

The Role of the Minimum Wage in the Evolution of U.S. Wage Inequality
over Three Decades: A Modest Re-Assessment*

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PRELIMINARY

We offer a fresh analysis of the effect of state and federal minimum wages on earnings inequality over 1979 to 2007, exploiting substantially longer state-level wage panels than were available to earlier studies as well as a proliferation of recent state minimum wage laws. We obtain identification using cross-state and over-time variation in the ‘bite’ of federal and applicable state minimum wages, as per influential studies by Lee (1999) and Teulings (2000, 2003). We address two econometric issues that may afflict earlier work: simultaneity bias stemming from both errors-in-variables and from a non-zero correlation between mean state wages and latent state wage variances. We find, consistent with prior work, that the minimum wage reduces inequality in the lower tail of the wage distribution. But the estimated effects, corrected for both sources of bias, are considerably smaller than suggested by earlier OLS estimates: the minimum wage explains at most 50% of the rapid rise in female inequality during the 1980s, 25% of the rise in male inequality, and 30 – 40% of the rise in pooled gender inequality. Though modest, these impacts are still larger than would be implied if the minimum wage only raised wages at or below the statutory minimum, suggesting the presence of spillovers from the minimum to higher percentiles. We estimate these spillovers by structurally fitting the latent wage distribution, calculating the mechanical effect of the minimum wage through truncation, and inferring spillovers by comparison of the mechanical and observed distributions. Spillovers appear to account for a substantial amount of the minimum’s modest impact on percentiles in the lower tail of the wage distribution. Subsequent analysis shows, however, that spillovers and measurement error have similar implications for the effect of the minimum wage on the shape of the *measured* wage distribution at the lower tail. With available precision, we cannot reject the hypothesis that the full effect of the minimum wage on the *actual* wage distribution is due exclusively to direct effects of the statutory minimum wage on the percentiles where it binds rather than spillovers to higher percentiles. 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—that is, the shape of the earnings distribution—was largely overlooked prior to the seminal 1996 contribution of DiNardo, Fortin and Lemieux (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 wage distribution. Most relevant to this paper, the female 10/50 (‘lower tail’) log hourly earnings ratio expanded by 23 log points (two thirds) between 1979 and 1988, while male and pooled-gender 10/50 ratios grew by 5.7 and 10.5 log points in the same interval (Table 1). To assess the causes of this rise, DFL constructed counterfactual wage distributions that potentially account 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 conclude 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 counterfactual wage distributions derive exclusively from reweighting of observed wage densities rather than controlled comparisons. As such, the DFL exercise is closer in spirit to simulation than 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.

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).

Building on this observation, Lee (1999) exploited cross-state 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 wage inequality during 1979 through 1991 was due to the falling minimum rather than changes in underlying (‘latent’) wage inequality. Amplifying the conclusions of DFL, Lee estimated that *more than* the entire rise of lower tail earnings inequality between 1979 and 1989 was due to the falling federal minimum wage; had the minimum been constant throughout this period, observed wage inequality would have fallen.²

These influential findings present a number of puzzles. First, the rise in *lower tail* inequality during the 1980s was accompanied by an equally pronounced increase in dispersion in the *upper-half* (90/50) of the distribution (Figure 1B), an area where the minimum is unlikely to be relevant. Though the contemporaneous rises in upper and lower tail inequality need not have identical causes, it would be surprising if they had no causes in common. Second, at no time between 1979 and 2007 were more than six percent of male hours paid at or below the federal (or applicable state) minimum wage (Table 1). If the falling minimum wage explains the bulk of the rise in male wage lower-tail inequality, this implies extremely large spillovers from the minimum wage to non-covered workers. Finally, the Lee analysis uncovers, and scrupulously reports, a number of puzzling results that cast some doubt on the validity of the exercise. Most surprisingly, the main estimates imply that the declining federal minimum wage substantially *reduced* the growth of upper-tail inequality in both the male and pooled-gender wage distributions during 1979 to 1991, a finding that appears implausible on a priori grounds.³

Spurred by these puzzles, we offer a fresh analysis of the impact of state and federal minimum wages on the shape of the US earnings distribution. Our work benefits from substantially longer state-level wage panels than were available to earlier studies, and from a

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.

³ See Lee (1999) Table II. The large, positive and highly significant coefficients in this table imply that a 1 log point in the effective minimum wage (defined as the difference between the log state minimum wage and the log state median wage), reduces male and pooled-gender 90/50 log wage inequality by 0.16 to 0.44 log points.

proliferation of state minimum wage laws enacted after 2000 that generate usable state variation in wage floors.⁴ Our statistical approach follows closely the model of Lee and Teulings; we obtain identification by using cross-state and over-time variation in the ‘bindingness’ of federal and applicable state minimum wages. The main advance of our approach is in estimation. Because the impact of the minimum wage will in part depend upon where in the wage distribution the statutory minimum falls, it is necessary to scale the statutory minimum by some measure of expected ‘bindingness.’ Lee (1999) proposes a natural scaling: the gap between the log state minimum and log state median wage, which Lee labels the ‘effective minimum.’

This approach introduces two potential confounds. The first arises if state median wages levels are correlated with the latent variance (i.e., absent the minimum wage) of state wage distributions, i.e., if states with high median wages have relatively high (or low) underlying wage variances.⁵ In this case, the use of the state median to calculate the ‘effective minimum wage’ measure will bias estimates of the effect of the minimum on wage inequality upward or downward, depending on the nature of the mean-variance correlation. The second, more mundane, concern with using the median to calculate the effective minimum is that the median wage appears on both sides of the estimating equation, i.e., in the effective minimum wage and in the 10/50 earnings ratio and other inequality metrics. This is problematic inasmuch as sampling variation in the median wage may generate simultaneity bias in OLS models that leads to inflated estimates of the effect of the minimum on state wage distributions.⁶

We find that both of these confounds are empirically important. In particular, median state log wages and log wage variances are strongly positively correlated, even in portions of the distribution where the variance of wages is unlikely to be affected by the minimum wage (such as the log(60)-log(40) gap). This pattern indicates that states with high median wages have

⁴ As of 2007, 30 states had established state minimum wages that exceeded the federal level (Table 1).

⁵ Lee (1999) is explicit on this point: The estimation assumes that the scale (variance) of state wage distributions is independent of state medians conditional on year effects.

⁶ Cognizant of the possibility of simultaneity bias, Lee takes a number of steps to minimize its impact. These steps do not appear to fully resolve the problem, as we show below.

relatively high and persistent levels of latent wage inequality, necessitating inclusion of state fixed effects (and in some cases trends) in our primary models. State effects exacerbate the problem of simultaneity bias resulting from errors-in-variables, however. The reason is that more of the remaining variation in the effective minimum wage is the result of sampling variation.

To purge this simultaneity bias, we apply the canonical (Durbin, 1954) technique of instrumenting the error-ridden measure with a set of variables that do not share common measurement error with the error-ridden variable. Our first instrumental variables strategy is to instrument the effective minimum wage (statutory minimum minus state median) with the statutory minimum wage in each state and year. This follows an approach first used by Card, Katz and Krueger (1993) in their reanalysis of the employment effects of minimum wage laws. A second approach is to employ split-sample instrumental variables ('SSIV,' cf. Angrist and Krueger, 1995). We use half of the estimation sample (chosen at random) to compute the effective minimum and wage percentiles, while using the other half to form a second estimate of the effective minimum wage that serves as an instrumental variable for the first. For purposes of comparison to these IV estimates, we also replicate the OLS models used in Lee (1999) and extend them to 2007.

Our main results are as follows. In partial confirmation of prior work, we find that the minimum wage significantly affects the shape of the US wage distribution during the 1980s, particularly for females. However, OLS estimates substantially overestimate the contribution of the minimum wage to inequality due to violation of the identification assumptions discussed above. The bias is most severe for the male and pooled-gender wage distributions, but is also pronounced for the female distribution.⁷ During the period of 1979 through 1988, when the erosion of the minimum wage was most rapid, OLS estimates suggest that latent wage inequality was mostly unchanged during 1979 to 1988 or increased modestly. By contrast, 2SLS models indicate that the minimum wage explains less than half of the substantial increase in

⁷ The problem is likely more severe for the male and the pooled distributions because the minimum wage is largely non-binding in these samples. Hence, the significant minimum wage coefficient in OLS models appears primarily due to a combination of the two identification issues outlined above.

female inequality during this period, about one quarter of the increase for males, and about 40% of the increase for the pooled gender distribution. Graphical comparisons of OLS and 2SLS estimates reinforce the conclusion that OLS estimates are unlikely to be reliable.

To benchmark the applicability of these findings outside of the closely studied period of 1979 through 1988, we also calculate the contribution of the minimum wage to inequality during 1998 to 2007. During this time, the employment-weighted average of state minimum wages fell by 10.6 log points. 2SLS estimates indicate that the falling minimum contributed modestly to male, female, and pooled-gender wage inequality during both periods. By contrast, OLS models generally suggest that the declining minimum either masked compressions of (latent) inequality or that latent growth in inequality was not as great as suggested by 2SLS estimates—a result that likely derives from simultaneity bias.

The modest effects of the minimum on inequality that we identify may arise through two channels: a direct (mechanical) impact whereby wages below the minimum are increased;⁸ and an indirect (spillover) effect whereby earnings above the minimum are also pushed upward (due perhaps to incentive or equity considerations). While our 2SLS models capture the net of these two effects, it is also of interest to analyze their separate contributions since any usable forecast of the effect of the minimum on wage inequality must account for spillovers (if present).

Identifying these spillovers requires an empirical model of the full latent distribution of wages (or at least its lower tail), purged of both direct and indirect minimum wage effects. We model each state's latent wage distribution as log-normal. We estimate the parameters of these distributions using wage observations from higher percentiles of the distribution, where the minimum wage is unlikely to be relevant. We then calculate the mechanical impact of the minimum wage by truncating the lower tail of the (estimated) latent distribution, and we infer spillovers by comparing the 'mechanical' distribution with the observed distribution.

⁸ 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.

Though the minimum wage had only a modest effect on inequality over 1979 to 2007, spillovers were a significant component of this impact. At its highest level (in 1979), the minimum wage mechanically raised the 10th percentiles of the female distribution by 20 log points, and spillovers raised percentiles by an additional 2 log points. Both the direct and spillover effects were considerably smaller for males and for the pooled distribution. As the real minimum eroded between 1979 and 2007, the direct impact of the minimum wage on observed 50/10 inequality fell substantially, so that by the mid-2000s, the majority of the observed minimum wage effect on the 50/10 was due to spillovers of the minimum wage onto percentiles above where it bound.

A drawback of these spillover estimates is that they may be in part be driven by measurement error in wage reporting rather true wage spillovers. In particular, if a subset of workers that are paid the minimum wage tends to report wage values that are modestly above or below the true minimum—and if the central tendency of this reporting error moves in tandem with the minimum wage—this may create the appearance of spillovers where none are present. Thus, despite the apparent existence of substantial spillovers in the *measured wage* distribution, it's possible that the spillovers to the *actual* wage distribution are smaller or non-existent.

To explore this possibility, we perform a bounding exercise that compares the estimated effect of the minimum wage on *mean* wages (which should *not* be biased by measurement error) with the magnitude of the spike in the wage distribution at the statutory minimum, corrected for measurement error. Under the null hypothesis that the minimum wage has direct effects but no spillovers, we show that the elasticity of the mean log wage with respect to the log minimum is equal to the size of this spike. For most years, the estimated mean effect remains within the upper and lower bounds of the estimated spike. Based on this analysis, we are unable to reject the 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 effects of the minimum wage on the actual wage distribution are even smaller than the effects of the minimum wage on the measured wage distribution.

The remainder of the paper proceeds as follows. Section I describes the data and presents simple, reduced-form estimates of the relationship between the statutory minimum wage and inequality throughout the distribution. Section II presents more fully parameterized models that, like Lee (1999), explicitly account for the bite of the minimum wage in estimating its effect on the wage distribution. This section compares parameterized OLS and 2SLS models, and documents the pitfalls that arise in the OLS estimation. Section III summarizes our counterfactual exercise in which, following Lee, we use point estimates from the main regression models to calculate counterfactual changes in wage inequality holding the real minimum wage constant. Section IV presents estimates of the magnitude of spillovers from the minimum wage onto percentiles above where it directly binds, derived from parametric estimates of the latent wage distribution that provide a full accounting of mechanical and spillover effects. Section V describes results from an exercise explores the potential contribution of measurement error to the identification of spillover effects. The final section concludes.

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

The Federal minimum wage remained constant in nominal terms over the nine-year period between 1981 and 1990. Similarly, the Federal minimum wage remained at \$5.15 between September 1997 and July 2007, and by July 2007, the real value of the Federal minimum was lower than it had been at any point in the past fifty years (Figure 1). The difference between the two periods is that by the late 1980s, only 15 states minimum wages exceeded the federal minimum wage; by 2007, 30 state minimum wages did. As a result, the average real value of the minimum wage applicable to workers in 2007 was not much lower than it was in 1997, and was significantly higher than if states had not enacted their own minimum wages. Appendix Table 1 illustrates the extent of state minimum wage variation between 1979 and 2007.

We use these differences in minimum wages across states and over time as one source of variation for identifying the impact of the minimum wage on the wage distribution. As an additional form of variation, we use the notion that the wage distribution of lower wage states

should be more affected for a given value of the real minimum wage. Table 1 provides examples of this. For 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 was equal to the 3rd percentile of the female wage distribution in Nevada, equal to the 31st percentile in Mississippi, and the median percentile at which it bound, across all states, was around the 12th percentile. In 1979, this variation in the “bite” or “bindingness” of the minimum wage is due mainly to cross-state differences in wage levels, since only Alaska had a state minimum wage that exceeded the federal minimum. In later years—particularly 2000 and after—this variation is 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 by pooling all individual responses from the Current Population Survey Merged Outgoing Rotation Group (CPS MORG) for each year. An individual’s wage is taken to be his reported hourly wage, if the individual reports being paid by the hour, and is otherwise calculated as weekly earnings divided by weekly hours worked. 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. We make no adjustment for individuals with particularly low wages (i.e. sub-minimum wages). We then take these individual wage data and calculate all percentiles of the male, female, and pooled state wage distributions for 1979-2007, weighting individual observations by their CPS sampling weight multiplied by their weekly hours worked.

Our primary analysis is at the state-year level. However, minimum wages often change during the middle of a year. We resolve this by assigning the value of the minimum wage that was in effect the longest throughout the calendar year to the state-year observation. For those states and years in which a different minimum wage was in effect for six months in the year, the maximum of the two is used. Alternatively, we have tried assigning the maximum of the minimum wage within a year as the applicable minimum wage, and this leaves our conclusions unchanged.

II. Parametric estimation of minimum wage effects on the wage distribution

A. Econometric framework

To properly make inference about the impact of the minimum wage at all percentiles of the wage distribution, we are interested in estimating specifications for which the impact of the minimum wage is a function of not only the real value of the minimum wage, but is also a function of the overall shape or location of the wage distribution. One way to do this is to scale the minimum wage by some measure of the general level of wages. Lee (1999) estimated minimum wage effects in this spirit, and used the log of the minimum relative to the median as his measure of the ‘bite’ of the minimum wage. We will also use this measure and refer to it as the effective minimum.

Use of the effective minimum can be justified in the following way, which fleshes out the arguments used by Lee (1999). Denote by $w(p)_{st}^*$ the log wage in state s at time t for percentile p in the absence of the minimum wage—call this the latent wage distribution. With a minimum wage, denoted in log form by w_{st}^m , the actual log wage at percentile p , which we will denote by $w_{st}(p)$ will deviate from the latent distribution for at least some percentiles. If, for example, the minimum wage had no effect on employment rates, and no spillovers then we would have the relationship:

$$w_{st}(p) = \max[w_{st}^*(p), w_{st}^m] \quad (1)$$

However, if there are spillovers or some employment effects, then the minimum wage will have an effect on percentiles above where it binds (see Lee, 1999, for more discussion of these arguments, or Teulings, 2000, for an explicit supply and demand model with this feature). So, let us generalize (1) to the form:

$$w_{st}(p) = \phi[w_{st}^*(p), w_{st}^m] \quad (2)$$

What are plausible restrictions on the function $\phi[.,.]$? We would expect it to be increasing in both its arguments and that it also satisfies a homogeneity property—that if the latent

percentile and the minimum wages both rise in the same proportion, the actual percentile also rises in that proportion. As the model is expressed in logs this restriction can be written as:

$$\phi[w_{st}^*(p) + a, w_{st}^m + a] = a + \phi[w_{st}^*(p), w_{st}^m] \quad (3)$$

Now set $a = -w_{st}^*(p)$ and applying (3) to (2) we have that:

$$w_{st}(p) = w_{st}^*(p) + \phi[0, w_{st}^m - w_{st}^*(p)] = w_{st}^*(p) + \psi(w_{st}^m - w_{st}^*(p)) \quad (4)$$

i.e., the deviation of the actual percentile from the latent percentile depends on the gap between the minimum and the latent percentile. What are the plausible restrictions on the function $\psi(\cdot)$? We would expect it to be positive everywhere (otherwise the minimum wage would reduce wages at some percentiles) and to have a positive first derivative. In addition, if the minimum wage is very low (or non-existent) we would expect the actual percentile to be very close to the latent percentile so that we have $\psi(-\infty) = 0$. On the other hand, if the minimum wage gets very high we would expect the actual percentile to be very close to the minimum wage so that we have $\lim_{x \rightarrow \infty} \psi(x) = x$. Graphically, we might expect that the relationship between deviations of the actual from the latent percentile and the difference between the minimum wage and the latent percentile looks something like that presented in Figure 2. In this figure, the x-axis plots the difference between the minimum and the latent value of percentile p . The y-axis plots the difference between the observed and latent values of percentile p . For low values of the minimum wage relative to the latent percentile, the minimum wage has no effect on the wage distribution so the observed value of the percentile is the latent value. For percentiles for which the minimum wage exceeds the latent percentile, the observed percentile will be equal to the minimum wage.

