bottom panel shows the cross-state relationship between the state trends in log(p60)-log(p40) and log(p50), when estimated over the same period. Alaska, which tends to be an outlier, is dropped for visual clarity, though this does not materially affect the slope of the line (Table 3 includes Alaska).

Figure 5: 2SLS estimates of the relationship between log(p)-log(p50) and log(min)-log(p50), 1979-2012



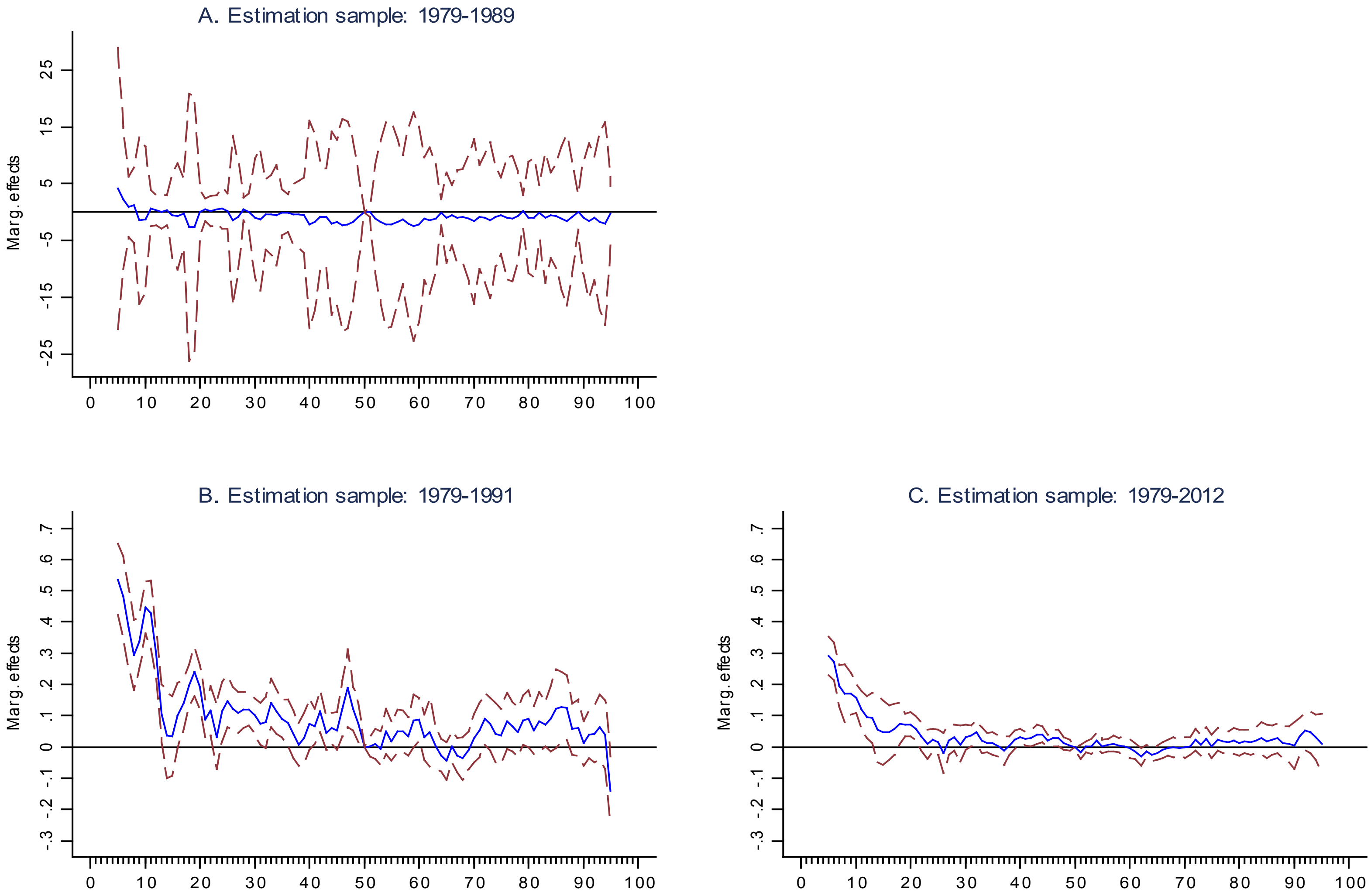
Note: Estimates are the marginal effects of log(min. wage)-log(p50), evaluated at the hours-weighted average of log(min. wage)-log(p50) across states and years. Observations are state-year observations. 95% confidence interval is represented by the dashed lines. Panels A and C correspond with column 4 of Table 2, and Panels B and D correspond with column 5.

