



Center on Wage and Employment Dynamics

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# Data and Methods for Estimating the Impact of Proposed Local Minimum Wage Laws

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In this technical report, we document a methodology developed by the UC Berkeley Labor Center to estimate the number of workers impacted by proposed local minimum wage laws, as well as the expected increase in wages. This methodology is similar to that used by researchers to generate impact estimates for national and state minimum wage proposals, but differs in several respects because of significant data limitations for city- or county-based analyses.

In Section A, we describe the data source, sample definition, and wage variable creation and cleaning. In Section B, we then describe the process for estimating the number of workers affected and the expected increase in wages.

## **A. Data and Wage Variable Creation**

### **1. Data source**

We use the 2012 IPUMS American Community Survey (ACS) (<https://usa.ipums.org/usa/>). We use the ACS rather than the Current Population Survey (CPS) because the ACS (a) has much larger sample sizes, which is critical for local analyses; (b) is representative at the city or county level which the CPS is not; and (c) allows us to construct a sample based on place of work, which the CPS does not. That said, the ACS does not have a respondent-reported measure of hourly wages; we address this issue below.

### **2. Sample definition**

The sample consists of U.S. civilians aged 18 to 64, who had non-zero income in the previous 12 months, who worked last week, and who were not self-employed, unpaid family workers, or federal or state government employees (these groups of workers are not covered by city or county minimum wage laws).

In addition, we select only respondents who worked more than 13 weeks last year and who usually worked more than 3 hours per week; the goal with this selection was to identify workers actively connected to the labor market. In practice, the impact of this selection is small; for those who work in the state of California, this selection drops 3.8% (unweighted) of the observations.

### **3. Geography**

We identify workers based on place-of-work, not place-of-residence, an important distinction given that low-wage workers are increasingly not able to afford to live in the cities where they work.

### **4. The hourly wage variable**

Following standard practice with the ACS, our hourly wage variable is a computed variable, based on the worker's annual earnings, reported number of weeks worked last year, and usual hours worked per week.<sup>1</sup> The 'weeks worked last year' variable is a categorical variable of intervals of weeks worked (such as 14-26 weeks or 50-52 weeks). We converted this variable to a continuous variable by setting the number of weeks worked to the midpoint of each interval.<sup>2</sup> The annual earnings measure includes wages, salary, commissions, cash bonuses, or tips from all jobs, before deductions for taxes.

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The ACS hourly wage variable is computed as annual earnings divided by the product of weeks worked last year and usual hours worked per week. We trimmed outliers by dropping wages less than \$0.50 or greater than \$100 in 1989 dollars.<sup>3</sup> Of those who worked in state of California, met our sampling criteria, and had a valid computed hourly wage value, this step drops 0.45% (unweighted) of the observations.

## 5. Checks on the computed hourly wage variable

Researchers have long recognized that there is measurement error in the ACS computed hourly wage variable. For example, for the state of California, the ACS variable yields a higher percentage of workers with hourly wages below the statutory minimum wage compared to the CPS. However, these differences are appreciably smaller when specific regions are examined. Also note that this is an imperfect comparison, because the ACS estimate is based on place of work, while the CPS estimate is based on place of residence (one might expect that the latter would omit low-wage commuters in the case of high cost-of-living cities, for example).

We more closely examined the distribution of the ACS computed hourly wage variable for those who work in California, and found that most of the observations below the state minimum wage in 2012 (\$8.00) were clustered within a few dollars of the minimum. For these respondents, we also tested for any patterns in the components that were used to calculate the hourly wage variable (weeks worked, hours per week, or yearly earnings) that might indicate incorrect reporting of one or more of the components; however, no patterns emerged. The large majority of these respondents had very low annual earnings (their median annual earnings were \$9,600 and the 90th percentile was \$15,500, unweighted). These are clearly low-wage workers; the measurement error appears to stem mainly from reporting of weeks and hours worked.

## B. Simulating the Impact of Proposed Local Minimum Wage Increases

In this section, we outline a method for estimating the number of workers that would be affected by a proposed minimum wage increase for a given city or county, using the dataset and wage variable described in Section A. For ease of exposition, we refer to ‘the city’ below; however, in many cases we have had to use county level data for the bulk of the estimation (see section B.4 below).

The logic of our method is to simulate the city’s wage distribution right before the proposed minimum wage law would go into effect, and then estimate the number of workers affected by the increase and the additional wages earned as a result.

In simulating this future wage distribution just prior to the minimum wage increase, we:

1. adjust for projected wage growth at the bottom of the wage distribution;
2. adjust for any interim increases in the state minimum wage; and
3. adjust for projected employment growth.

We then estimate (a) the number of workers impacted by the proposed minimum wage increase, both directly and indirectly, and (b) the additional wages earned as a result of the increase. As we describe below, we generate “high” and “low” estimates, yielding an impact range.

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For proposed minimum wage laws that have multiple phase-in steps, we repeat the above simulation for each successive step, cumulating the number of workers affected and the increase in wages over those steps.

### 1. Method to estimate wage growth

We first inflate wages from 2012 to 2013, using Occupational Employment Statistics (OES) growth estimates for the metropolitan region's 25th wage percentile between Q1 2012 and Q1 2013. Because wages typically grow more slowly than average at the bottom of the wage distribution, this is a more accurate inflator than the regional Consumer Price Index.<sup>4</sup>

We then inflate 2013 wages to the year and month that the proposed minimum wage law would go into effect. We again draw on the OES; this time, we use the average annual growth for the metropolitan region's 25th wage percentile between 2003 and 2006 as a proxy of expected future wage growth (data from more recent years would be confounded by the 2007-2009 recession).