Figure 2 also allows for the possibility of ‘spillovers’ where the minimum either raises wages that are latently below the minimum to a value exceeding the minimum, or raises wages that are latently above the minimum to a value exceeding their latent level. If present, such spillovers would be largest at the location where the minimum wage exactly equals the latent

wage value (in Figure 2, this is the intersection of the x and y axes).⁹ Spillovers would be expected to attenuate in either direction from this point: further down the wage distribution, the minimum becomes extremely binding and so the mechanical effect dominates; further upward, the minimum wage becomes increasingly less relevant.

This discussion should make it clear that non-linearity is likely to be an important feature of (4) so that some thought needs to be given to the functional form of the estimating equation. In what follows, our main specification uses a quadratic approximation (as does Lee, 1999), and we approximate (4) by:

$$w_{st}(p) = w_{st}^*(p) + \alpha_0 + \alpha_1(w_{st}^m - w_{st}^*(p)) + \alpha_2(w_{st}^m - w_{st}^*(p))^2 \quad (5)$$

However, it should be noted that a quadratic cannot have a shape similar to that drawn in Figure 2 over the whole of its range so that we have to exercise caution in estimating minimum wage effects outside the observed sample. In particular, this specification cannot be used for an assessment of what the distribution of wages would be like if there was no minimum wage.

To make (5) into an estimable equation wage we need to put some additional structure on the form taken by the latent wage distribution. We follow Lee (1999) in assuming that the latent wage distribution can be summarized by 2 parameters – the median and the variance – so that we can write:

$$w_{st}^*(p) = \mu_{st} + \sigma_{st}F^{-1}(p) \quad (6)$$

We have the normalization $F^{-1}(50) = 0$ so that μ_{st} is the median log wage in state s at time t. Plugging (6) into (5) and collecting terms we have that:

$$w_{st}(p) - \mu_{st} = \alpha_0 + \sigma_{st}(1 - \alpha_1)F^{-1}(p) + \alpha_2[\sigma_{st}F^{-1}(p)]^2 + [\alpha_1 - 2\alpha_2\sigma_{st}F^{-1}(p)](w_{st}^m - \mu_{st}) + \alpha_2(w_{st}^m - \mu_{st})^2 \quad (7)$$

The first two terms are related to the overall evolution of wage inequality and last two terms to the effect of the effective minimum. Note that the coefficients in (7) will vary with the

⁹ Any effect of the minimum at this location is a pure spillover since the minimum wage is non-binding at $w^m = w^*$.

percentile, not just because p appears in the linear term of the effective minimum but also because, as pointed out by White (1980), the coefficients α will vary with the data. Intuitively we would expect that a rise in latent wage inequality leads to a larger impact on lower percentiles for a given effective minimum.

For (7) to be estimable one also needs models for the median and variance. There are a number of potential options, and we start our discussion with the choices made by Lee. Lee replaces μ_{st} by the observed median, σ_{st} by a set of time dummies and assumes that any cross-state variation in latent wage inequality is uncorrelated with the median and can therefore be subsumed into the error without causing bias in the estimated impact of the minimum wage. Hence, equation (7) can be written as:

$$w_{st}(p) - w_{st}(50) = \alpha_t + \beta_1(w_{st}^m - w_{st}(50)) + \beta_2(w_{st}^m - w_{st}(50))^2 + \varepsilon_{st} \quad (8)$$

In columns (1), (6), and (11) of Table 2 we present estimates of the marginal effects of the effective minimum when estimated at the weighted average of the effective minimum over all states and all years between 1979-2007 for selected percentiles. If we look at the lower percentiles, we find, as Lee did, large significant effects of the minimum wage extending throughout *all* percentiles below the median for the male, female and pooled wage distributions. Additionally, we estimate modest effects of the minimum wage at the top of the male and pooled wage distributions. Figures 3A, 4A, and 5A plot the estimated marginal effects of the minimum wage at each percentile. Taking these results at face value would seemingly suggest that the minimum wage affects the entirety of the wage distribution, and implies a systematic relationship between the effective minimum wage and upper wage percentiles of the male and pooled distributions.

One possible form of misspecification is that the identifying assumption that state latent wage inequality is uncorrelated with the median is false. Indeed if we regress the log(60)-log(40) on the median (which should be uncorrelated if the density function is symmetric around the median) and time dummies (to capture the controls put in equation (8)), the log median has a t-statistic of 16 for females, 3.7 for men and 13.6 for the combined sample. This suggests that those states with high median wages have high levels of latent wage inequality. Since this

seemingly indicates permanent differences in latent wage inequality across states, state fixed effects should be included in estimation of (8). Lee also reports this type of specification (Tables II and III), and we display estimates from OLS estimation of (8) with state fixed effects in columns (2), (7), and (12) of Table 2. Columns (3), (8), and (13) add state-specific time trends, and the marginal effects as implied by these estimates are plotted in Figures 3B, 4B, and 5B. The inclusion of state fixed effects or state-specific time trends yields a large and positive relationship between the effective minimum wage and upper tail percentiles for all samples. The last two columns in panels A, B, and C estimate first-differenced analogues to equation (8). Estimated marginal effects remain similar to what is observed when estimating the equation in levels.

The explanation for this problem is almost certainly a point made by Lee (1999)—the presence of the median in both the dependent and independent variables in (8) induces an artificial positive correlation caused by sampling variation. This potentially gets worse when state fixed effects are included, as more of the remaining variation is the result of sampling variation.

Lee (1999) is aware of this problem and, as a potential solution, uses two different measures of central tendency in the dependent and independent variables: the median in the dependent variable, but trimmed mean on the right-hand side (i.e. the mean after excluding the bottom and top 30 percentiles). Although this does reduce the correlation, it does not eliminate it. In fact, one can show 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 one, but very high (see the derivation in the Appendix). So, this method does not necessarily solve the problem.

Here, we use another method to estimate the relationship represented by (8). Instead of estimating with OLS, we instrument the effective minimum terms. We use two distinct sets of instruments. For the first set, we use the legislated minimum wage (the maximum of the federal minimum wage and the state's minimum wage) and its square, and the minimum wage interacted with a measure of the average wage in the state between 1979 and 2007 (we use the average of each state's median). This latter instrument is to give us instruments which

differ in their ability to discriminate between the linear and quadratic terms¹⁰. Since legislated minimum wages provide identification using changes to state minimum wage laws, the instrument identifies minimum wage effects for the wage distribution of states which increase their minimum wages above the federal minimum. A shortcoming of this instrument is that there is quite limited cross-state variation in the legislated minimum wage during the 1980s. This makes identification based on the legislated minimum wage instrument tenuous in this period.

As an alternative instrument, which provides broad identification for all states and all years, we use a variant on split sample instrumental variables (Angrist and Krueger 1995). In particular, we split the sample in two halves (choosing observations at random). We use the first half to calculate wage percentiles and the effective minima by state and by year. We use the second half to produce a second estimate of the effective minima (again, by state and by year), which then serve as instrumental variables for the first set. We repeat this procedure 50 times (each time drawing a new random division of the data), and average the resulting coefficients. The bottom two rows of Table 3 provide F-statistics from testing the joint significance of the five instruments—the legislated minimum wage and the legislated minimum squared, the interaction term, and the effective minimum and its square as estimated in the other half of the sample. Jointly, the instruments are highly significant across all specifications.

Columns (1), (6), and (11) of Table 3 present estimates of the marginal effect of the effective minimum wage from equation (8) with 2SLS. The estimated impact of the minimum wage is large and significant throughout the lower half of the female, male, and pooled wage distributions. Adding state fixed effects reduces the magnitude of minimum wage effects everywhere throughout the distribution, though also results in a significant positive relationship between the effective minimum wage and upper tail inequality in all samples. This correlation

¹⁰ More precisely, the instruments for equation (8) are w_{st}^m , $(w_{st}^m)^2$, $w_{st}^m \cdot \overline{w_s(50)}$, $w_{st}^m - \widetilde{w_{st}(50)}$, and $(w_{st}^m - \widetilde{w_{st}(50)})^2$, where $\overline{w_s(50)}$ is the average median within a state between 1979 and 2007, and the last two expressions are the effective minimum and its square as estimated from the second half of the sample. The instruments for the first-differenced analogue, which we describe more fully below, are Δw_{st}^m , $\Delta(w_{st}^m)^2$, $\overline{w_s(50)} \cdot \Delta w_{st}^m$, $\Delta(w_{st}^m - w_{st}^m(50))$, and $\Delta(w_{st}^m - w_{st}^m(50))^2$, where Δw_{st}^m represents the annual change in the log of the legislated minimum wage.

with upper tail inequality suggests that shocks to the wage distribution may be correlated with changes in minimum wages. Consistent with this, the addition of state-specific time trends (columns (3), (8), and (13)) somewhat breaks the association between the effective minimum and upper-tail percentiles.¹¹ Figures 3C, 4C, and 5C provide a clearer picture of how the minimum wage is estimated to affect inequality throughout the wage distribution using this specification. After including state trends, the association between the effective minimum wage and upper-tail inequality is much more modest, and minimum wage effects are significant through the 30th percentile of the wage distribution for each of the three samples. The magnitude of the effects is largest at the bottom of the female wage distribution, and smallest at the bottom of the male wage distribution, which is as expected given the overall higher male wage levels.

In addition to estimating equation (8) in levels with state fixed effects, we also estimate the equation in its first-differenced form. Columns (4), (9), and (14) provide estimates of the first-differenced analogue to the levels specification with state fixed effects, and columns (5), (10), (15) include state fixed effects as well (and is therefore analogous to the inclusion of state trends in the levels estimation). Figures 4D, 5D, and 6D plot the marginal effects across all wage percentiles for this last set of estimates. The estimated impact of the minimum wage is somewhat smaller in magnitude throughout the lower tail of the distribution than when the causal effects are estimated in levels. In addition, the effects are less precisely estimated¹².

To summarize, our estimates imply that a 10 log point increase in a state's effective minimum reduces female 50/10 inequality by between 1.3-2.7 log points, male inequality by about 1 log point, and pooled gender inequality by 1.5-2 log points. OLS estimates are at least 2.5 times as large as 2SLS estimates (and typically greater), and imply a substantial impact of the minimum wage on inequality throughout most of the wage distribution.

¹¹ Recent work on the employment effects of the minimum wage have argued for the inclusion of state trends for this reason. See, for instance, Allegretto, Dube, and Reich (2008).

¹² As robustness checks, we have also estimated models with a cubic in the effective minimum, and estimated using monthly or quarterly data rather than yearly data, and found similar results (results available upon request).

III. Benchmarking the effect of the minimum wage on the shape of the wage distribution

Our analysis confirms a significant impact of the minimum wage on wage inequality. To develop a precise sense of the size of this contribution, we conduct two sets of analyses. The first, following Lee (1999), uses point estimates from the main models to estimate the changes in wage inequality that would counterfactually have occurred had the minimum wage held constant at a given real level. This analysis provides an estimate of the net contribution of the minimum to wage inequality. It does not distinguish between mechanical and spillover effects, however. The second analysis decomposes these two effects through a more ambitious modeling exercise.

A. Counterfactual wage inequality estimates with the real minimum held constant

A straightforward approach to gauging the contribution of the minimum wage to inequality trends is to use the earlier regression estimates to calculate counterfactual wage distributions, holding the effective minimum wage constant. Following Lee (1999), we calculate for each observation in the dataset its rank in its respective state-year wage distribution. We then adjust each wage by the quantity:

$$\Delta w_{st}^p = \hat{\beta}_1(\tilde{m}_{s,\tau 0} - \tilde{m}_{s,\tau 1}) + \hat{\beta}_2(\tilde{m}_{s,\tau 0}^2 - \tilde{m}_{s,\tau 1}^2) \quad (9)$$

where $\tilde{m}_{s,\tau 1}$ is the observed end-of period effective minimum in state s in some year $\tau 1$, $\tilde{m}_{s,\tau 0}$ is the corresponding beginning-of-period effective minimum in $\tau 0$, and $\hat{\beta}_1, \hat{\beta}_2$ are point estimates from the OLS and 2SLS estimates in Tables 2 and 3. 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.¹³ One feature of this simulation procedure bears note: it does not permit estimation of the full ‘latent’ distribution of wages—i.e., in the absence of any minimum wage—since the effective minimum

¹³ Also distinct from Lee, we use states’ observed median wages when calculating \tilde{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.

wage measure, equal to the logarithm of the minimum minus the logarithm of the median, is undefined at a minimum wage of zero. This simulation tool is therefore appropriate for estimating the impact of the minimum wage over ranges observed in the data. We address this infirmity in the subsequent sub-section.

Panel A of Table 4 shows that the female 50/10 log wage ratio increased by 23.4 log points between 1979 and 1988. To form counterfactual estimates of what the 50/10 would have been in 1979 had the minimum wage been at its lower 1988 value throughout, we adjust 1979 wages by the procedure outlined above. Applying the OLS point estimates from Table 2 (column 1) to this exercise, we calculate that the 50/10 would counterfactually have risen by approximately 3.2 log points over this period had the state 1979 effective minimums actually been at 1988 levels, using coefficients obtained by estimating equation (8) over the full 1979 to 2007 sample (column 1) or 1979 to 1988 (column 2). Thus, consistent with Lee (1999), OLS estimates imply that the minimum wage can account for the bulk (20.2 of 23.4 log point increase, or 85%) of the observed expansion of lower tail female wage inequality in this period.¹⁴

The next four rows of the table present analogous counterfactuals estimated using 2SLS in lieu of OLS. We present four sets of counterfactuals. The first two counterfactuals are based upon 2SLS estimates of equation (8), including state and year fixed effects and state-specific time trends (that is, estimates from columns 3, 8, and 13 of Table 3). The second set are based on first-differenced 2SLS estimates of (8), including state and year fixed effects (columns 5, 10, and 15 of Table 3). For each set of estimates, we use two different instrument sets. The first uses split-sample IV only. The second also includes the log of the legislated minimum wage, its square, and its interaction with the average median wage for a state.

Using coefficients estimated for the full sample duration (column 1), the 2SLS first-differenced estimates imply that the falling minimum wage explains no more than 7.6 of the 23 log point expansion of the female lower tail (33%) during 1979 through 1998. Fixed effect

¹⁴ Lee (1999, Table IV) estimates that the female 50/10 rose by 18.6 log points between 1979 and 1989, and that the falling minimum accounts for all but 4.5 log points of this increase. We focus on the interval of 1979 to 1988 rather than 1979 to 1989 because wage lower tail wage inequality for males had already begun to reverse course by 1989. If we instead focus on 1979 to 1989, our results are substantively identical.

estimates imply a somewhat larger contribution, however, (around 16 or 17 log points, or about 50%). Using estimated coefficients from models estimated only over 1979 to 1988 (column 2), the estimated contribution of the minimum wage is similar to that from the full sample when the instrument set includes only split-sample instruments. When including state minimum wages as additional instruments, the minimum is estimated to have a large impact, with contributions approaching those from OLS models. Since at most 10 states have minimum wages that exceed the federal minimum during this period, the identifying variation from using state minimum wages is stronger for these states than for others. For this reason, we view the inclusion of state minima in the instrument set as inappropriate when using the shortened 1979 to 1988 sample.

For the most part, these counterfactual estimates represent significant downward revisions in the contribution of the minimum wage to rising female inequality over the 1980s from what is implied by OLS estimates. When these calculations are repeated for the male and pooled-gender wage distributions (panels B and C), the contrast between OLS and 2SLS estimates is at least as sharp. OLS models imply that male and pooled-gender lower-tail inequality would have contracted in the absence of a falling minimum wage. 2SLS estimates instead suggest that the minimum explains no more than one-fifth of the total expansion of the male 50/10, and no more than 40% of the rise in the 50/10 for the pooled distribution.

How robust are these findings across time periods and specifications? In columns (4), (5), and (6) of Table 4, we calculate identical regression-based counterfactuals for 1998 to 2006, during which real minimum also dropped rapidly.¹⁵ While expansion of lower tail inequality was much smaller in the male and female wage distributions during these intervals, and though lower tail inequality contracted slightly in the pooled sample, the pattern of counterfactuals is still quite similar. OLS estimates again imply that, were the effective minimum held at its end of period level throughout, inequality would either have decreased (male wage distribution), decreased more than it actually did (pooled wage distribution), or remained relatively stable

¹⁵ We study the period to 2006 because the state minimums make a large jump in 2007, reversing the drop that informs the counterfactual.

(female wage distribution) during these time intervals. 2SLS estimates instead suggest that the falling minimum had a much more modest effect on inequality. We estimate that the minimum accounts for roughly 20% to 30% of the rise in female lower tail inequality, which is a bit smaller than the contribution that we estimate for the 1979-1988 period. Estimates for the male and pooled gender distribution display more variability across the estimation sample and instruments used, but in all cases imply a smaller contribution from the minimum wage than what is implied by OLS estimates. The discrepancy between OLS and 2SLS results is therefore not specific to the extensively studied 1979 through 1988 interval.