Figure 5 (cont.): 2SLS estimates of the relationship between log(p)-log(p50) and log(min)-log(p50), 1979-2012



Note: Estimates are the marginal effects of log(min. wage)-log(p50), evaluated at the hours-weighted average of log(min. wage)-log(p50) across states and years. Observations are state-year observations. 95% confidence interval is represented by the dashed lines. Panel E corresponds with column 4 of Table 2, Panel F with column 5.

Figure 6: 2SLS estimates of the relationship between log(p)-log(p50) and log(min)-log(p50) over various time periods



Note: Estimates are the marginal effects of log(min. wage)-log(p50), using regression coefficients from the listed years (1979 to 1989, 1991, or 2012), and evaluated at the hours-weighted average of log(min. wage)-log(p50) across states from 1979-2012. Observations are state-year observations. 95% confidence interval is represented by the dashed lines.

Figure 7A: Actual and counterfactual change in log(p)-log(p50)
Female wage distribution, 1979 to 1989

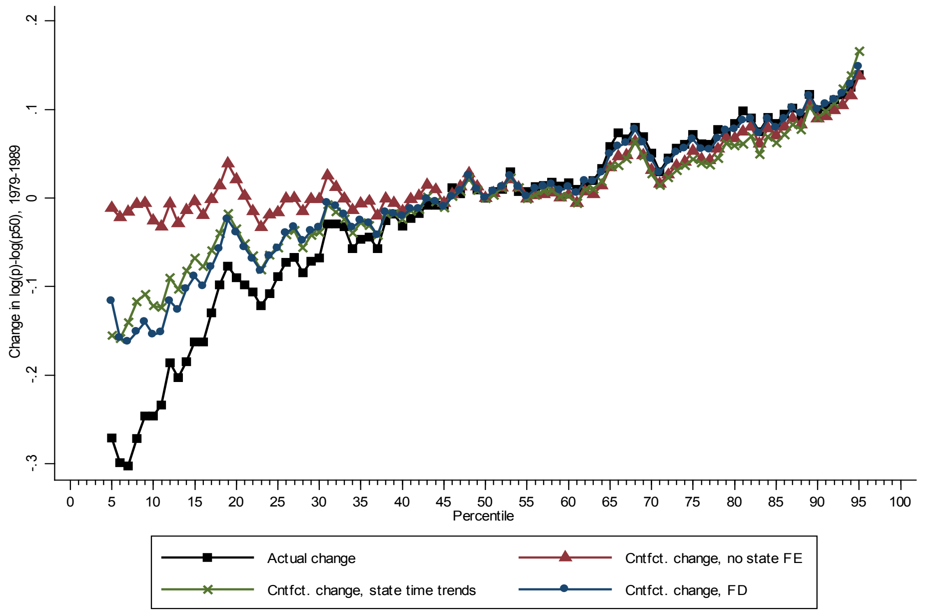
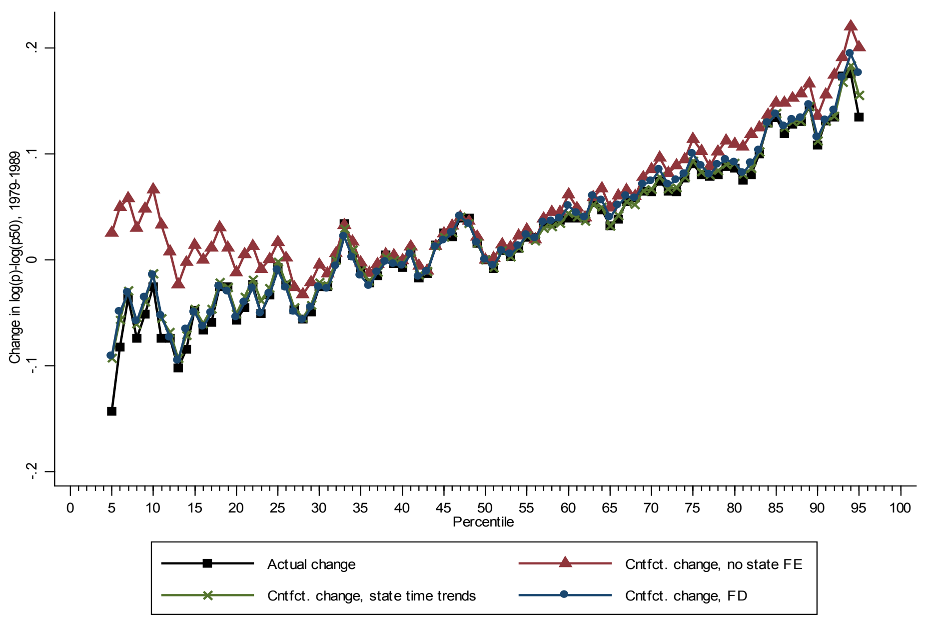


Figure 7B: Actual and counterfactual change in log(p)-log(p50),
Male wage distribution, 1979 to 1989



Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the male wage distribution. Counterfactual changes are calculated by adjusting the 1979 wage distributions by the value of states' effective minima in 1989 using coefficients from OLS regressions without state fixed effects (column 1 of table 2) and 2SLS regressions with state fixed effects and time trends or first-differenced 2SLS regressions with state fixed effects (columns 4 and 5 of table 2).

