Title

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

Permalink
https://escholarship.org/uc/item/5q0593k6

Authors
Perry, Ian
Thomason, Sarah
Bernhardt, Annette

Publication Date
2016-06-01

CWED

Center on Wage and Employment Dynamics

DATA BRIEF
June 2016

Institute for Research on Labor and Employment
University of California, Berkeley

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

By Ian Perry, Sarah Thomason, and Annette Bernhardt

Ian Perry is a graduate student at the UC Berkeley Goldman School of Public Policy. Sarah Thomason is a researcher at the UC Berkeley Center for Labor Research and Education. Annette Bernhardt is a senior researcher at the UC Berkeley Institute for Research on Labor and Employment and the Center for Labor Research and Education.

INTRODUCTION

In this technical report we document a methodology developed by the UC Berkeley Center on Wage and Employment Dynamics to estimate the number of workers affected 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 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 IPUMS American Community Survey (ACS) (https://usa.ipums.org/usa/), typically pooling several years to generate large enough sample sizes. 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 generally not; and (c) allows us to construct a sample based on place of work, which the CPS does not. The drawback is that 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 16 to 64, who had positive 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). Depending on the city or county being studied, we also exclude other workers when they would not be covered by the proposed minimum wage law. In California, typically these workers include In-Home Supportive Services (IHSS) workers and employees of public school districts.

In addition, we select only respondents who worked more than 13 weeks in the previous 12 months, and who usually worked more than 3 hours per week. The goal with this selection is to identify workers actively connected to the labor market. In practice, this step only excludes a very small percent of the observations.

3. Geography

We identify workers based on place-of-work rather than place-of-residence, an important distinction given that low-wage workers are increasingly unable 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.[1] The annual earnings measure includes wages, salary, commissions, cash bonuses, and tips from all jobs, before deductions for taxes. "Weeks worked last year" is a categorical variable of intervals of weeks worked (such as 14-26 weeks or 50-52 weeks). We convert this variable to a continuous variable by setting the number of weeks worked to the midpoint of each interval.[2]

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. To address the clustering of observations at whole-number wage levels, we smooth the wage distribution by randomly adding or subtracting up to $0.25 from each observation's computed wage. We trim outliers by dropping wages less than $0.50 or greater than $100 in 1989 dollars (typically less than one percent of the sample).[3] Finally, if the calculated wage for tipped wait staff working in restaurants is greater than the current minimum wage, we recode the wage to the minimum wage in order to eliminate tips from their hourly wage.

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 of $8.00 in 2013 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, indicating they are clearly low-wage workers. The measurement error appears to stem mainly from reporting of weeks and hours worked.

B. SIMULATING THE IMPACT OF LOCAL MINIMUM WAGE INCREASES

In this section, we outline our method for estimating the number of workers that would be affected by a proposed minimum wage law 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.5 below).

The logic of our method is to simulate the city's future wage distribution, with and without the proposed minimum wage law. First, we model the "baseline" scenario, simulating what the wage distribution would look like under the current minimum wage law. We then model the "proposal" scenario, simulating what the wage distribution would look like under the proposed minimum wage law.

In cases when the proposed minimum wage law has multiple phase-in steps, we repeat the minimum wage simulation for each successive step, cumulating the number of workers affected and the increase in wages over those steps. We also repeat the simulation for the baseline scenario in cases where current laws call for increases in the minimum wage during the study timeline. For both the baseline and proposal simulations, we adjust for projected employment growth and projected wage growth.

Finally, we compare the baseline and proposal wage distributions to identify the impact of the minimum wage increase, above and beyond any currently scheduled minimum wage increases. With this comparison, we are able to estimate (a) the number of workers affected by the proposed minimum wage increase, both directly and indirectly, and (b) the additional wages earned as a result of the increase.

1. Method to estimate wage growth

We first inflate wages in our dataset to the current year using the appropriate regional CPI for Urban Wage Earnings and Clerical Workers (CPI-W). In some cases, a minimum wage increase has recently gone into effect but is not reflected in our dataset because it occurred after the ACS survey data was collected. When this occurs, we inflate wages to the month and year of that minimum wage increase, simulate the increase as describe in B.2, and then inflate wages to the current year.

At this point, our dataset is ready to model the proposal and baseline scenarios.