The counterfactual estimates presented thus far are for a single measure of inequality – the 50/10. In addition, we estimate the contribution of the minimum wage to changes in $\log(p)$ - $\log(50)$ between 1979 and 1988 for all percentiles in Figures 6, 7, and 8. Figures 6 and 7 present counterfactual estimates at all percentiles throughout the male and female distributions, using coefficients obtained from OLS estimates without state fixed effects, from 2SLS first-differenced estimates with state fixed effects, and from 2SLS fixed effects estimates with state-specific time trends. Again, it is clear that OLS estimates imply a much greater contribution of the minimum wage to growing lower-tail inequality in the 1980s, while our preferred specifications imply a less substantial effect. Reassuringly, 2SLS models suggest that the minimum wage had no effect on upper-tail inequality over this period. Figure 8 plots counterfactual distributions for the pooled gender distribution. Panel A displays counterfactual changes after adjusting the 1979 distribution by the 1988 effective minimum. Panel B displays counterfactual changes between 1979 and 2007 after adjusting *both* distributions by the 1988 effective minimum. These counterfactuals are in effect estimates of how inequality throughout the distribution would have changed over the three decades had states' effective minimums remained at their relatively low 1988 values. OLS models imply compression in the lower tail of the wage distribution after accounting for changes in the minimum wage, while 2SLS estimates suggest that there was continued expansion even after holding the effective minimum constant at 1988 levels.

IV. Decomposing the direct and spillover effects of the minimum wage

One intriguing implication of the results so far is that the minimum wage must have spillovers. Table 1 showed that even at its most binding, the minimum wage was never above the 13th percentile of the male wage distribution in any state, and was always at or below the 10th percentile after 1981. Yet, the main estimates imply that the minimum wage compressed the male 50/10 ratio modestly, even in the late 1990s, indicating the presence of spillovers. A natural question then arises as to the relative size of the direct and spillover effects on the wage distribution. This section seeks to quantify the spillover and direct effects with a more parametric approach that is unrelated in methodology to the preceding sections. After estimating these spillovers, we consider in section V how the presence of measurement error in wages may contribute to apparent spillovers.

Inferring the exact magnitude of spillover and direct effects first requires an estimate of the counterfactual wage level at for all percentiles in the absence of the minimum wage (what we have called the latent wage distribution). Recall that our previous estimation strategy allows the estimation of wage distribution counterfactuals for alternative levels of the effective minimum wage, but is unable to estimate counterfactuals for the *absence* of a minimum wage. With an estimate of the latent wage distribution, however, we could compute the total effect of the minimum wage on percentile p in state s at time t as the gap between the observed and latent distributions i.e.:

$$w_{st}(p) - w_{st}^*(p) \tag{10}$$

The direct effect of the minimum wage will be given by:

$$\max [w_{st}^m - w_{st}^*(p), 0] \tag{11}$$

And the spillover effect is the gap between (10) and (11).

Of course these estimates will only be as good as the estimate of the latent wage distribution, and we need an estimate of this for all percentiles, even for those that are always below where the minimum binds. Hence, estimating these effects requires more structure, and thus more stringent assumptions, than we have previously imposed.

The first step in estimating the total, direct, and spillover effects is to form an estimate of the latent log wage distribution. We proceed by assuming that the latent log wage distribution is normal—i.e., we use the model of (6) with F having the standard normal form. We estimate the parameters of this distribution using a part of the wage distribution where we think the minimum has no effect, and we use wages between the 50th and 75th percentiles for this purpose.¹⁶ We model both μ_{st} and σ_{st} of (6) as additive year and state dummies plus state-level trends - that is, we allow both mean and variance to vary across state and time.¹⁷ Armed with these estimates, we can then estimate the latent wage distribution for all percentiles.

To give some idea of the adequacy of the assumption that the latent wage distribution can be well-approximated by the normal, Figure 9 plots the average deviation (across states and years) between the actual observed percentile and the estimated latent distribution for percentiles from the 3rd to the 90th.¹⁸ This is done separately for women, men and the pooled distribution. Because the model is estimated on the 50th through 75th percentiles the average residuals over those percentiles must be zero. But, if the normality assumption is false we would see systematic variation of the residuals with the percentile. For all three samples this deviation is very close to zero for all percentiles between the 50th and 75th percentiles – this indicates that the normal distribution is a good approximation for the sample on which the data is estimated. The model also seems to do well when applied out of sample up to the 90th percentile (not shown)¹⁹.

¹⁶ We have experimented with the percentiles used to estimate the latent wage distribution and the results do not seem very sensitive to the choices made.

¹⁷ Specifically, we estimate μ_{st} and σ_{st} by pooling the 50th through 75th log wage percentiles, regressing 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). This procedure assumes that the wage distribution is unaffected by the minimum wage between the 50th and 75th percentiles; hence, 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.

¹⁸ The lowest percentiles are excluded because these are typically below the minimum wage which would imply negative spillover effects.

¹⁹ As is well-known the very highest percentiles are not well-approximated by a normal distribution and the actual observed are well above the predicted latent.

For the lower percentiles the deviation between the observed and the estimated latent is positive, exactly what one would expect if the minimum wage has a positive impact. This deviation happens for higher percentiles in the female and pooled distributions than in the male, consistent with what one would expect if the minimum wage has a smaller effect on the male distribution. There is perhaps some inkling for men that the normality assumption over-predicts observed wages in the 15th-50th percentiles, though the absolute magnitude is small.

Although Figure 9 is suggestive of the impact of the minimum wage, it does not provide direct evidence that the gap between the actual and the latent wage is high when the minimum wage is high, as is implied by the relationship depicted in Figure 2. The assumptions behind (6) suggest we should examine the relationship between the actual minus the latent and the log minimum minus the latent. This is plotted for the 3 samples in Figure 10. Each observation here is a state-year. Because of the large number of observations, this Figure plots the average value of the actual minus the latent for 1 log point bins of the estimated log minimum minus the latent. In all samples one can see the general shape of the relationship between the deviation between the actual and latent and the minimum and latent that is consistent with that predicted by theory and drawn previously in Figure 3. As the vertical axis in Figure 10 is the gap between the actual and the latent wage distribution, one can think of it as an estimate of the total impact of the minimum wage if one assumes that the entire difference is the result of the minimum wage. This total impact can then be broken down into a direct effect and a spillover effect. The direct effect will be zero up to the point where the minimum exceeds the latent percentile (i.e. up to the point where the log minimum wage minus the latent percentile—which is plotted on the x-axis—is zero). The direct effect will be a 45-degree line thereafter. The spill-over is the difference between the total effect and the direct effect. In other words, we first estimate the total impact of the minimum wage as the difference between the actual and latent percentiles. We then decompose this into a spillover and direct effect, by value of the log min minus log latent percentile. The direct effect is either 0 or is on the 45 degree line, and the spillover effect is the difference between the total and direct effects.

Figure 10, shows that, for all samples, the spill-over effect is highest at the point where the latent wage just equals the minimum. On either side the spill-over effect decays to zero. For those for whom the minimum wage is very high relative to the latent (the right-hand side of Figure 10) the direct effect of the minimum is very large but the spill-over effect is zero – these are people who will be observed being paid the minimum wage. For those for whom the minimum wage is very low relative to the latent (the left-hand side of Figure 10) both the direct and spill-over effects of the minimum are zero – these are people for whom the minimum wage is irrelevant. Because the spill-over is not monotonic in the bindingness of the minimum wage, it is not obvious whether an increase in the minimum wage will raise or lower the spillover – we will see this later on. Finally it is worth noting that the size of the spillover at its maximum impact is between 11 and 12 log points.

We can use the estimates of the direct and spill-over effects of the minimum implied by Figure 10 to investigate the relative importance of direct and spill-over effects on different percentiles of the aggregate wage distribution. We do this by first calculating the value of the log minimum minus log latent value for each state-year percentile. Using the estimates from Figure 10, we attach an estimate of the total, direct and spill-over effect to each state-year-percentile. Using these effects we then estimate the relative size of direct and spillover effects at each percentile of the aggregate wage distribution by using the mapping between the percentile at the state-year level to the aggregate percentile at the year level²⁰. This then gives us an estimate of the direct and spillover effects at every percentile of the aggregate wage distribution.

The results of this exercise for the years 1979 and 1988 are shown in Figure 11 for percentiles 8th through 50th²¹. For the female and pooled samples, the results are very sensible. The total effect of the minimum decays through the percentiles. In 1979 when the

²⁰ More precisely, what we do here to estimate the effect at percentile p of the aggregate distribution is to average the direct and spillover effects across all observations that are estimated to be in the interval $[p-0.5, p+0.5]$, to reduce the sensitivity of the estimates to a small number of observations.

²¹ The problem with including lower percentiles is that the observed percentiles, especially for women in 1979, are considerably (and implausibly) below the minimum wage. The decomposition then implies that the measured spill-over effect is very negative. If these observations are included they distort the picture.

minimum wage was high, the direct effect of the minimum was very large at the lowest percentiles and the spill-over effect small. Spillover effects are estimated to be largest at the 20th percentile for women (where they raise wages by 9 log points) and the 12th percentile for the pooled distribution (where they raise wages by 7 log points). But, by 1988, the decline in the level of the minimum wage means that the overall effects are smaller, that the spillover effects are largest at the lowest percentiles, and that the direct effect is small even at the 10th percentile.

The results of this exercise for men are less informative, because the effect of the minimum wage is small and because, as seen in Figure 9, the gap between the actual and estimated latent wage distributions is slightly negative between the 25th and 50th percentiles suggesting some deviation from the normality assumption. For these two reasons, the methodology does not work so well for men.

We can also use our estimates to compute the total contribution of the minimum wage to inequality at any point in the wage distribution, and to decompose this contribution into a direct and spill-over effect. Using the methodology described above, we compute the effect of the minimum wage on the aggregate 10th and 50th percentiles in each year and then take the difference to give us the contribution to the log 50/10. Because the minimum wage is estimated to have virtually no effect on the median, the resulting estimates can also be thought of as estimates of the effect on the 10th percentile. These estimates are reported in Figure 12.

For men the estimated effects are always very close to zero. For women the total effect in the late 1970s is about 20 log points, all of it a direct effect as the minimum wage bound at a rather high point in the distribution (see Table 1). As the minimum declines the total effect declines but remains sizeable at around 10 log points. Except in the years when the minimum is raised, most of this is estimated to be due to spillovers since the minimum wage binds lower in the distribution. The level of spillovers is remarkably stable after the mid-1980s, in the region of 7-8 log points—this is because, on average, the minimum wage tends to bind at about the same place in the observed wage distribution throughout the 1990s and 2000s.

For the pooled distribution the results are very much what one would expect. The overall effect is smaller than what is estimated in the female distribution, but it has declined since the late 1970s. The importance of the direct effect is tiny after 1982, so all of the effect of the minimum wage on wage inequality reflects a spillover effect.

V. Separating spillover effects from measurement error

A. A Framework for Separating the Spillover Effects from Measurement Error

We have provided evidence that changes in the minimum wage affects the earnings of some workers who are perceived to be paid strictly above the minimum. One interpretation of this is that they are true “spillover effects” and represent the actual wage response for workers initially earning above the minimum. There are reasons why one might expect such a response even in a perfectly competitive labor market – for instance, Teulings (2003) presents a model in which labor markets at different percentiles are inter-dependent so that a change in the minimum wage labor market affects the demand for workers paid above the minimum.

However, there is an alternative, more mundane, potential explanation for these spillovers—measurement error. Suppose that a subset of workers who are paid the minimum wage tends to report wage values that are modestly above or below the true minimum—that is, they report with error. Moreover, suppose (plausibly) that the central tendency of this reporting error moves in tandem with the minimum wage. That is, 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. Concretely, imagine that the minimum wage is located at the 5th percentile of the wage distribution and that it has no spillover effects but that the measurement error cloud surrounding it extends from the 1st through the 9th percentiles. If the legislated minimum wage rises to the 9th percentile and measurement error remains constant, the rise in the minimum wage will compress the *measured* wage distribution up to the 13th percentile (thus, reducing the measured 50-10 wage gap). Yet, it will have no impact on the *actual* distribution—the

apparent spillover is due to measurement error affecting nearby percentiles.²² Thus, despite the apparent existence of substantial spillovers in the *measured* wage distribution, it's possible that the spillovers to the *actual* wage distribution are smaller or non-existent.

Our exercise from Section IV cannot distinguish between these two possible explanations for spillovers, and we attempt to do so in this section. Specifically, we seek to test the null hypothesis that the minimum wage only affects the earnings of those at or below the minimum, while the effects on the observed wage distribution at percentiles above the minimum wage are explained by measurement error. To do so, we need to be able to estimate the extent of measurement error in our data.

To begin, suppose the true percentile is denoted by p^* (i.e. the percentile absent measurement error) and that the latent wage associated with it is given by $w^*(p^*)$. Assuming that there are only direct effects of the minimum wage—there are no true spillovers and no dis-employment effects—then the true wage at true percentile p^* will be given by:

$$w(p^*) = \max[w^m, w^*(p^*)] \quad (12)$$

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

$$w^*(\hat{p}(w^m)) = w^m \quad (13)$$

Now assume there is measurement error so that for someone at true percentile p^* we actually observe:

$$w_i = w(p^*) + \varepsilon_i \quad (14)$$

Where ε_i is the error which we assume to be independent of the true wage. Assume the error has a density function $g(\varepsilon)$. This implies that the density of wages among workers whose true percentile is p^* is given by $g(w - w(p^*))$. Hence the observed density of wages is simply the average of this across true percentiles:

$$f(w) = \int_0^1 g[w - w(p^*)] dp^* \quad (15)$$

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.

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

$$F(w) = \int_{-\infty}^w \int_0^1 g[x - w(p^*)] dp^* dx \quad (16)$$

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

$$p = \int_{-\infty}^{w(p)} \int_0^1 g[x - w(p^*)] dp^* dx \quad (17)$$

We can now differentiate this to derive the effect of changes in the minimum wage at observed percentile p , $\frac{\partial w(p)}{\partial w^m}$. The details are in the Appendix but an important result is:

Result 1: Assuming no spillovers for the true wage distribution, the elasticity of an observed percentile with respect to the minimum wage is the fraction of people at that observed percentile whose true wage is equal to the minimum.

On reflection, this is simple to understand. If changes in the minimum wage only affect the wage of those directly affected (and affect their wage with an elasticity of one) then the wage at an observed percentile can only change to the extent that some of those workers are really paid the minimum wage. If the minimum wage goes up by 1% and 10% of workers at a percentile are paid the minimum, the observed percentile will rise by 0.1%. One implication of this result is the following:

Result 2: Under the null hypothesis of no true spillovers, the elasticity of the mean log wage with respect to the minimum wage is the fraction of people really paid the minimum wage – that is, the size of the true spike.

The proof of this claim is also in the Appendix. Note that no assumption about measurement error beyond independence is needed for either result. The intuition for the second result is that all individuals who are really paid the minimum wage must appear somewhere in the observed wage distribution and the change in the mean picks up any change in wages.

The usefulness of Result 2 is that we can readily estimate the effect of changes in the minimum wage on the mean using the methodologies developed earlier in the paper. Under the null hypothesis that we seek to test, 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 and there are true spillovers we would expect the elasticity to be above the size of the true spike since others not earning the minimum wage would have their wages increased as well.

B. Estimating the Effect of the Minimum Wage on the Mean Log Wage

To estimate the impact of the minimum wage on the mean of the wage distribution, we first estimate a first-differenced form of (8), with the log of the state’s mean wage as the dependent variable. Using observations for the full sample of states from 1979-2007, we find that a 10 log point increase in the effective minimum increases the mean wage for females by 4.8 log points (with a standard error of 3.2) on average, for males by 1.3 log points (with a standard error of 2.7) on average, and for the pooled sample by 1.5 log points (with a standard error of 2.0) on average. Figure 14 plots 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, these estimates of the effect of changes in the minimum on changes in the mean are an estimate of the size of the true spike. We next test whether the null hypothesis can be rejected by exploring whether estimates of the true spike are plausible or not. To do this, we develop another estimate of the true spike under the null hypothesis, which is based on an estimate of the extent of measurement error.

C. Modeling Measurement Error

To get a handle on the extent of measurement error, we exploit the fact that under the assumption of perfect compliance with the minimum wage, there is a lower bound for the distribution of the true wage – the minimum wage – and all observations observed below the

minimum must be observations with measurement error²³. We exploit this institutional feature to provide estimates of the extent of measurement error. 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 the measurement error is symmetric, that is, that $g(\varepsilon) = g(-\varepsilon)$.

In what follows, we use the information on two statistics – the fraction of workers observed to be paid at the minimum (i.e. the size of the observed spike), and the fraction observed to be paid strictly below the minimum. We will assume that the ‘true’ wage distribution only has a mass point at the minimum wage so that $w^*(p^*)$ has a continuous derivative. We will also assume that the measurement error 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 explain the existence of a spike in the observed wage distribution at the minimum wage. Denote the probability that the wage is correctly reported by γ . For those who do report an 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 will denote by, \tilde{p} , will be given by:

$$\tilde{p} = \gamma \hat{p} \tag{18}$$

The observed spike is the true spike times the probability of the wage being correctly reported. 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

²³ Of course there are likely to be some individuals who correctly report sub-minimum wage 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 2007, about 45 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 mis-reporting. So, we proceed by doing the following analysis on a sample from which we have excluded employees in low-paying occupations for which commonly receive tips or commission (food service jobs, barbers and hairdressers, retail salesmen and telemarketers).

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. Note that (18) implies that if we can get an estimate of γ we can get an estimate of the true spike from the observed spike.

Now, consider the fraction of workers paid strictly below the minimum, denoted by Z . Under the assumption of full compliance all of these observations must represent negative measurement error. We will have:

$$Z = (1 - \gamma) * \left[0.5 \hat{p} + \int_{\hat{p}}^1 G(w^m - w^*(p^*)) dp^* \right] \quad (19)$$

$(1 - \gamma)$ appears because all these observations must represent error which happens with that probability. Of those reporting an error-ridden wage, half of those at the true spike will report wages below the minimum (using the symmetry assumption) – this is the first term in square brackets. For someone really paid above the minimum, one only reports a wage below the minimum if the error is sufficiently negative – this is the second term.

