

Response to Cengiz

Jeffrey Clemens, Lisa B. Kahn, and Jonathan Meer*

October 27, 2018

*Clemens: University of California at San Diego, Economics Department, 9500 Gilman Drive #0508, La Jolla, CA 92093-0508. Telephone: 1-509-570-2690. E-mail: clemens.jeffrey@gmail.com. Kahn: University of Rochester, Department of Economics, 280 Hutchison Rd, PO Box 270156, Rochester, NY, 14627. Telephone: 1-585-275-1871. E-mail: lisa.kahn@rochester.edu. Meer: Texas A&M University, TAMU 4228, College Station, TX 77843. Telephone: 1-979-845-7309. E-mail: jmeer@tamu.edu.

In Clemens, Kahn, and Meer (2018), we find robust evidence of declines in employer-provided health insurance (EPHI) following minimum wage increases, especially for workers in the lowest earning occupations. Cengiz (2018) replicates our result using both our dataset – the American Community Survey (ACS) – as well as the March Supplement of the Current Population Survey (CPS). He then analyzes variables unique to the CPS which differentiate between employer coverage in one’s own name and coverage as a dependent through a family member. Cengiz claims our results are entirely driven by “dependent” rather than “own” coverage, concluding that our findings are spurious. This claim is false.

The ACS asks respondents whether they are “currently covered by health insurance through an employer or union,” which may include both own coverage and coverage through a family member. This is a limitation since the effect of interest for us is on own-employer coverage. Recognizing this issue, we analyzed samples for which coverage through a family member’s employer could not, by construction, drive any relationship between the minimum wage and EPHI. These samples range in restrictiveness from individuals with no higher earning spouse or no employed spouse in the household, to those who are the only adult in their household. We consistently find that our effects hold at similar magnitudes in these subsamples (see Table A.7 of our paper). Our results therefore cannot be driven exclusively by dependent coverage.

We next show that Cengiz’s findings are unstable due to small sample sizes and data quality issues in the CPS. The ACS samples are nearly 20 times the size of the associated CPS samples. As such, results using the CPS are not robust to modest changes in sample selection, specification, or to excluding imputed values.

Table 1 illustrates these points. We report results for the two occupation groups highlighted in our paper, “Very Low ” wage (panels A and B) and “Low” wage (panels C and D) occupations. For each of these groups, we compare results using the ACS (panels A

and C) and the CPS (panels B and D). The first four columns use our key dependent variable, which indicates whether the respondent has employer-provided health insurance. The estimates in column 1 of panels A and C replicate the full controls specification presented in Table 4 of our paper. To explore robustness, we impose various sample restrictions: whether the respondent is currently employed, whether the respondent is the only adult in the household (meaning the respondent must be the one responsible for employer coverage), and whether the dependent variable was imputed.

In panel A, we find that the ACS yields similar coefficients regardless of the subsample. Importantly, column 3 shows that our effect holds when we restrict to respondents who are the only adult in the household. As mentioned, this group cannot be impacted through coverage of family members, by construction. In addition, column 4 shows that results are similar when excluding imputed observations.

In contrast, panel B shows that estimates using the CPS are fragile. Furthermore, standard errors are 2-3 times larger than in panel A, suggesting the CPS may be insufficiently powered to explore the factors underlying insurance changes. Indeed, when we restrict to respondents with no other adult in the household (column 3), the coefficient is as large as those in columns 1 and 2, but with the *opposite* sign. When we drop imputed observations, the effect is smaller in magnitude and imprecise. Columns 5 and 7 replicate the core of Cengiz's analysis, showing no effect on "own" coverage (column 5) and large negative effects on "dependent" coverage. Once again, these estimates are highly sensitive to the use of imputed data. In fact, the 95% confidence intervals in columns 6 and 8 include both 0 and the full effect estimated in column 4. Therefore, in the no-imputes CPS sample, we can make no conclusions about "own" versus "dependent" coverage.

Splitting out the "Very Low" wage category in the small CPS samples is inadvisable. This drives Cengiz's odd finding that the EPHI effect loads on coverage from *others*,

rather than own coverage. As we note in our paper (Table 3), workers in the “Very Low” wage occupation group are distinct in that they are the most exposed to minimum wage increases based on pay data in the period before the increases. While this is a small subset of workers – a third the size of the “Low” wage category – the large ACS samples allow us to track these workers with sufficient precision.

In “Low” wage occupations, panels C and D, the results are more consistent across datasets. The coefficients still shift more in the CPS than the ACS, but the overall picture is the same across data sets and sample restrictions. We show in our paper that this group will still be mechanically affected by minimum wage increases; it also has larger sample sizes, which help for the CPS analysis. Importantly, columns 5 through 8 show that the effect for “own” coverage is similar in magnitude to that for “dependent” coverage, though estimates are noisy. It is again the case that the 95% confidence interval for each estimate includes both 0 and the full effect from column 4. Cengiz does not discuss this result but it goes against his conclusion that effects are only driven by “dependent” coverage.