In cases where a state minimum wage increase will precede the city's proposed minimum wage law, we inflate 2013 wages to the month and year of the state minimum wage increase, "apply" the state increase using the method in B.2 below, and then inflate wages to the month and year of the proposed city increase. We also follow this method for state minimum wage increases following the city's proposed minimum wage law in order to estimate the change in annual earnings resulting from the proposed measure.

### 2. Method to adjust wages based on changes to the statutory minimum wage

We next simulate the impact of the proposed minimum wage law, yielding a "high" and "low" estimate. Both estimates identify workers affected directly and indirectly (via spill-over effects) by the minimum wage increase.

The two estimates differ in (1) how they treat respondents with wages below 90% of the old minimum wage ("subminimum wage workers") and (2) how they define the spill-over effect. Table 1 details these differences:

- The main group of impacted workers – minimum wage workers – consists of those who earn between the old minimum wage and the new minimum wage. Given measurement error, we include in this group workers who earn somewhat below the old minimum wage (down to 90% of the old minimum wage).
- For subminimum wage workers, Scenario 1 includes those earning between 50% to just under 90% of the old minimum wage and Scenario 2 includes everyone earning less than 90% of the old minimum wage.
- For indirectly affected workers, Scenario 1 defines the spill-over band as reaching from the new minimum wage up to 115% of the new minimum wage. Scenario 2 defines the spill-over band as reaching from the new minimum wage up to the sum of the new minimum wage plus the absolute value of the minimum wage increase.<sup>5</sup>

We build a "low" and "high" estimate of impacted workers from these components (different combinations yield the upper and lower bound depending on the details of the proposed minimum wage increase).

We then estimate the additional wages earned by impacted workers as a result of the proposed minimum wage law, as summarized in Table 1. Minimum wage workers simply receive the new minimum wage. Subminimum wage workers receive a percentage wage increase of the same size as the percentage change in the statutory minimum wage. Indirectly affected workers receive a quarter of the difference between their current wage and the upper bound of the spill-over band.

### 3. Method to adjust for employment growth

We apply a final adjustment to our estimates of the number of workers impacted by the proposed minimum wage law, to account for the city’s employment growth from 2012 to the month and year of implementation of the proposed law. Specifically, we draw on the Quarterly Census of Employment and Wages (QCEW) data series to get observed employment growth from 2012 to 2013, and then official state employment growth projections from 2013 to the month and year of implementation. We do not make any adjustments for potential positive or negative changes in employment due to the minimum wage increase.

### 4. Method to generate city estimates with county data

The smallest geographic unit for the ACS place-of-work variable is the county. For some cities, the county is the same geographic unit as the city. But for many cities, the county is larger than the city contemplating the minimum wage increase. In these cases, we perform steps 1-3 above on county-level data, and then reduce the estimated number of impacted workers (and the total wage increase) by the city’s percentage of county employment. This step introduces additional assumptions; namely, that the wage distribution of those who work in the city (not all of whom live in the city) is the same as the wage distribution of those who work in the county, and that wage and employment growth trends in the city mirror those at the county level. Finally, in some cases, the ACS imputed estimate of the size of the city’s workforce differs sufficiently from the more accurate QCEW counts, that we recalibrate our estimate of the city’s workforce to match the QCEW counts.

**Table 1. Summary of method to identify workers that will be impacted by a proposed minimum wage increase**

	Definition of which workers are estimated to receive an increase	Estimate of new wage after the increase
Minimum wage workers	Wage = 90% of OMW to NMW	NMW
Subminimum wage workers		
Scenario 1	Wage = 50-89% of OMW	$OW + OW * ((NMW-OMW)/OMW)$
Scenario 2	Wage = 0-89% of OMW	$OW + OW * ((NMW-OMW)/OMW)$
Indirectly affected workers		
Scenario 1	Wage = NMW to 115% of NMW	$OW + 0.25 * (1.15 * NMW - OW)$
Scenario 2	Wage = NMW to $((NMW-OMW) + NMW)$	$OW + 0.25 * (((NMW-OMW) + NMW) - OW)$

Note: OMW = Old Minimum Wage, NMW = New Minimum Wage, OW = Old Wage, NW= New Wage

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## Endnotes

<sup>1</sup> Since the ACS surveys respondents over the course of the year and asks about earnings in the previous 12 months, we apply the ACS-provided *adjust* variable to convert reported earnings to 2012 dollars.

<sup>2</sup> We tested the validity of the interval mid-point using the continuous version of weeks worked last year in the Current Population Survey (March supplement). For low-income workers in California, average weeks worked in each of the intervals was not substantially different from the interval midpoint (except for the first interval, which is dropped in our sample).

<sup>3</sup> This step follows the methodology of *The State of Working America*, Economic Policy Institute.

<sup>4</sup> This is the method adopted by [Cooper \(2013\)](#). For or California county estimates, see [http://www.labormarketinfo.edd.ca.gov/LMID/OES\\_Employment\\_and\\_Wages.html](http://www.labormarketinfo.edd.ca.gov/LMID/OES_Employment_and_Wages.html).

<sup>5</sup> There is no single consensus estimate of the size of the ripple-effect from minimum wage increases. For our lower bound, we draw on [Wicks-Lim \(2006\)](#), who finds a modal ripple effect of 115% across state and federal minimum wage increases from 1983-2002. For our upper bound, we draw on [Cooper \(2013\)](#), who uses a common convention of defining the ripple-effect band as equal to the new minimum wage plus the absolute value of the minimum wage increase being studied.

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