D. Empirical implementation of the measurement error model

We assume that the true latent log wage distribution is normal with mean γ and variance σ_w^2 , and that the measurement error distribution is normal with mean 0 variance σ_ε^2 . Our estimation strategy is a two-step strategy. First, we use observations on the top part of the wage distribution to estimate the median and variance of the observed latent wage distribution – essentially the model we used Section III.B – and this allows variation across state and time. Next, we estimate $(\sigma_\varepsilon^2, \gamma)$ to minimize the squared differences between the observed spikes and fractions below the minimum and those predicted by the model. We assume that $(\sigma_\varepsilon^2, \gamma)$ vary by time but not across states. More precise details and derivations are in the Appendix. As previously discussed, we perform this analysis on a sample that excludes individuals from lower-paying occupations that tend to earn tips or commission.

Figure 13 shows estimates of γ for males, females, and the pooled sample. Though there is some variation over time, this is generally estimated to be around 90 percent. We can 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 true size of the spike only for the estimation sample (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 this at all. Rather we simply note that the spike for tipped employees must be between zero and one, and use this to bound the ‘true’ spike for the whole workforce. These bounds are not too wide because the fraction of workers in tipped occupations is not very high.

Figure 14 compares our bounds on the estimates of the ‘true’ spikes with the estimated effect of the minimum on the mean for 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. For most years, the estimated mean effect remains within the bounds on the ‘true’ spike. Based on this analysis, we therefore must conclude that we are unable to reject the hypothesis that all of the apparent effect of the minimum wage on percentiles above the minimum is the consequence of measurement error.

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

Two points deserve emphasis. 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 still valid. What is unusual in this case is that observed and actual wage effects may differ systematically in a manner that overstates the role of the minimum wage. And of course, from the perspective of policymakers, the minimum wage is presumably valuable to the degree it affects actual wages rather than wages measured in survey data. A second point of equal importance is that our conclusion of no spillovers is tentative. We would not want to assert that our approach is perfect, and the power of the test may be small. Better wage data—perhaps real payroll data—is the way forward.

VI. Conclusion

This paper offers an updated assessment 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 an instrumental variables specification that purges estimates of simultaneity bias stemming from errors in variables. We estimate that 25-50% of the growth in lower tail inequality in the female wage distribution between 1979 and 1988—a period of significant expansion in lower tail inequality, as measured by the differential between the log of the 50th and 10th percentiles—is attributable to the decline in the real value of the minimum wage, while around one-fifth of the growth in male lower tail inequality over this period could be attributed to the minimum wage. These estimates imply that the minimum wage made a smaller contribution to growth in lower tail inequality than previous OLS estimates suggest. Similarly, calculations indicate that the declining minimum wage made only a modest contribution to growing lower tail inequality between 1998 and 2006 as well.

Despite these modest total effects, we estimate minimum wage effects that extend 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). We estimate the shape of the latent distribution with a simple structural estimation technique (by assuming log normality and estimating the mean and variance of the state-year wage distribution using 50th to 75th wage percentiles), and use this to separately infer the direct impact and spillover effects from changes in the minimum wage. While the contribution of direct and spillover effects vary

across percentiles, and over the years, spillover effects account for a modest fraction of the minimum wage effect in 1979, and almost the entirety of the effect in 1988.

One interpretation of these significant spillover effects is that they represent a true wage response 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 exercise in Section V 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, this analysis suggests that there was 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.

VII. 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:

$$Cov[w(p_1), w(p_2)] = \frac{p_1(1-p_2)}{Nf[w(p_1)]f[w(p_2)]}, \quad p_1 \leq p_2 \quad (\text{A.1})$$

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:

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

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

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

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

$$Cov[\bar{w}^t, w(0.5)] = \frac{1}{0.4} \int_{0.3}^{0.7} Cov[w(p), w(0.5)] dp \quad (\text{A.4})$$

The variance of the trimmed mean can be written as:

$$Var(\bar{w}^t) = \frac{1}{0.4^2} \int_{0.3}^{0.7} \int_{0.3}^{0.7} Cov[w(p), w(p')] dp dp' \quad (\text{A.5})$$

The formulae in (A.2), (A.4) and (A.5) can be used to compute the correlation coefficient between the median and trimmed mean. 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:

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

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

$$\text{Var}[w(0.5)] = \frac{\pi\sigma^2}{2N} \quad (\text{A.7})$$

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

B. Proof of Result 1:

Differentiate (17) to give:

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

Now we have that:

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

Which, from (12) is:

$$\begin{aligned} \frac{\partial g[x - w(p^*)]}{\partial w^m} &= -g[x - w^m], \quad p^* \leq \hat{p}(w^m) \\ &= 0, \quad p^* > \hat{p}(w^m) \end{aligned} \quad (\text{A.10})$$

Substituting (15) and (A.10) into (A.8) and re-arranging we have that:

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

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, \bar{w} . We have that:

$$\frac{\partial \bar{w}}{\partial w^m} = \int_0^1 \frac{\partial w(p)}{\partial w^m} dp = \int_0^1 \frac{\hat{p} \cdot g[w(p) - w^m]}{f[w(p)]} dp \quad (\text{A.17})$$

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

$$dw = w'(p) dp = \frac{1}{f[w(p)]} dp \quad (\text{A.18})$$

Hence (A.17) becomes:

$$\frac{\partial \bar{w}}{\partial w^m} = \hat{p} \int_{-\infty}^{\infty} g[w - w^m] dw = \hat{p} \quad (\text{A.19})$$

i.e. 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:

$$w^* \sim N(\mu, \sigma_w^2) \quad (\text{A.20})$$

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

$$w = \min(w^m, w^*) \quad (\text{A.21})$$

And the observed wage is given by:

$$v = w + D\varepsilon \quad (\text{A.22})$$

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:

$$\Pr(D = 1) = 1 - \gamma \quad (\text{A.23})$$

We assume that ε is normally distributed according to:

$$\varepsilon \sim N(\mu, \sigma_\varepsilon^2) \quad (\text{A.24})$$

We assume that (w^*, D, ε) are all mutually independent. With these assumptions, the ‘true’ size of the spike is given by:

$$\hat{p} = \Phi\left(\frac{w^m - \mu}{\sigma_w}\right) \quad (\text{A.25})$$

And the size of the observed ‘spike’ is given by:

$$\tilde{p} = \gamma \Phi\left(\frac{w^m - \mu}{\sigma_w}\right) \quad (\text{A.26})$$

Now let us consider the fraction observed below the minimum wage. For those with D=0, there is no-one below so we can just consider those with D=1. For those who are truly paid the minimum wage and have a mis-reported wage, a half will be below, so the fraction of the total population is:

$$\frac{1}{2} \cdot \Phi\left(\frac{w^m - \mu}{\sigma_w}\right) \quad (\text{A.27})$$

Now, consider those whose true wage is above the minimum but have $D=1$. For this group we observe their true latent wage so we need to derive:

$$\Pr(w^* > w^m, v < w^m) \quad (\text{A.28})$$

Define:

$$v^* = w^* + \varepsilon \quad (\text{A.29})$$

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

From (A.20) and (A.22):

$$\begin{pmatrix} v^* \\ w^* \end{pmatrix} \sim N \left[\begin{pmatrix} \mu \\ \mu \end{pmatrix}, \begin{pmatrix} \sigma_w^2 + \sigma_\varepsilon^2 & \sigma_w^2 \\ \sigma_w^2 & \sigma_w^2 \end{pmatrix} \right] \quad (\text{A.30})$$

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

$$\begin{aligned} \Pr(w^* > w^m, v^* < w^m) &= \Pr(w^* > w^m, v^* < w^m) \\ &= \Pr(v^* < w^m) - \Pr(w^* \leq w^m, v^* < w^m) \\ &= \Phi \left(\frac{w^m - \mu}{\sqrt{\sigma_w^2 + \sigma_\varepsilon^2}} \right) - \Phi \left(\frac{w^m - \mu}{\sqrt{\sigma_w^2 + \sigma_\varepsilon^2}}, \frac{w^m - \mu}{\sigma_w}, \rho \right) \end{aligned} \quad (\text{A.31})$$

where:

$$\rho = \text{Corr}(v^*, w^*) = \frac{\sigma_w}{\sqrt{\sigma_w^2 + \sigma_\varepsilon^2}} \quad (\text{A.32})$$

This implies that the fraction of the population observed to be paid below the minimum is given by:

$$Z = (1 - \gamma) \left[\frac{1}{2} \Phi \left(\frac{w^m - \mu}{\sigma_w} \right) + \Phi \left(\frac{w^m - \mu}{\sqrt{\sigma_w^2 + \sigma_\varepsilon^2}} \right) - \Phi \left(\frac{w^m - \mu}{\sqrt{\sigma_w^2 + \sigma_\varepsilon^2}}, \frac{w^m - \mu}{\sigma_w}, \rho \right) \right] \quad (\text{A.33})$$

There are three parameters in this model $(\sigma_w, \sigma_\varepsilon, \gamma)$. Our estimation procedure is to first use a part of the distribution unaffected by the minimum wage to estimate the variance of the observed wage distribution – this puts a one-dimensional restriction on $(\sigma_w, \sigma_\varepsilon, \gamma)$. We then estimate the values of the two effective parameters remaining to minimize the weighted sum

of the squared differences between the actual and predicted spikes and sub-minimum proportion.

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

	# states w/higher min.	Female					Male				
		Min. binding pctile	Med. binding pctile	Max. binding pctile	Share of hours at or below min.	Avg. log(50)- log(10)	Min. binding pctile	Med. binding pctile	Max. binding pctile	Share of hours at or below min.	Avg. log(50)- log(10)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1979	1	3	12.0	31	0.132	0.273	2	4.0	13	0.049	0.586
1980	1	3	13.0	26	0.132	0.291	2	5.0	12	0.056	0.604
1981	1	3	13.0	27	0.138	0.300	1	5.5	12	0.059	0.623
1982	1	3	10.5	23	0.109	0.359	2	4.5	10	0.052	0.643
1983	1	3	10.0	19	0.098	0.399	2	4.5	10	0.049	0.651
1984	1	2	9.0	17	0.089	0.427	1	4.0	9	0.041	0.671
1985	2	2	8.0	14	0.080	0.455	1	3.0	8	0.038	0.670
1986	5	2	7.0	18	0.074	0.481	1	3.0	7	0.035	0.680
1987	6	2	4.0	9	0.065	0.490	1	2.5	5	0.031	0.664
1988	10	2	4.0	9	0.060	0.492	1	2.0	6	0.030	0.631
1989	12	1	4.0	7	0.055	0.484	1	2.0	5	0.028	0.628
1990	11	1	6.0	16	0.059	0.476	1	3.0	7	0.029	0.608
1991	4	2	8.0	22	0.074	0.452	1	3.0	10	0.037	0.606
1992	7	2	6.0	16	0.065	0.460	1	3.0	8	0.036	0.609
1993	7	2	5.0	12	0.058	0.465	1	3.0	6	0.034	0.606
1994	8	2	5.0	12	0.059	0.472	1	3.0	5	0.032	0.595
1995	9	2	4.5	9	0.052	0.469	1	3.0	4	0.029	0.582
1996	11	1	4.0	11	0.047	0.463	1	2.0	6	0.028	0.579
1997	10	2	5.0	9	0.062	0.455	1	3.0	7	0.036	0.559
1998	7	3	5.5	14	0.065	0.436	2	3.0	8	0.039	0.533
1999	10	2	4.0	10	0.053	0.434	1	2.5	5	0.030	0.538
2000	10	2	4.0	10	0.048	0.439	1	2.0	6	0.028	0.537
2001	10	1	4.0	8	0.045	0.444	1	2.0	6	0.028	0.531
2002	11	1	4.0	8	0.042	0.453	1	2.0	6	0.028	0.535
2003	11	1	4.0	8	0.039	0.458	1	2.0	5	0.026	0.538
2004	12	2	3.5	7	0.038	0.475	1	2.0	4	0.025	0.542
2005	15	1	3.0	8	0.040	0.468	1	2.0	5	0.025	0.543
2006	19	1	3.0	8	0.039	0.480	1	2.0	6	0.025	0.551
2007	30	2	4.0	12	0.050	0.467	1	3.0	6	0.031	0.538

Notes: Column 1 displays the number of states with a minimum that exceeds the federal minimum. Columns (2) and (7) display estimates of the smallest percentile (across states) at which the minimum wage binds. Columns (3) and (8), and (4) and (9) display estimates of the median and largest percentile at which the minimum wage binds across states, respectively. For some states in some years, multiple percentiles in the wage distribution were equal to the value of the minimum wage. For these state/years, the minimum wage is recorded as binding at the highest of these percentiles. Columns (5) and (10) display the share of hours worked for wages at or below the minimum wage. Columns (6) and (11) display the weighted average value of the $\log(p50)-\log(p10)$ for the male and female wage distributions across states.

Table 1 (cont.) - Summary Statistics for Bindingness of State and Federal Minimum Wages

	# states w/higher min.	Min. binding pctile	Males and females, pooled		Share of hours at or below min.	Avg. log(50)- log(10)
	(1)	(2)	Med. binding pctile	Max. binding pctile	(5)	(6)
1979	1	3	7.0	20	0.082	0.491
1980	1	3	8.0	18	0.087	0.497
1981	1	2	9.0	17	0.091	0.500
1982	1	2	7.0	15	0.076	0.530
1983	1	2	6.0	14	0.070	0.547
1984	1	2	6.0	12	0.061	0.572
1985	2	2	5.0	11	0.056	0.585
1986	5	2	5.0	12	0.051	0.595
1987	6	2	3.0	7	0.046	0.591
1988	10	1	3.0	7	0.043	0.582
1989	12	1	3.0	5	0.040	0.574
1990	11	1	4.0	11	0.042	0.550
1991	4	2	5.0	15	0.053	0.540
1992	7	2	4.0	11	0.049	0.532
1993	7	1	4.0	8	0.045	0.537
1994	8	2	4.0	7	0.044	0.549
1995	9	2	3.0	6	0.039	0.540
1996	11	2	3.0	7	0.036	0.530
1997	10	2	3.0	8	0.047	0.515
1998	7	2	4.0	9	0.050	0.491
1999	10	1	3.0	7	0.040	0.493
2000	10	2	3.0	7	0.037	0.488
2001	10	2	3.0	7	0.035	0.487
2002	11	1	3.0	7	0.034	0.494
2003	11	1	3.0	6	0.032	0.503
2004	12	2	3.0	5	0.031	0.509
2005	15	2	3.0	6	0.031	0.512
2006	19	1	3.0	7	0.031	0.521
2007	30	2	3.0	9	0.039	0.501

Notes: Column 1 displays the number of states with a minimum that exceeds the federal minimum. Column (2) displays estimates of the smallest percentile (across states) at which the minimum wage binds. Columns (3) and (4) display estimates of the median and largest percentile at which the minimum wage binds across states, respectively. For some states in some years, multiple percentiles in the wage distribution were equal to the value of the minimum wage. For these state/years, the minimum wage is recorded as binding at the highest of these percentiles. Column (5) displays the share of hours worked for wages at or below the minimum wage. Column (6) displays the weighted average value of the $\log(p_{50})-\log(p_{10})$ for the pooled wage distributions across states.

Table 2: OLS Relationship between log(p)-log(p50) and log(min. wage)-log(p50), for select percentiles

P	A. Females					B. Males					C. Males and females				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
5	0.615 (0.038)	0.400 (0.031)	0.442 (0.047)	0.502 (0.043)	0.509 (0.045)	0.518 (0.040)	0.293 (0.032)	0.286 (0.030)	0.423 (0.029)	0.429 (0.030)	0.603 (0.030)	0.381 (0.024)	0.384 (0.042)	0.425 (0.037)	0.431 (0.039)
10	0.510 (0.036)	0.213 (0.048)	0.330 (0.029)	0.448 (0.031)	0.454 (0.033)	0.350 (0.039)	0.118 (0.058)	0.174 (0.025)	0.336 (0.031)	0.344 (0.032)	0.423 (0.033)	0.170 (0.039)	0.258 (0.050)	0.357 (0.031)	0.365 (0.034)
15	0.366 (0.034)	0.086 (0.061)	0.218 (0.021)	0.336 (0.035)	0.343 (0.035)	0.268 (0.035)	0.059 (0.053)	0.107 (0.030)	0.244 (0.028)	0.251 (0.029)	0.292 (0.033)	0.047 (0.073)	0.105 (0.028)	0.249 (0.034)	0.256 (0.035)
20	0.272 (0.029)	0.026 (0.058)	0.147 (0.019)	0.273 (0.034)	0.279 (0.034)	0.185 (0.031)	0.021 (0.046)	0.082 (0.025)	0.230 (0.027)	0.240 (0.027)	0.235 (0.029)	0.045 (0.048)	0.103 (0.031)	0.234 (0.025)	0.242 (0.025)
25	0.197 (0.024)	0.001 (0.055)	0.123 (0.022)	0.269 (0.040)	0.277 (0.040)	0.113 (0.024)	-0.004 (0.054)	0.069 (0.025)	0.177 (0.031)	0.184 (0.031)	0.180 (0.025)	0.018 (0.046)	0.090 (0.022)	0.227 (0.015)	0.236 (0.016)
30	0.144 (0.019)	0.001 (0.041)	0.091 (0.013)	0.229 (0.029)	0.235 (0.029)	0.076 (0.018)	-0.002 (0.038)	0.078 (0.021)	0.182 (0.018)	0.190 (0.019)	0.126 (0.018)	0.014 (0.042)	0.074 (0.013)	0.192 (0.025)	0.200 (0.025)
40	0.061 (0.009)	0.000 (0.024)	0.061 (0.012)	0.156 (0.020)	0.160 (0.021)	0.025 (0.011)	0.016 (0.017)	0.078 (0.019)	0.131 (0.015)	0.136 (0.016)	0.054 (0.009)	0.014 (0.021)	0.046 (0.013)	0.160 (0.015)	0.165 (0.016)
75	-0.039 (0.022)	0.093 (0.023)	0.111 (0.015)	0.213 (0.025)	0.217 (0.026)	0.110 (0.040)	0.174 (0.013)	0.139 (0.020)	0.248 (0.023)	0.252 (0.024)	0.026 (0.024)	0.122 (0.022)	0.113 (0.016)	0.227 (0.022)	0.231 (0.024)
90	-0.020 (0.037)	0.171 (0.025)	0.164 (0.024)	0.326 (0.032)	0.330 (0.034)	0.132 (0.071)	0.175 (0.020)	0.127 (0.035)	0.290 (0.036)	0.294 (0.038)	0.049 (0.045)	0.183 (0.019)	0.145 (0.028)	0.270 (0.037)	0.040 (0.040)

Levels or FD?	Levels	Levels	Levels	FD	FD	Levels	Levels	Levels	FD	FD	Levels	Levels	Levels	FD	FD
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes
State trends	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes	No	No

Notes: N=1450 for levels estimation, N=1400 for first-differenced estimation. 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. 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.