We conclude by noting that health economists have devoted considerable effort to understanding the relative strengths and weaknesses of ACS and CPS insurance data. As a result, researchers have identified several technical issues that limit the value of the CPS for this purpose. Non-response to health insurance questions was more than twice as prevalent in the CPS as in the ACS. This can also be seen in Table 1 by comparing sample sizes in columns 1 and 4 across the different panels. There are also important changes in survey participation, question design, and sampling frame in the CPS.¹ Finally, for analyses dependent on variations across states and small population sub-groups, the

¹While ACS participation remains above 90 percent, CPS participation has dropped below 80 percent in recent years. The ACS posed the same health insurance question to its respondents in each year in our sample, the CPS sequence of insurance questions changed substantially in 2014. And the ACS’s sampling frame was similarly constructed throughout our sample period, but the March CPS’s sampling frame has been revised.

superiority of the ACS and its large samples is broadly recognized. For these reasons, leading health economists have relied overwhelmingly on ACS data for understanding the effects of the Affordable Care Act (ACA) on insurance coverage (see, for example, Courtemanche, Marton, Ukert, Yelowitz, and Zapata (2016); Duggan, Goda, and Jackson (2017); Freaan, Gruber, and Sommers (2017); Kaestner, Garrett, Gangopadhyaya, and Fleming (2015)). Our analyses bear these concerns out, as our ACS estimates are robust while CPS estimates prove to be fragile.

Table 1: Employer-Sponsored Health Insurance and Minimum Wages: ACS-CPS Comparison

Dependent Variable	Individual Has Employer Coverage		Own Coverage		Coverage from Other			
	All (1)	Employed (2)	Only Adult (3)	No Impute (4)	All (5)	No Impute (6)	All (7)	No Impute (8)
<i>Panel A:</i>								
Minimum Wage	-0.0188*** (0.00603)	-0.0205*** (0.00653)	-0.0258** (0.0110)	-0.0213*** (0.00593)	NA			
Observations	333,948	228,891	104,210	301,698				
<i>Panel B:</i>								
Minimum Wage	-0.0345*** (0.0127)	-0.0412** (0.0171)	0.0341 (0.0219)	-0.00901 (0.0177)	-0.000641 (0.0102)	0.00837 (0.0131)	-0.0338** (0.0148)	-0.0194 (0.0201)
Observations	17,741	14,174	5,404	13,372	17,741	13,262	17,741	13,262
<i>Panel C:</i>								
Minimum Wage	-0.0120*** (0.00383)	-0.0128*** (0.00442)	-0.0106** (0.00399)	-0.0132*** (0.00386)	NA			
Observations	967,696	676,224	270,024	879,766				
<i>Panel D:</i>								
Minimum Wage	-0.0262** (0.0126)	-0.0263** (0.0125)	-0.0380* (0.0192)	-0.0213 (0.0154)	-0.0115 (0.00920)	-0.00688 (0.0101)	-0.0146 (0.00891)	-0.0134 (0.0117)
Observations	51,348	41,686	15,777	38,727	51,348	38,433	51,348	38,433
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels respectively. See table 4 of the main text. The dependent variable in columns 1-4 is an indicator for whether an individual has employer provided insurance coverage. In columns 5-6 (7-8), the dependent variable is an indicator equaling 1 if the individual has coverage through their own (another family member's) employer. Panels A and B restrict to "Very Low Wage" occupations (the bottom quarter of the bottom decile of occupations based on their decile of the 10th percentile wage distribution); panels C and D restrict to "Low Wage" occupations (the remainder of the bottom decile). Panels A and C replicate results from our paper using American Community Survey (ACS) data from 2011-2016. Panels B and D use the Current Population Survey March Supplement (CPS) as a comparison, using survey years 2012-2017 (where answers reflect the previous calendar year). We use our "full controls" specification from the text; occupation-by-year and occupation-by-state fixed effects, macroeconomic controls (log of personal income, a housing price index, and the employment rate in the state-year), and ACA expansion controls (indicators for whether a medicaid expansion is in effect in the state-year, the expansion indicator interacted with an after 2013 indicator, and the health insurance market concentration for providers to large and small firms.) Standard errors are clustered at the state level.

References

- CENGIZ, D. (2018): "Seeing Beyond the Trees: Using Machine Learning to Estimate the Impact of Minimum Wage on Affected Individuals," .
- CLEMENS, J., L. B. KAHN, AND J. MEER (2018): "The Minimum Wage, Fringe Benefits, and Worker Welfare," Working Paper 24635, National Bureau of Economic Research.
- COURTEMANCHE, C., J. MARTON, B. UKERT, A. YELOWITZ, AND D. ZAPATA (2016): "Impacts of the Affordable Care Act on Health Insurance Coverage in Medicaid Expansion and Non-Expansion States," Working Paper 22182, National Bureau of Economic Research.
- DUGGAN, M., G. S. GODA, AND E. JACKSON (2017): "The Effects of the Affordable Care Act on Health Insurance Coverage and Labor Market Outcomes," Working Paper 23607, National Bureau of Economic Research.
- FREAN, M., J. GRUBER, AND B. D. SOMMERS (2017): "Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act," *Journal of Health Economics*, 53, 72 – 86.
- KAESTNER, R., B. GARRETT, A. GANGOPADHYAYA, AND C. FLEMING (2015): "Effects of ACA Medicaid Expansions on Health Insurance Coverage and Labor Supply," Working Paper 21836, National Bureau of Economic Research.