For the proposal scenario, we next inflate wages to the month and year of the proposed minimum wage increase and simulate the increase as described in B.2. We use the average annual change in the Consumer Price Index (CPI) over the past ten years for future wage growth. (We use whichever version of the Consumer Price Index (CPI) is specified in the proposed minimum wage law for cost-of-living adjustments; if the proposed minimum wage law does not contain cost-of-living adjustments, we use the appropriate regional CPI for Urban Wage Earnings and Clerical Workers (CPI-W)).

If the proposed law includes a series of phase-in steps, we inflate wages once again to the month and year of the second proposed minimum wage increase. However, we assume that workers who were directly affected by the first minimum wage increase only receive 50% of the future wage growth rate (since they just received a wage increase). Subminimum wage, indirectly-affected, and not-affected workers receive the full wage growth rate (see B.2 for definitions of these groups). We then repeat this process for any additional minimum wage increases in the proposed law.

For the baseline scenario, we inflate wages from the current year to the month and year of the final proposed minimum wage increase. If minimum wage increases are already planned under existing laws, we model the effect of those scheduled increases and apply future wage growth using the same method as we use in the proposal scenario.

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

Our method for simulating minimum wage increases identifies workers affected directly and indirectly (via spill-over effects) by the minimum wage increase.

We divide workers into four groups depending on their wage just prior to conducting the simulation:

- *Directly-affected*: workers earning 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). This is the main group of affected workers.
- *Subminimum wage*: workers earning between 50% and just under 90% of the old minimum wage. We drop from the estimation workers earning less than 50% of the old minimum wage.
- *Indirectly-affected*: workers already earning the new minimum wage or just above it, up to 115% of the new minimum wage. These are the workers who receive raises due to spill-over effects.[4]
- *Not-affected*: workers already earning more than 115% of the new minimum wage. These workers are unaffected by the proposed minimum wage increase.

We adjust individual workers' wages based on which group they belong to, as summarized in Table 1. Workers who are directly affected by the minimum wage increase 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 115% of the new minimum wage. Not-affected workers do not receive a raise.

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

	Wage before increase	Estimate of new wage after the increase
Directly-affected workers	**90% of OMW to NMW**	**NMW**
Subminimum wage workers	**50-89% of OMW**	**OW + (OW * ((NWM-OMW)/OMW))**
Indirectly-affected workers	**NMW to 115% of NMW**	**OW + (0.25 * ((1.15*NMW) - OW))**
Not-affected workers	**Greater than 115% of NMW**	**OW**

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

3. Method to obtain employment totals and adjust for employment growth

To obtain employment totals, we use data from the Quarterly Census of Employment and Wages (QCEW), which gives us an official count of the total number of workers covered by the law. We then multiply that total by the estimated share of affected workers to get the total number of affected workers. To account for the city's employment growth to the month and year of implementation of the proposed law, we draw on official state employment growth projections. 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 considering the proposed minimum wage increase. In these cases, we perform steps 1-3 above on the county-level sample. 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.

To improve our estimates, we therefore adjust the county-level ACS data using city-level QCEW data. Specifically, we reweight the ACS county-level data so that its industry and sector distribution matches the city's industry and sector distribution reported in the QCEW data. Additionally, we adjust wages in certain industries where QCEW data shows a large discrepancy in the industry's average earnings between the city and county.

ENDNOTES

[1] 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 account for inflation across this reporting window.

[2] We tested the validity of the interval midpoint 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).

[3] This step follows the methodology of *The State of Working America*, Economic Policy Institute.

[4] There is no single consensus estimate of the size of the ripple-effect from minimum wage increases. For our estimation, we draw on Wicks-Lim (2006), who finds a modal ripple effect of 115% across state and federal minimum wage increases from 1983-2002.

Institute for Research on Labor and Employment

irle.berkeley.edu

IRLE promotes multidisciplinary research on all aspects of the world of work and conducts numerous outreach programs. Its funding sources include the University of California, research grants and contracts, revenue from programs and publications, and contributions from individuals, business, unions, and community-based organizations.

Center on Wage and Employment Dynamics

irle.berkeley.edu/cwed

CWED was established within IRLE in 2007 to provide a focus for research and policy analysis on wage and employment dynamics in contemporary labor markets.

Center on Wage and Employment Dynamics
University of California, Berkeley
2521 Channing Way #5555
Berkeley, CA 94720-5555
(510) 643-8140
http://www.irle.berkeley.edu/cwed