Table 3: 2SLS Relationship between log(p)-log(p50) and log(min. wage)-log(p50), for select percentiles

P	A. Females					B. Males					C. Males and females				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
5	0.598 (0.009)	0.326 (0.017)	0.374 (0.034)	0.348 (0.071)	0.340 (0.063)	0.513 (0.008)	0.214 (0.016)	0.222 (0.024)	0.182 (0.043)	0.175 (0.042)	0.600 (0.005)	0.342 (0.009)	0.342 (0.014)	0.286 (0.033)	0.282 (0.031)
10	0.508 (0.006)	0.138 (0.016)	0.268 (0.020)	0.146 (0.038)	0.130 (0.038)	0.350 (0.007)	0.040 (0.017)	0.107 (0.022)	0.072 (0.045)	0.077 (0.044)	0.419 (0.005)	0.117 (0.011)	0.208 (0.017)	0.168 (0.033)	0.165 (0.034)
15	0.367 (0.007)	0.012 (0.015)	0.161 (0.023)	0.106 (0.040)	0.094 (0.040)	0.260 (0.007)	-0.017 (0.016)	0.036 (0.023)	0.009 (0.045)	0.006 (0.044)	0.288 (0.005)	-0.007 (0.013)	0.049 (0.021)	0.029 (0.030)	0.024 (0.031)
20	0.270 (0.007)	-0.042 (0.014)	0.093 (0.023)	0.049 (0.038)	0.038 (0.037)	0.181 (0.006)	-0.041 (0.015)	0.023 (0.025)	0.031 (0.041)	0.034 (0.040)	0.228 (0.005)	-0.008 (0.011)	0.046 (0.016)	0.045 (0.028)	0.054 (0.027)
25	0.193 (0.006)	-0.065 (0.012)	0.054 (0.017)	0.036 (0.030)	0.029 (0.029)	0.110 (0.006)	-0.054 (0.012)	0.024 (0.018)	-0.005 (0.034)	0.000 (0.032)	0.175 (0.004)	-0.023 (0.010)	0.044 (0.016)	0.067 (0.030)	0.068 (0.030)
30	0.140 (0.006)	-0.058 (0.013)	0.022 (0.015)	0.035 (0.031)	0.035 (0.030)	0.070 (0.006)	-0.043 (0.014)	0.039 (0.022)	0.002 (0.035)	0.006 (0.034)	0.120 (0.005)	-0.022 (0.011)	0.033 (0.016)	0.010 (0.026)	0.015 (0.026)
40	0.057 (0.005)	-0.037 (0.008)	0.014 (0.015)	0.014 (0.032)	0.013 (0.032)	0.021 (0.005)	-0.011 (0.011)	0.044 (0.018)	-0.001 (0.033)	0.003 (0.032)	0.048 (0.004)	-0.007 (0.008)	0.013 (0.014)	0.028 (0.024)	0.027 (0.024)
75	-0.058 (0.005)	0.061 (0.012)	0.003 (0.019)	-0.038 (0.040)	-0.039 (0.038)	0.092 (0.006)	0.146 (0.012)	0.048 (0.016)	0.049 (0.033)	0.049 (0.031)	0.013 (0.005)	0.106 (0.010)	0.046 (0.015)	0.045 (0.031)	0.043 (0.030)
90	-0.043 (0.007)	0.140 (0.018)	0.044 (0.026)	0.015 (0.050)	0.011 (0.048)	0.115 (0.008)	0.126 (0.015)	0.012 (0.025)	0.016 (0.047)	0.013 (0.047)	0.029 (0.006)	0.154 (0.012)	0.060 (0.017)	0.027 (0.043)	0.023 (0.043)
First stage F-stats and p-values															
Linear term	5358 (0.000)	535 (0.000)	412 (0.000)	268 (0.000)	244 (0.000)	3941 (0.000)	579 (0.000)	324 (0.000)	334 (0.000)	325 (0.000)	5471 (0.000)	957 (0.000)	772 (0.000)	417 (0.000)	416 (0.000)
Quad. term	4746 (0.000)	502 (0.000)	462 (0.000)	261 (0.000)	225 (0.000)	3746 (0.000)	550 (0.000)	338 (0.000)	327 (0.000)	319 (0.000)	5108 (0.000)	873 (0.000)	843 (0.000)	454 (0.000)	458 (0.000)
Levels or FD?	Levels	Levels	Levels	FD	FD	Levels	Levels	Levels	FD	FD	Levels	Levels	Levels	FD	FD
State FE	No	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes
State trends	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes	No	No

Notes: N=1450 for levels estimation, N=1400 for first-differenced estimation. 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. 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. F-stats are estimated F-statistics and associated p-values (in parentheses) from testing the significance of the five instruments in the first-stage regression for the linear and quadratic functions of the effective minimum.

Table 4: Actual and counterfactual changes in log(p50)-log(p10) between 1979 and 1988, and 1998 and 2006

	Change, 1979-1988			Change, 1998-2006		
	Coeffs: 1979-2007	Coeffs: 1979-1988	Coeffs: 1998-2007	Coeffs: 1979-2007	Coeffs: 1979-1988	Coeffs: 1998-2007
	(1)	(2)	(3)	(4)	(5)	(6)
A. Females						
Actual change in log(p50)-log(p10)	0.234	0.234	0.234	0.095	0.095	0.095
Counterfactual change, OLS	0.032	0.031	0.058	0.014	0.031	0.016
Counterfactual change, 2SLS (FE)						
IVs: split sample	0.124	0.120	0.177	0.069	0.055	0.085
IVs: split sample + leg. minimum	0.112	0.076	0.192	0.062	0.043	0.084
Counterfactual change, 2SLS (FD)						
IVs: split sample	0.169	0.121	0.224	0.081	0.050	0.094
IVs: split sample + leg. minimum	0.157	0.058	0.222	0.070	0.031	0.090
B. Males						
Actual change in log(p50)-log(p10)	0.077	0.077	0.077	0.050	0.050	0.050
Counterfactual change, OLS	-0.002	0.003	0.021	-0.012	-0.014	0.005
Counterfactual change, 2SLS (FE)						
IVs: split sample	0.068	0.032	0.053	0.041	0.015	0.032
IVs: split sample + leg. minimum	0.059	-0.006	0.069	0.037	0.004	0.039
Counterfactual change, 2SLS (FD)						
IVs: split sample	0.069	-0.028	0.055	0.042	0.064	0.039
IVs: split sample + leg. minimum	0.062	-0.011	0.066	0.039	0.000	0.045
C. Male and female pooled						
Actual change in log(p50)-log(p10)	0.108	0.108	0.108	-0.014	-0.014	-0.014
Counterfactual change, OLS	-0.011	-0.011	0.021	-0.074	-0.068	-0.058
Counterfactual change, 2SLS (FE)						
IVs: split sample	0.069	0.041	0.087	-0.026	-0.037	-0.019
IVs: split sample + leg. minimum	0.062	0.020	0.095	-0.031	-0.048	-0.019
Counterfactual change, 2SLS (FD)						
IVs: split sample	0.081	0.068	0.095	-0.019	-0.027	-0.010
IVs: split sample + leg. minimum	0.075	0.036	0.090	-0.025	-0.044	-0.017

Note: Estimates represent changes in the actual and counterfactual log(p50)-log(p10) between 1979 and 1988, and 1998 and 2006. Counterfactual wage distributions are wage distributions adjusted by the effective minimum wage in the later year of the period, and represent the 50/10 had the effective minimum wage of the earlier year actually been equal to the lower effective minimum wage of the later year for each state. OLS estimates are counterfactuals formed by adjusting the 1979 and 1998 wage distributions by states' effective minimums of the latter year, and using coefficients from estimation reported in columns 1, 6, and 11 of Table 2. 2SLS fixed effect counterfactuals (including the leg. minima as instruments) use coefficients from columns 3, 8, and 13 of Table 3. 2SLS FD counterfactuals (including the leg. minima as instruments) use coefficients from columns 5, 10, and 15 of Table 3. We do not present marginal effects for regressions using only split sample instruments in the earlier tables (results available upon request).

Appendix Table 1 - Variation in State Minimum Wages

	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
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
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
Arizona															
Arkansas															
California										4.25	4.25	4.25			
Colorado															
Connecticut										3.75	4.25	4.25	4.27	4.27	4.27
Delaware															
Florida															
Georgia															
Hawaii															
Idaho										3.85	3.85	3.85		4.75	5.25
Illinois															
Indiana															
Iowa															
Kansas												3.85		4.65	4.65
Kentucky															
Louisiana															
Maine															
Maryland							3.45	3.55	3.65	3.65	3.75	3.85			
Massachusetts															
Michigan								3.65	3.65	3.75	3.75				
Minnesota															
Mississippi										3.55	3.85	3.95			
Missouri															
Montana															
Nebraska															
Nevada															
New Hampshire															
New Jersey									3.45	3.55	3.65				
New Mexico														5.05	5.05
New York															
North Carolina															
North Dakota															
Ohio															
Oklahoma															
Oregon															
Pennsylvania												4.25	4.75	4.75	4.75
Rhode Island															
South Carolina								3.55	3.65	4.00	4.25	4.25	4.45	4.45	4.45
South Dakota															
Tennessee															
Texas															
Utah															
Vermont															
Virginia								3.45	3.55	3.65	3.75	3.85			
Washington															
West Virginia											3.85	3.85			
Wisconsin															
Wyoming											3.65				

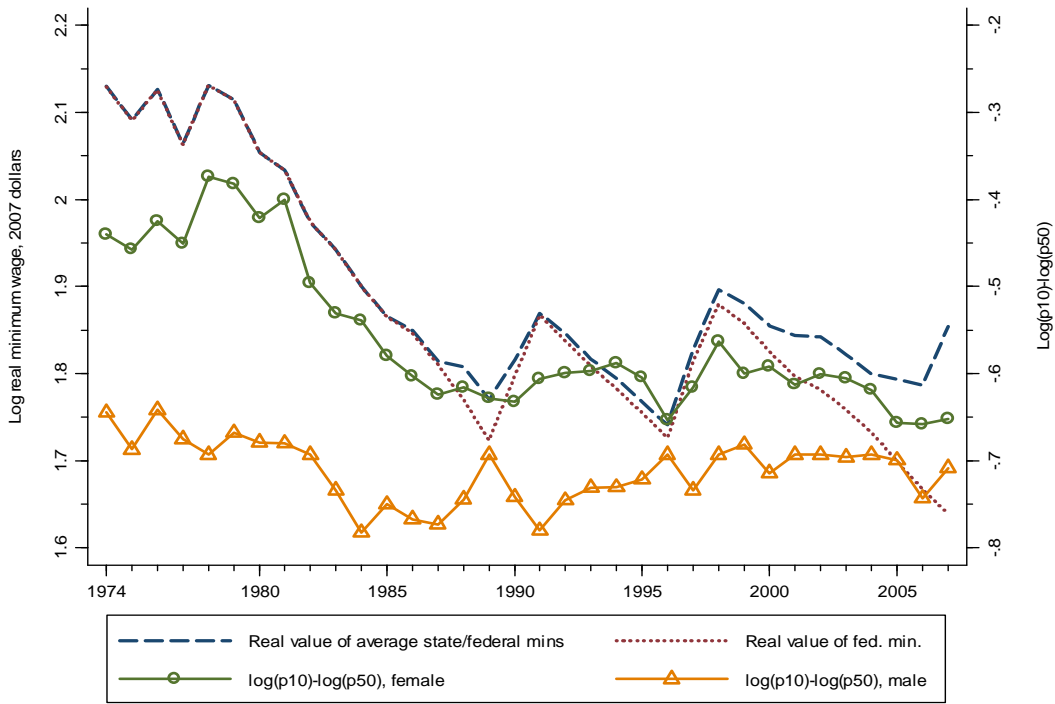
Note: Table indicates years in which each state had a state minimum wage that exceeded the federal minimum wage for at least 6 months of the year.

Appendix Table 1 - Variation in State Minimum Wages, cont.

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Federal min. wage	4.25	4.25	4.25	4.75	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15
Alabama														
Alaska	4.75	4.75	4.75	5.25	5.65	5.65	5.65	5.65	5.65	7.15	7.15	7.15	7.15	7.15
Arizona														6.75
Arkansas														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
Colorado														6.85
Connecticut	4.27	4.27	4.27	4.77	5.18	5.65	6.15	6.40	6.70	6.90	7.10	7.10	7.40	7.65
Delaware			4.65			5.65	5.65	6.15	6.15	6.15	6.15	6.15	6.15	6.65
Florida														
Georgia												6.15	6.40	6.67
Hawaii														
Idaho	5.25	5.25	5.25	5.25	5.25	5.25	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.25
Illinois														
Indiana											5.50	6.50	6.50	6.50
Iowa														
Kansas	4.65	4.65	4.65											6.20
Kentucky														
Louisiana														
Maine														
Maryland									5.75	6.25	6.25	6.35	6.50	6.75
Massachusetts													6.15	6.15
Michigan			4.75	5.25	5.25	5.25	6.00	6.75	6.75	6.75	6.75	6.75	6.75	7.50
Minnesota														7.15
Mississippi													6.15	6.15
Missouri														
Montana														6.50
Nebraska														6.15
Nevada														
New Hampshire														6.33
New Jersey														
New Mexico	5.05	5.05	5.05	5.05									6.15	7.15
New York														
North Carolina												6.00	6.75	7.15
North Dakota														6.15
Ohio														
Oklahoma														6.85
Oregon														
Pennsylvania	4.75	4.75	4.75	5.50	6.00	6.50	6.50	6.50	6.50	6.90	7.05	7.25	7.50	7.80
Rhode Island														7.15
South Carolina	4.45	4.45	4.45	5.15		5.65	5.65	6.15	6.15	6.15	6.75	6.75	7.10	7.40
South Dakota														
Tennessee														
Texas														
Utah														
Vermont														
Virginia		4.50	4.75	5.00	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.00	7.25	7.53
Washington														
West Virginia	4.90	4.90	4.90	4.90		5.70	6.50	6.72	6.90	7.01	7.16	7.35	7.63	7.93
Wisconsin													5.85	6.55
Wyoming												5.70	6.50	6.50

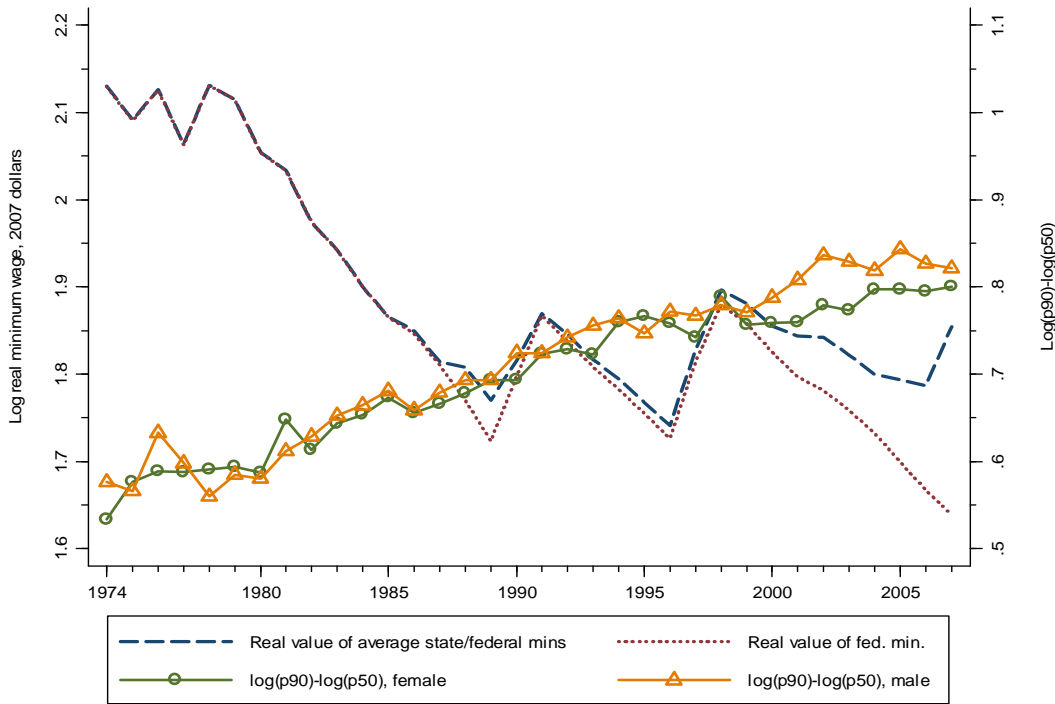
Note: Table indicates years in which each state had a state minimum wage that exceeded the federal minimum wage for at least 6 months of the year.