Figure 8A: Actual and counterfactual change in log(p)-log(p50),
Male and female pooled wage distribution, 1979 to 1989

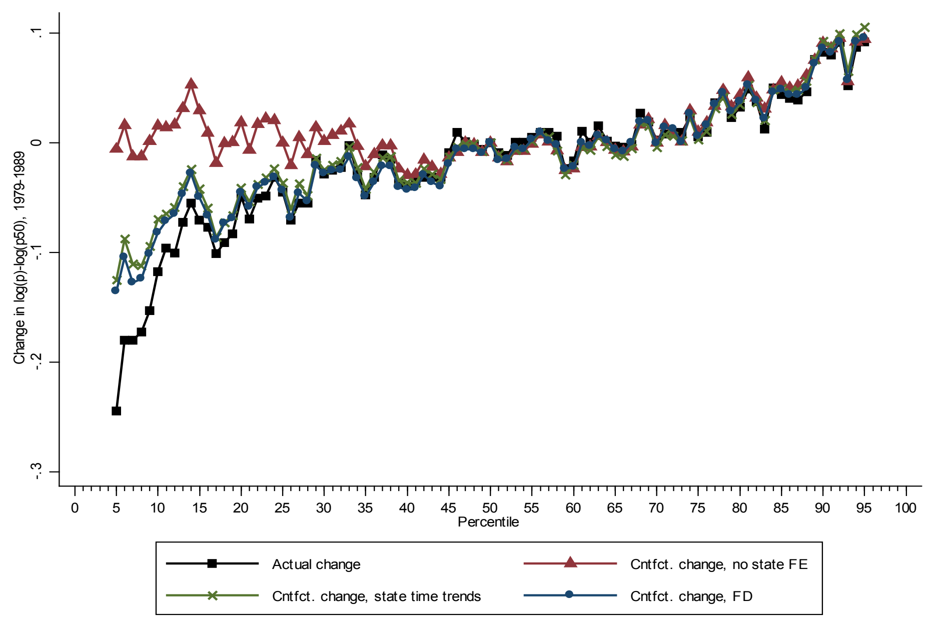
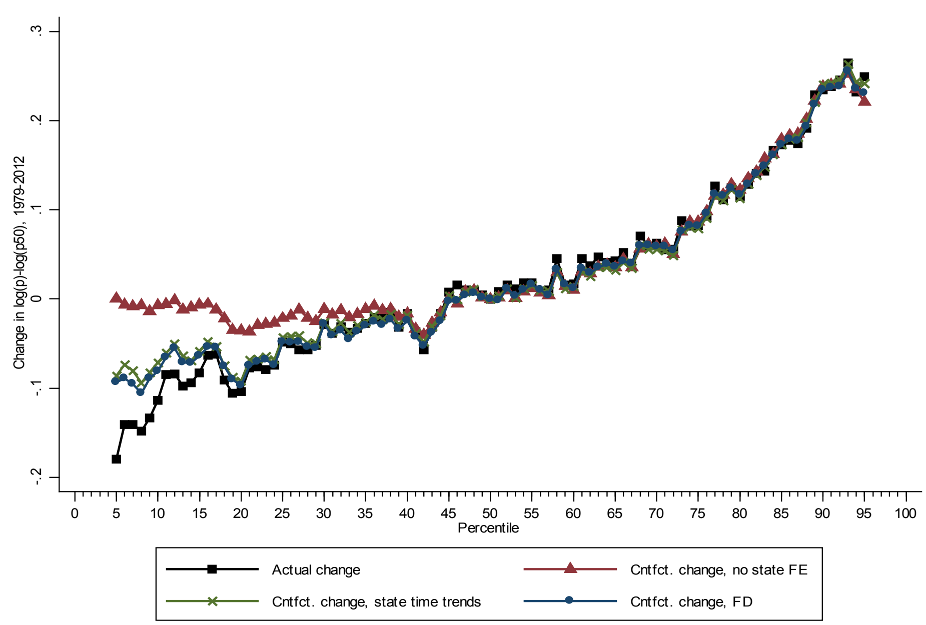
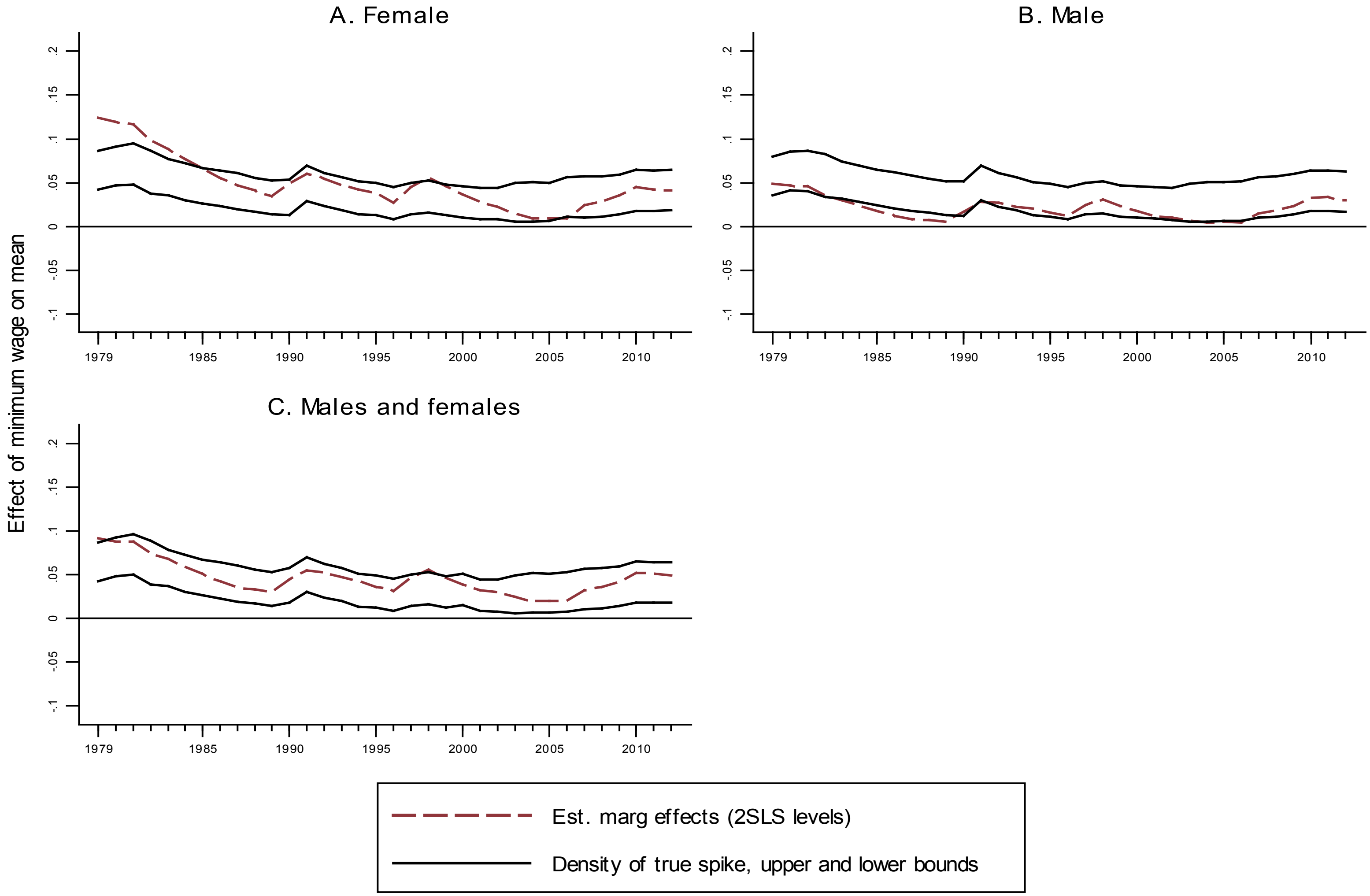


Figure 8B: Actual and counterfactual change in log(p)-log(p50),
Male and female pooled wage distribution, 1979 to 2012



Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the male and female pooled wage distribution. Counterfactual changes in Panel A are calculated by adjusting the 1979 wage distributions by the value of states' effective minima in 1989 using coefficients from OLS regressions (column 1 of table 2) and 2SLS regressions (columns 5 and 6 of table 2). Counterfactual changes in Panel B are calculated by adjusting both the 1979 and 2012 wage distributions by the value of states' effective minima in 1989 using coefficients from OLS regressions (column 1 of table 2) and 2SLS regressions (columns 4 and 5 of table 2).

Figure 9: Comparison of estimated effects of the minimum on the mean and density at the true spike



Notes: Mean effects represent the average marginal effects of the minimum wage (weighted across states), estimated from 2SLS regressions of log(mean) on the effective minimum and its square, year and state fixed effects, state time trends, and the log median, where the effective minimum and its square are instrumented as in the earlier analysis. The bounds for the density of the true spike are estimated from a maximum likelihood procedure procedure described in Appendix D.