Figure 1A: Trends in state and federal minimum wages, and log(p10)-log(p50)



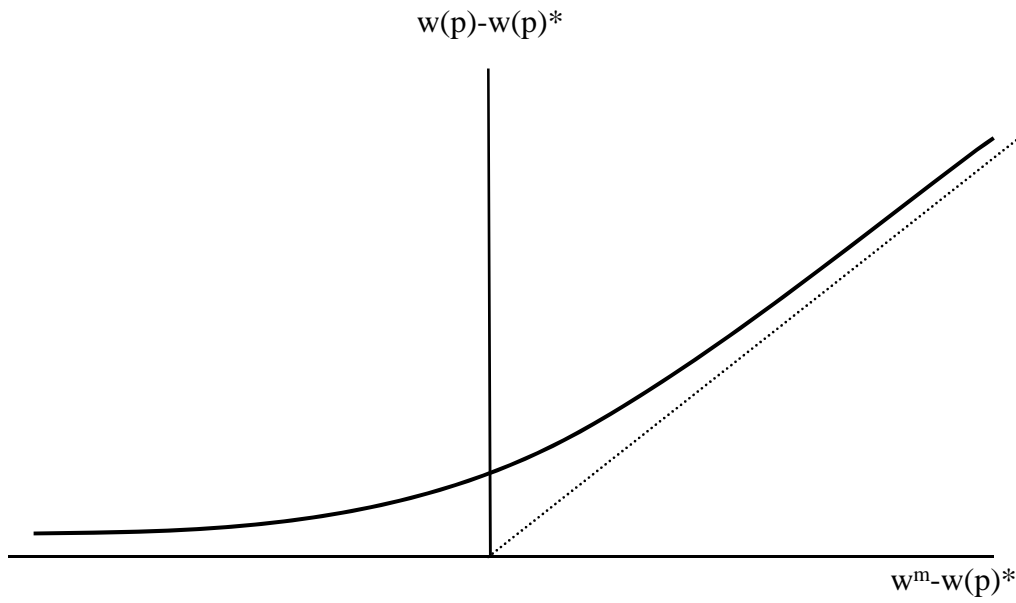
Note: Annual data on state and federal minimum wages and log percentiles. Minimum wages are in 2007 dollars.

Figure 1B: Trends in state and federal minimum wages, and log(p90)-log(p50)



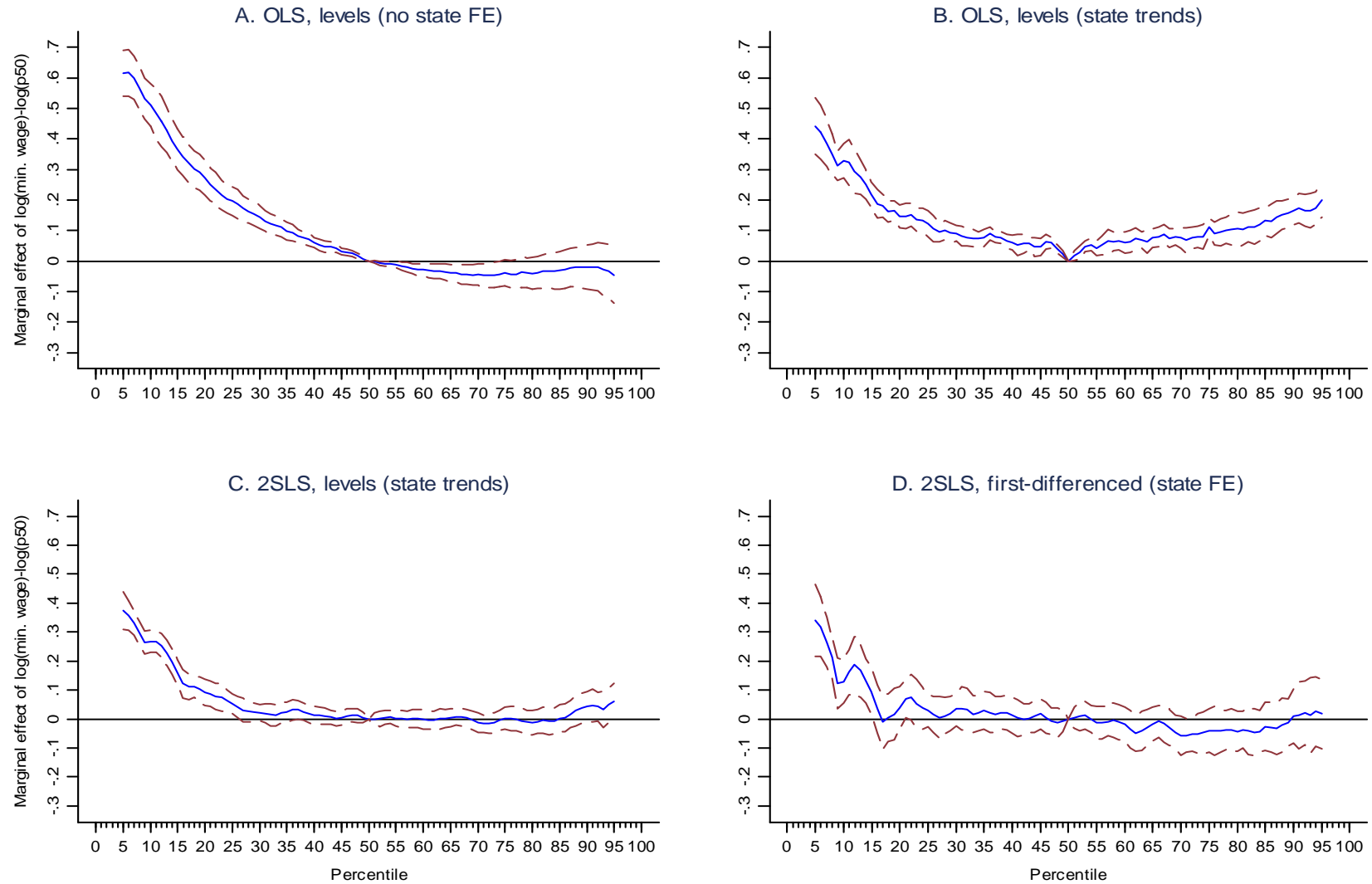
Note: Annual data on state and federal minimum wages and log percentiles. Minimum wages are in 2007 dollars.

Figure 2: The theoretical relationship between deviations in the minimum and latent wage percentile, and differences between the minimum wage and latent percentile



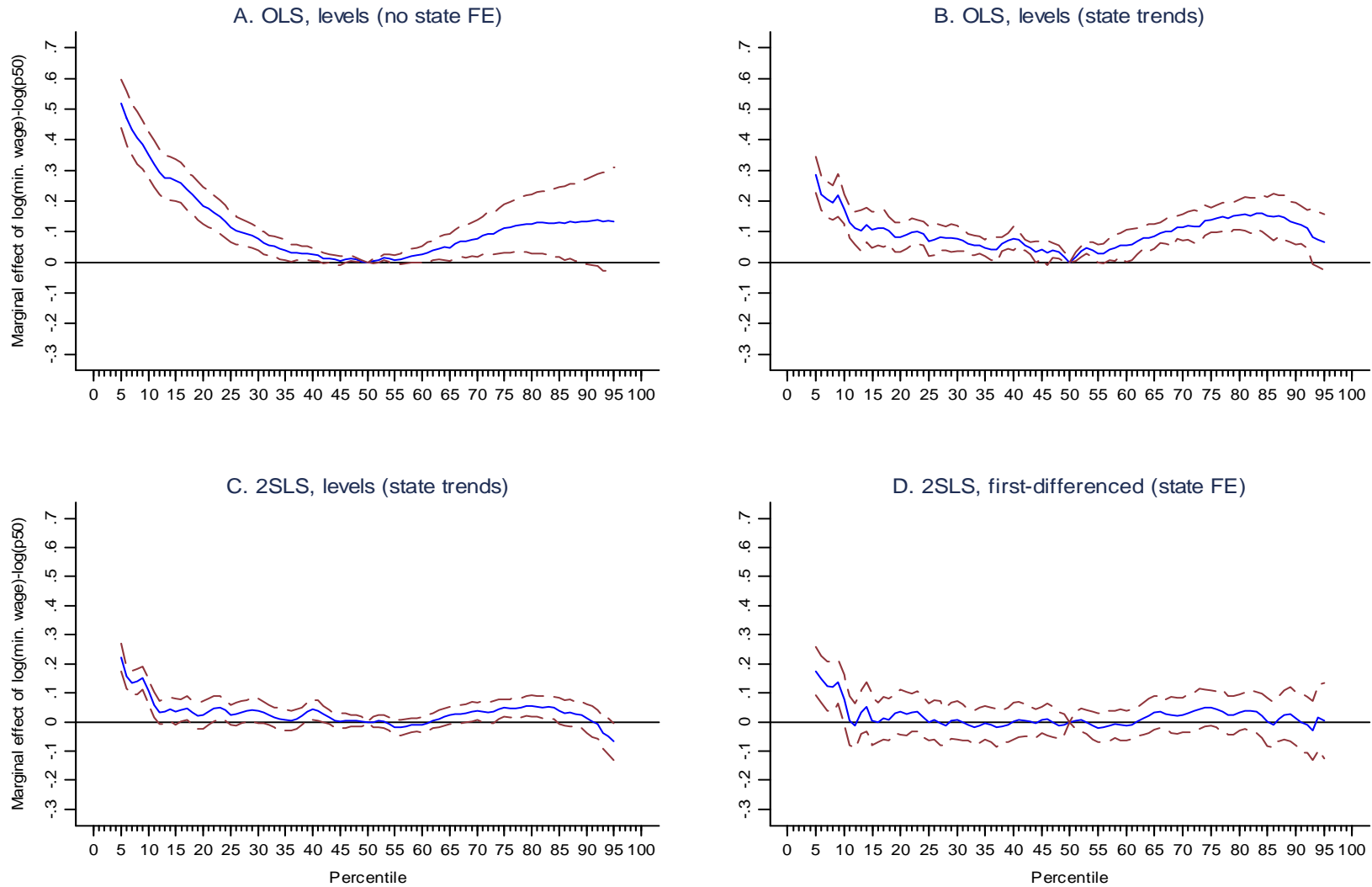
Note: $w(p)-w(p)^*$ is the difference between the actual (observed) value of percentile p and the latent value of percentile p (i.e. its value in the absence of a minimum wage). $w^m-w(p)^*$ is the difference between the minimum and the latent value of percentile p .

Figure 3: OLS and 2SLS estimates of the relationship between $\log(p) - \log(p50)$ and $\log(\min) - \log(p50)$
 Female wage distribution, 1979-2007



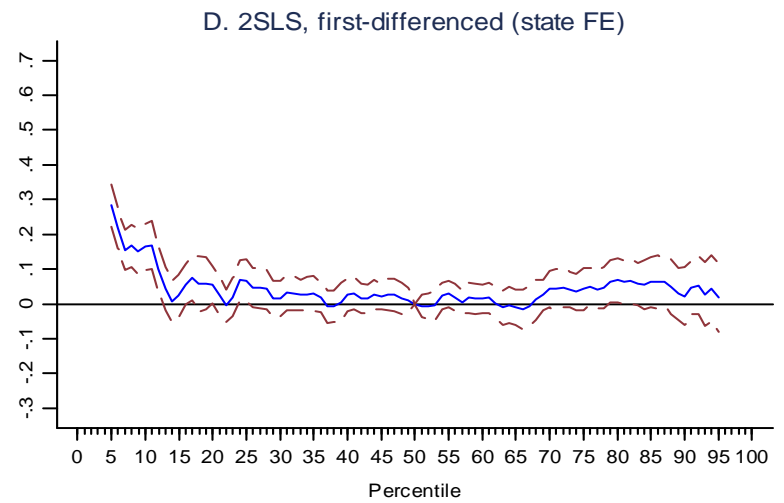
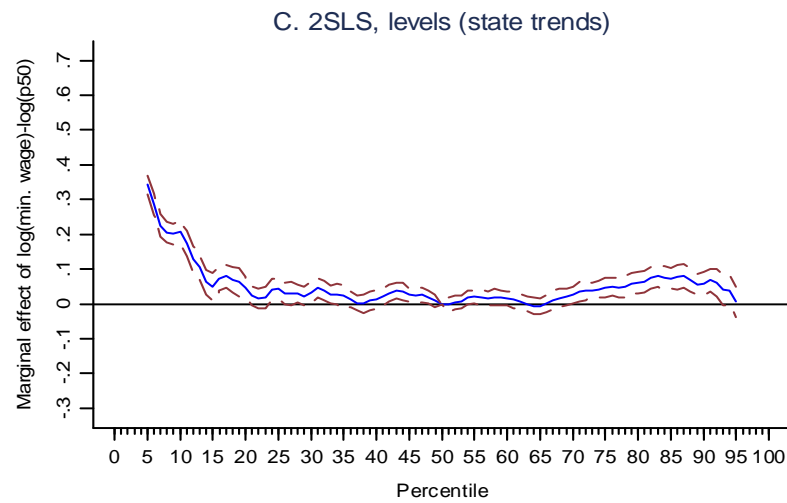
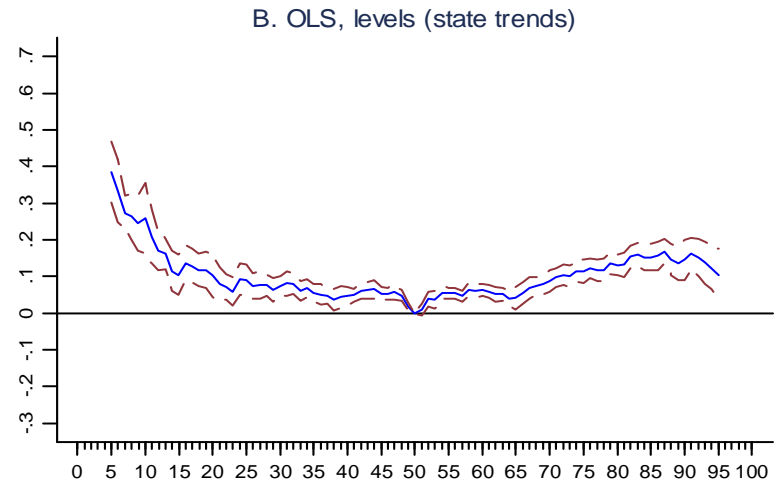
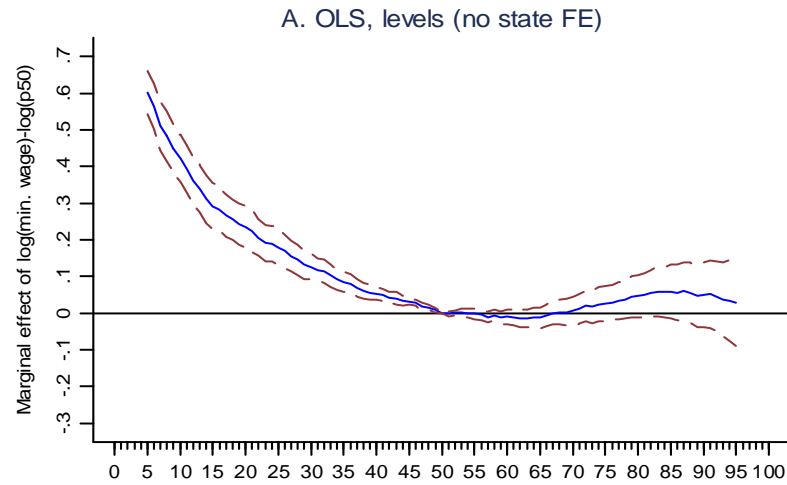
Note: Estimates are the marginal effects of $\log(\min. \text{ wage}) - \log(p50)$, evaluated at the hours-weighted average of $\log(\min. \text{ wage}) - \log(p50)$ across states and years. Observations are state-year observations. 95% confidence interval is represented by the dashed lines. Panel A corresponds with column 1 of Table 2. Panel B corresponds with column 3 of Table 2. Panel C corresponds with column 3 of Table 3. Panel D corresponds with column 5 of Table 3.

Figure 4: OLS and 2SLS estimates of the relationship between $\log(p)-\log(p50)$ and $\log(\min)-\log(p50)$
 Male wage distribution, 1979-2007



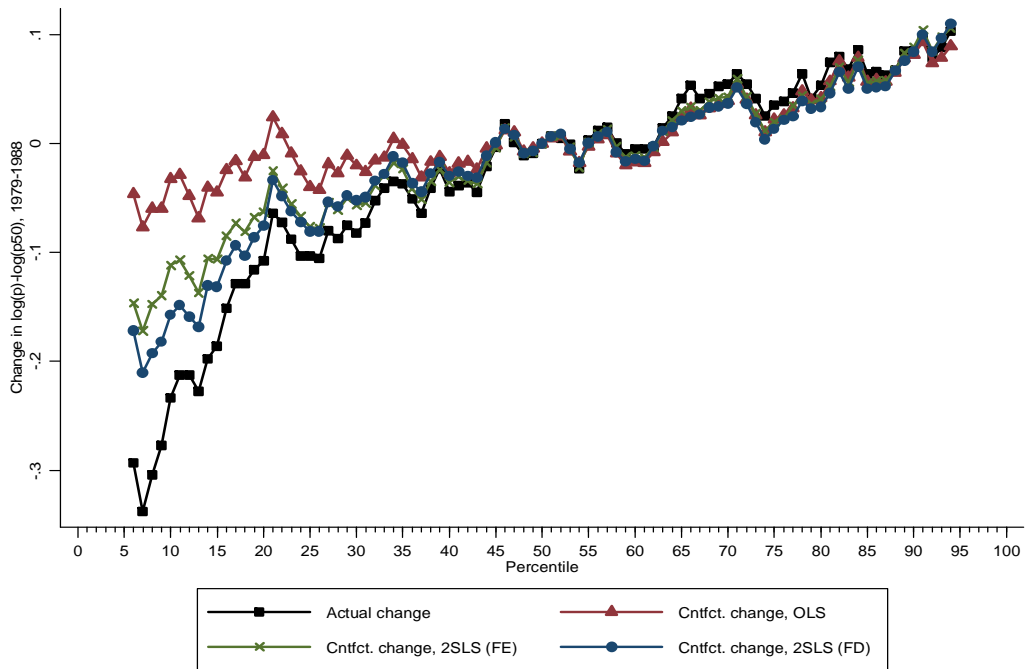
Note: Estimates are the marginal effects of $\log(\min. \text{ wage}) - \log(p50)$, evaluated at the hours-weighted average of $\log(\min. \text{ wage}) - \log(p50)$ across states and years. Observations are state-year observations. 95% confidence interval is represented by the dashed lines. Panel A corresponds with column 1 of Table 2. Panel B corresponds with column 3 of Table 2. Panel C corresponds with column 3 of Table 3. Panel D corresponds with column 5 of Table 3.

Figure 5: OLS and 2SLS estimates of the relationship between $\log(p)-\log(p50)$ and $\log(\min)-\log(p50)$
 Male and female wage distribution, 1979-2007



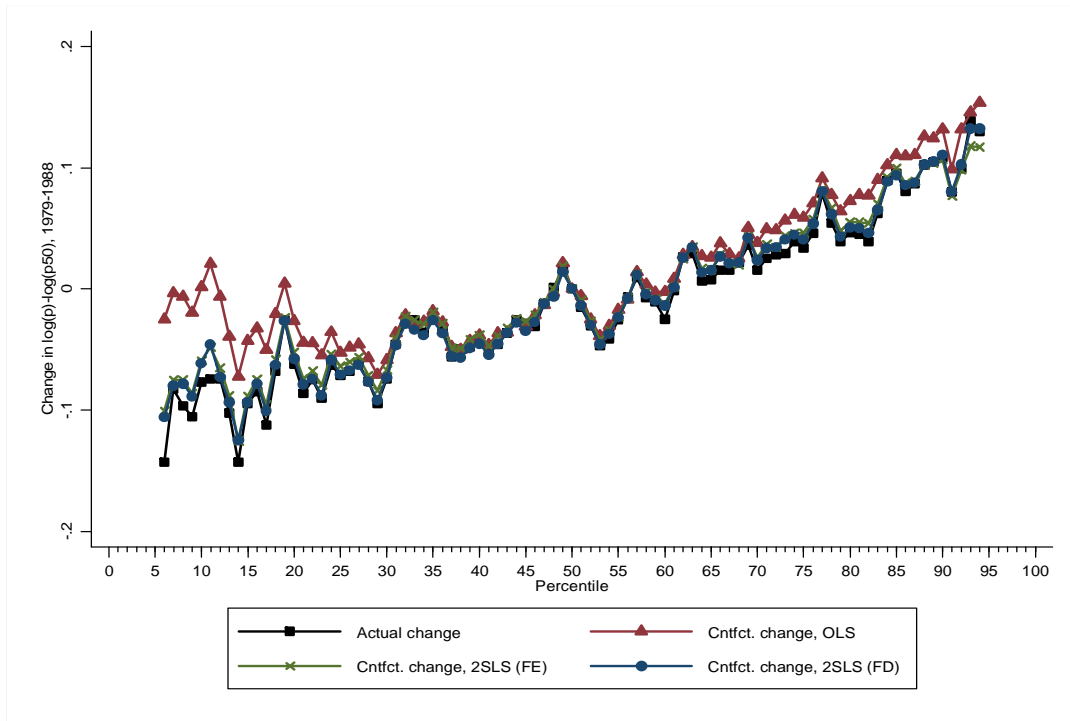
Note: Estimates are the marginal effects of $\log(\min. \text{ wage})-\log(p50)$, evaluated at the hours-weighted average of $\log(\min. \text{ wage})-\log(p50)$ across states and years. Observations are state-year observations. 95% confidence interval is represented by the dashed lines. Panel A corresponds with column 1 of Table 2. Panel B corresponds with column 3 of Table 2. Panel C corresponds with column 3 of Table 3. Panel D corresponds with column 5 of Table 3.

Figure 6: Actual and counterfactual change in $\log(p)-\log(p50)$
 Female wage distribution, 1979 to 1988



Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the female wage distribution. Counterfactual changes are calculated by adjusting the 1979 wage distributions by the value of states' effective minima in 1988 and coefficients from OLS regressions (column 1 of Table 2) and 2SLS first-differenced regressions (column 5 of Table 3).

Figure 7: Actual and counterfactual change in $\log(p)-\log(p_{50})$
 Male wage distribution, 1979 to 1988



Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the female wage distribution. Counterfactual changes are calculated by adjusting the 1979 wage distributions by the value of states' effective minima in 1988 and coefficients from OLS regressions (column 1 of Table 2) and 2SLS first-differenced regressions (column 5 of Table 3).

Figure 8a: Actual and counterfactual change in $\log(p)-\log(p50)$
Male and female pooled wage distribution, 1979 to 1988

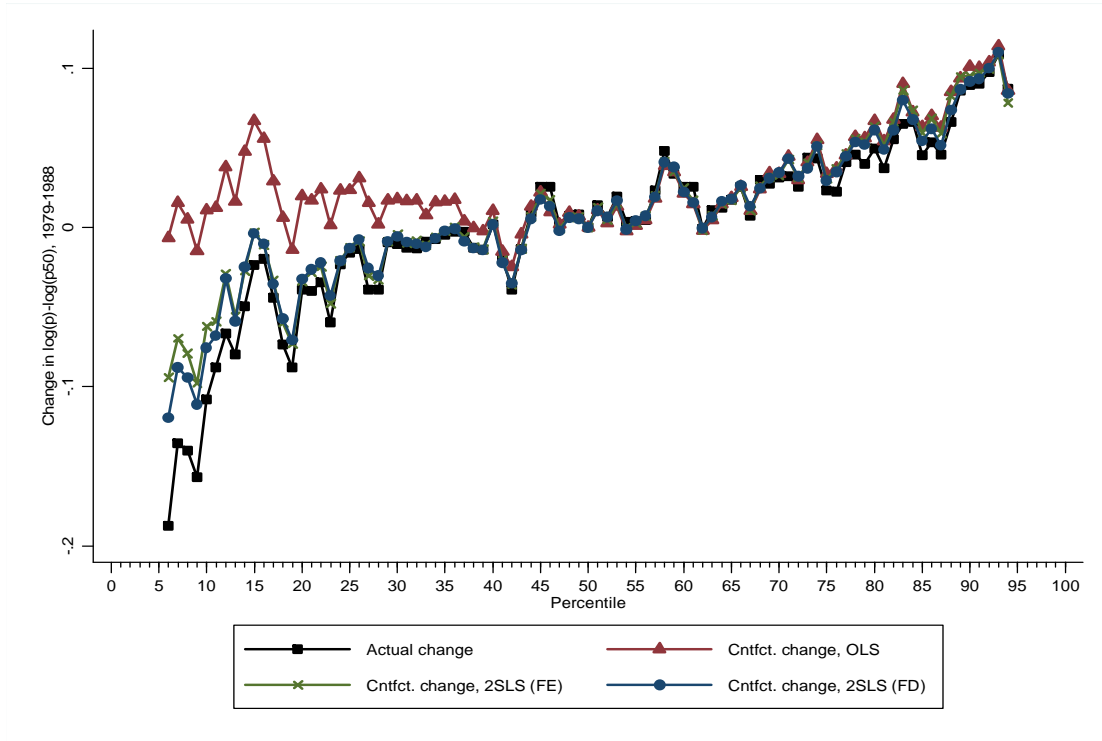
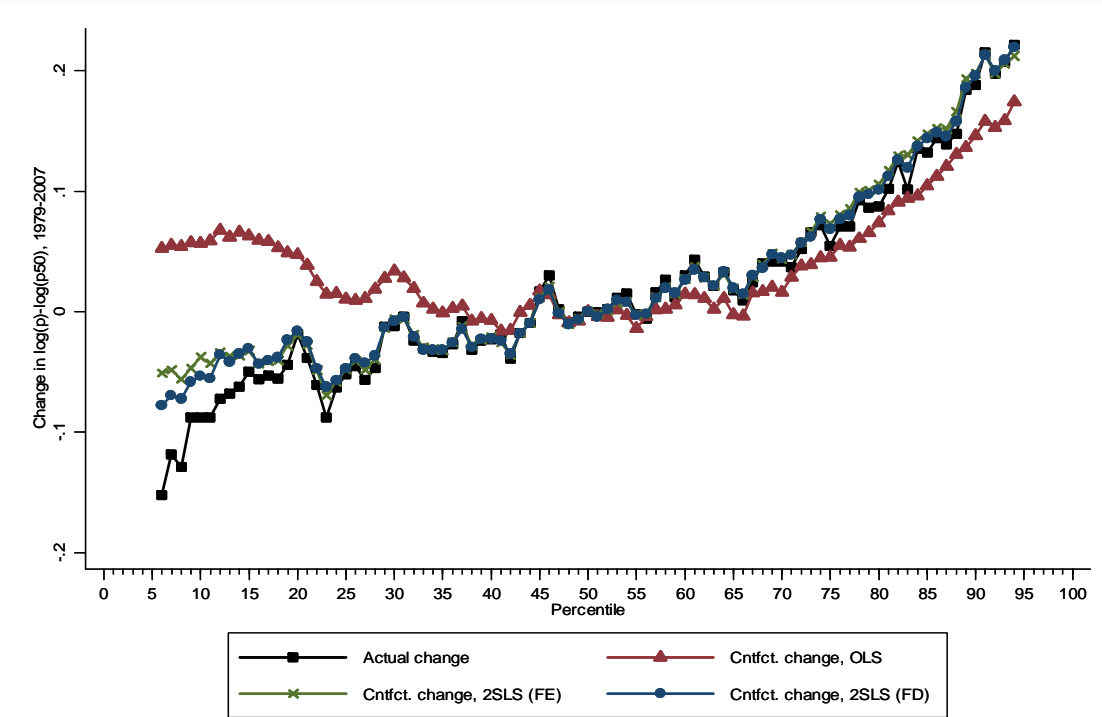
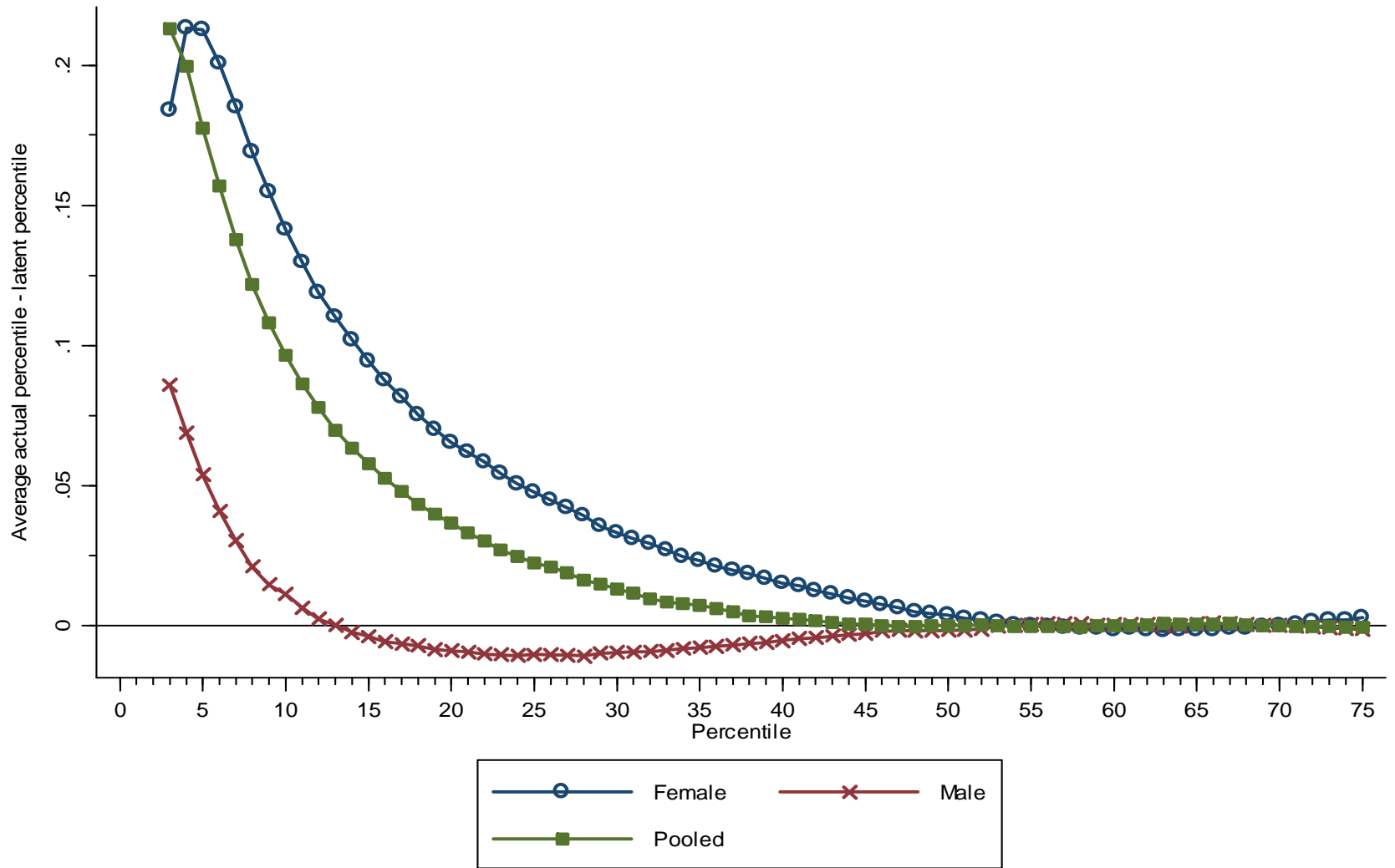


Figure 8b: Actual and counterfactual change in $\log(p)-\log(p50)$
Male and female pooled wage distribution, 1979 to 2007



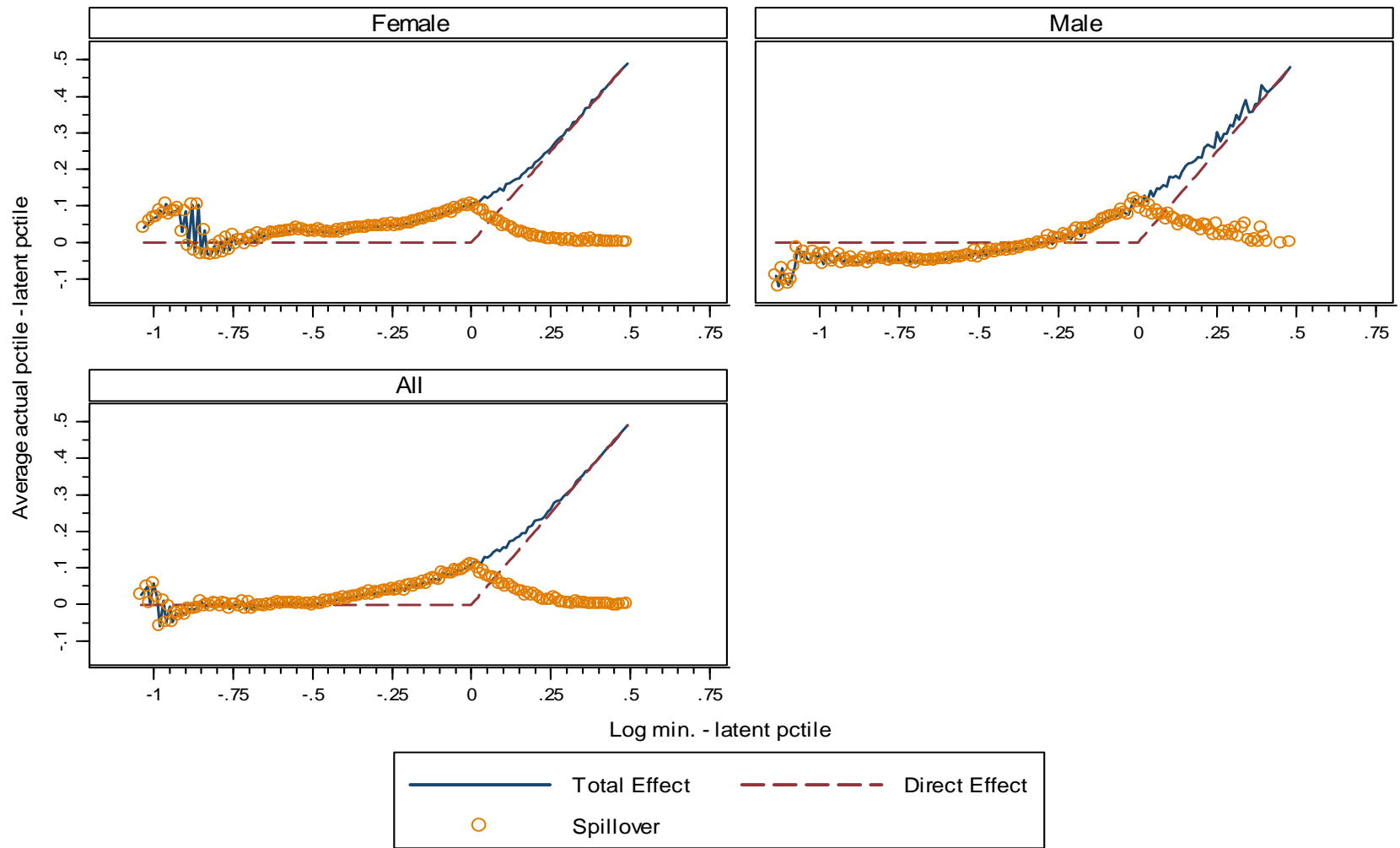
Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the female wage distribution. Counterfactual changes are calculated by adjusting the 1979 and 2007 wage distributions by the value of states' effective minima in 1988 and coefficients from OLS regressions (column 1 of Table 2), 2SLS levels regressions with state trends (column 3 of Table 3), and 2SLS first-differenced regressions (column 5 of Table 3).

Figure 9 - Average difference between actual and latent percentiles



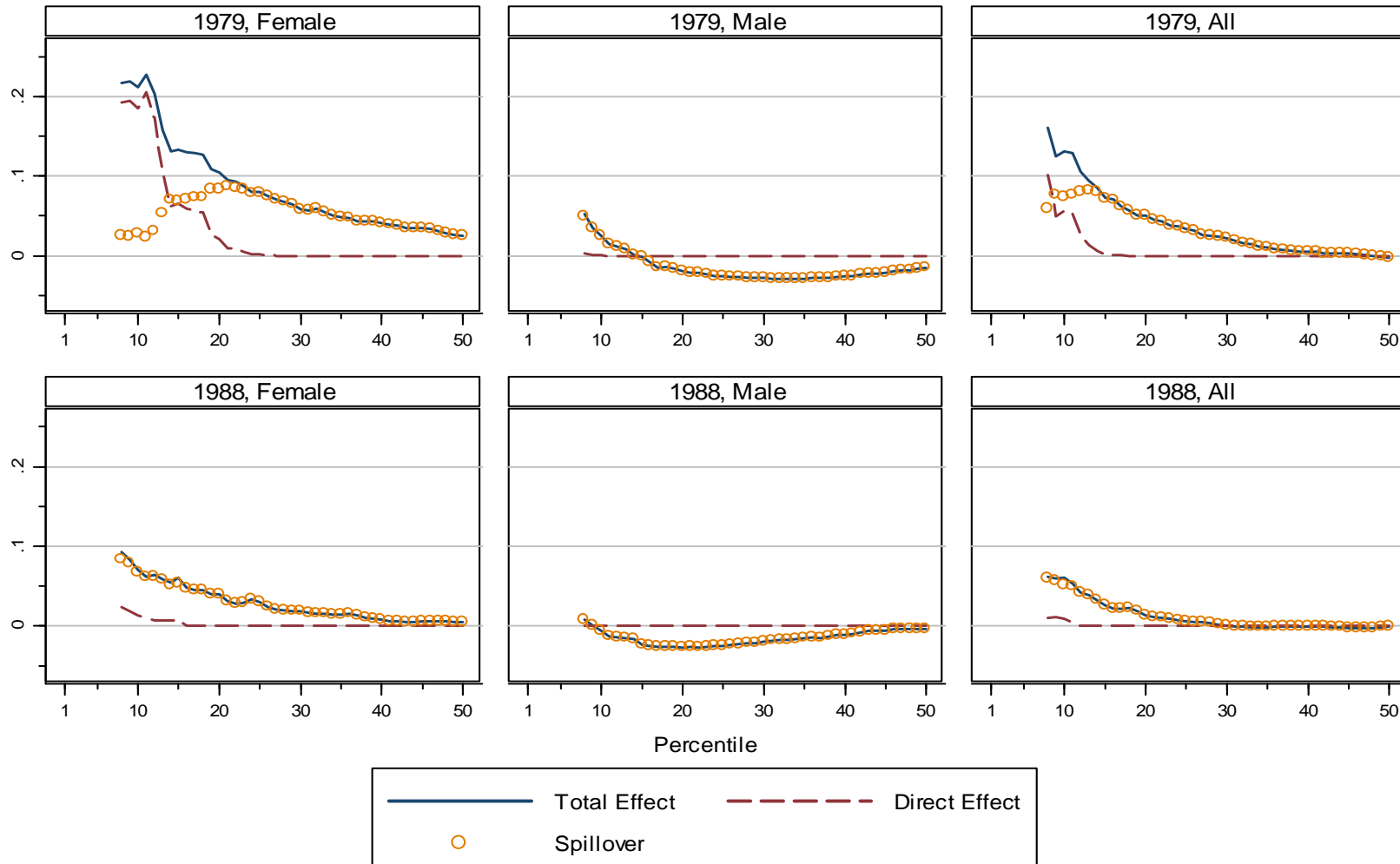
Note: Deviations are averaged across all states and years. See text for description of how devs. are computed.

Figure 10 - Total effect, direct effect, and spillover effect of the minimum wage



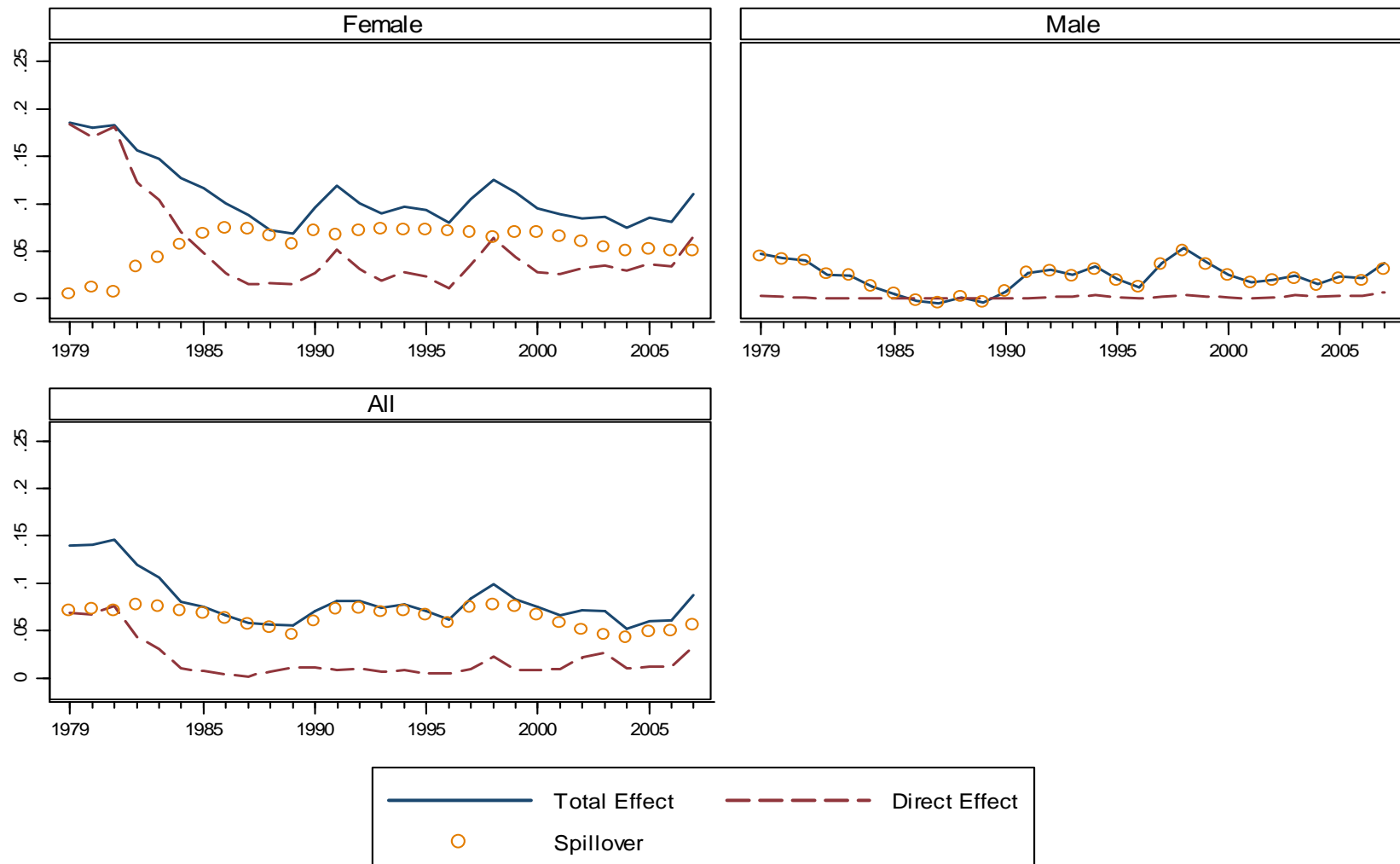
Note: Differences between the actual and latent pctiles, and the minimum wage and latent pctiles are averaged across all states and years (1979-2007). The total effect is defined as the actual value of a pctile minus the estimated latent value.

Figure 11 - Total, direct, and spillover effects of the minimum wage in 1979 and 1988 on lower percentiles, by gender



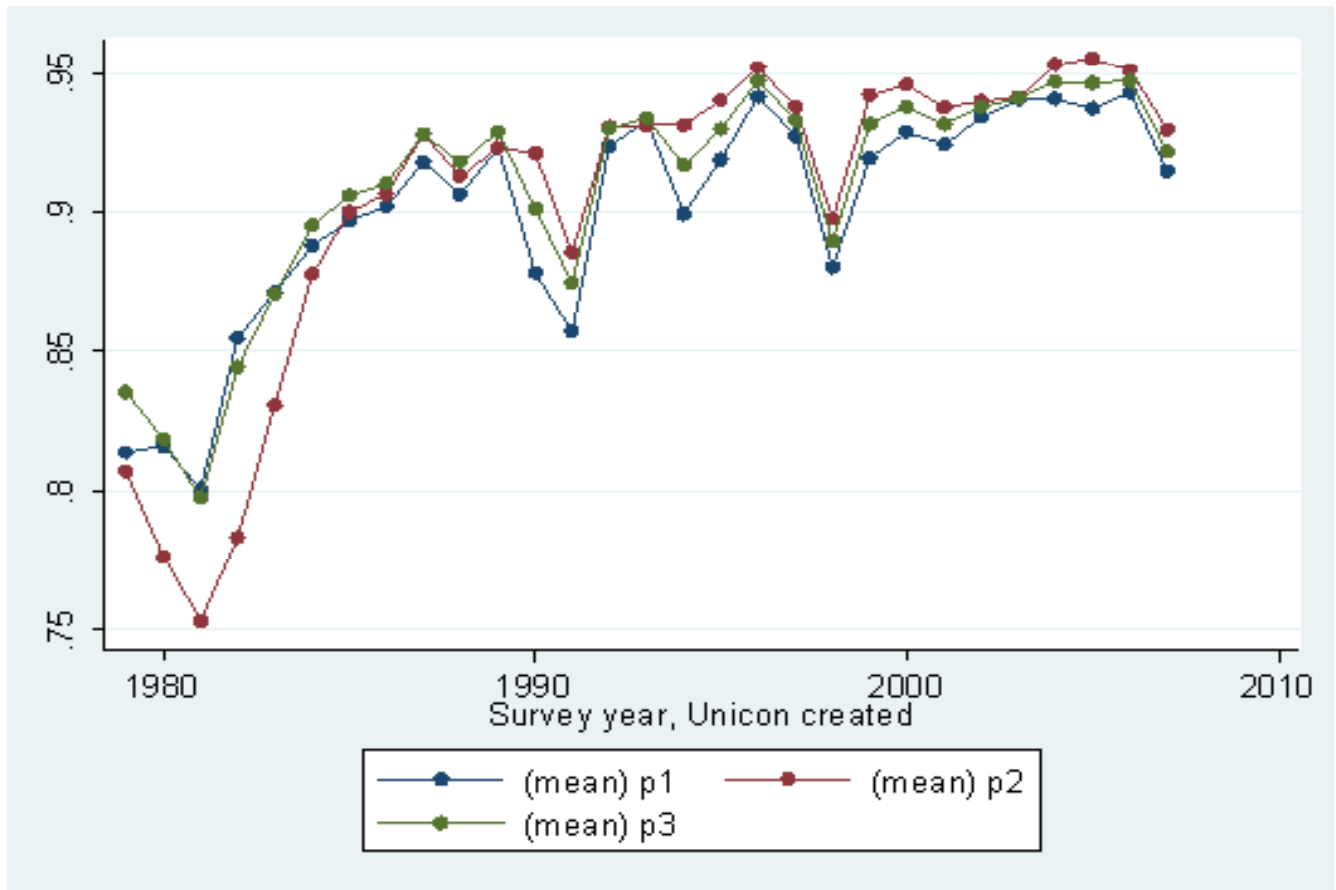
Plots display the total effect of the minimum wage, and the total effect decomposed into the direct and spillover effects. For some graphs, the total effect is difficult to view because the total and spillover effects overlap quite closely.

Figure 12 - Total, direct, and spillover effects of the minimum wage on the log(50)-log(10), by gender and year



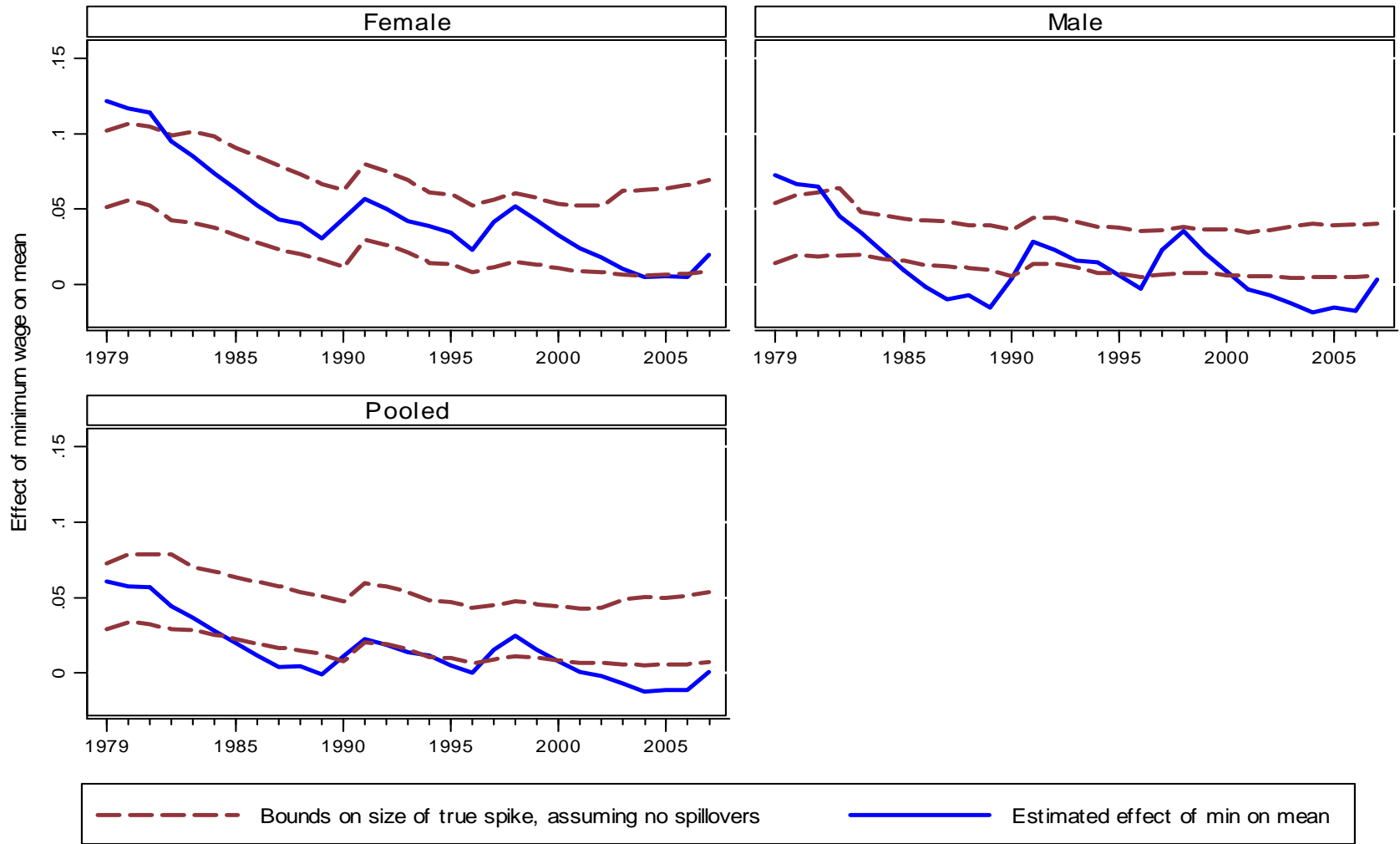
Plots display the total effect of the minimum wage, and the total effect decomposed into the direct and spillover effects. For some graphs, the total effect is difficult to view because the total and spillover effects overlap quite closely.

Figure 13 - Estimates of the probability of correctly reporting the wage, by gender and year



Note: p1 indicates probability for women, p2 is the probability for males, and p3 is the probability for the pooled sample.

Figure 14 - Estimates of the effect of the min. on the mean, and bounds for the size of the spike at the min. wage in the absence of spillovers



Plots display the estimated average marginal effects of the minimum wage on the mean, and the upper and lower bounds for the size of the true spike assuming no spillovers.