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DISCUSSION PAPER SERIES

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ABSTRACT

Does Measurement Error Explain the Increase in Subminimum Wage Payment Following Minimum Wage Increases?*

In analyses of minimum wages, positive "ripple effects" and subminimum wages are difficult to distinguish from measurement error. Indeed, prior work posits that a simple, symmetric measurement process may underlie both phenomena in Current Population Survey data for the full working age population. We show that the population-wide symmetry between spillovers and subminimum wage payment is illusory in that spillovers accrue to older individuals while underpayment accrues to the young. Symmetric measurement error cannot explain this heterogeneity, which increases the likelihood that both spillovers and subminimum-wage payment are real effects of minimum wage increases rather than artifacts of measurement error.

JEL Classification: J08, J38, K42

Keywords: minimum wage, subminimum wage, noncompliance

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* We thank Duncan Hobbs for excellent research assistance.

Understanding the minimum wage's effects on the wage distribution is of longstanding interest. A considerable amount of research has considered the possibility of spillovers up the wage distribution (*e.g.*, Lee, 1999; Neumark, Schweitzer, and Wascher, 2004). Attention has also been paid to whether minimum wage increases lead to subminimum wage payment, due perhaps to evasion (Goraus-Tańska and Lewandowski, 2019; Rani et al, 2013; Clemens and Strain, 2020). Because they can be difficult to distinguish from measurement error in self-reported survey data, however, both of these phenomena are difficult to estimate.

A highly cited paper by Autor, Manning, and Smith (2016, hereafter AMS) contends that measurement error has the potential to explain both spillovers and subminimum wages in the Current Population Survey (CPS). AMS focus on upward spillovers, arguing that true spillovers are difficult to distinguish from measurement error. This has contributed to economists downgrading the likely importance of both wage theft and wage spillovers as consequences of minimum wage increases.

In this paper, we confirm AMS's conclusion that predictions from their measurement error model are consistent with observed patterns in self-reported wage data on a sample of workers spanning the working-age population. We also show, however, that the AMS model does not provide evidence that measurement error offers a better explanation for self-reported subminimum wage payment than actual wage theft. Specifically, we show that the pattern of spillovers and subminimum wage payment among younger workers, the group most likely to experience wage theft, cannot be explained by the AMS model of measurement error.

The question at hand is whether a simple model of measurement error is *sufficient* to explain patterns of spillovers and underpayment in self-reported wage data. AMS investigate this by simulating how wage data would look if the minimum wage did not generate spillovers, subminimum wage payment, or employment declines. Their first step is to generate a “true and latent” wage distribution. “True” here refers to the absence of measurement error, and “latent” refers to the hypothetical distribution that would prevail in the absence of any minimum wage. Their second step is to generate a “true and actual” distribution in which the minimum wage is introduced but measurement error is not. Their third step is to inject a symmetric form of measurement error into the wage distribution. The measurement error process has two key components: (1) the probability that respondents report wages with error, and (2) the variance of the (assumed) normal distribution of errors for those who report incorrectly. The AMS analysis delivers the following conclusion: when the simulated measurement error is calibrated to match subminimum wage payment, then measurement error can also explain the upward spillovers observed in the wage data.

We investigate whether the AMS model can explain the spillovers and high prevalence of subminimum wages, specifically among younger workers in the wake of a minimum wage increase. To do this, we begin by using CPS data to calculate the mean and variance of the distribution of log wages for the samples we analyze. Following AMS, we then use those parameters to generate a “true and latent” simulated wage distribution. We then divide the simulated sample into 4 cells of equal size to simulate the effects of a hypothetical minimum wage increase. These cells correspond with 2 “states” and 2 “time periods,” where state 1 has a minimum wage of $8 in both time periods while state 2 has a minimum wage of $8 in period 1 and $9.50 in period 2. This is representative of the typical minimum wage change that occurred during the 2011-2019 period we analyze.

We select the two measurement error parameters to match key moments in the data. The first involves the mass of individuals who report working for wage rates at the minimum wage itself. The effect of a minimum wage change on this mass can, under the assumptions AMS impose, be used to infer the fraction of individuals who misreport their wage rates. The assumptions in this exercise are that minimum wage increases have no employment effects and result in neither positive spillovers nor true instances of underpayment. This is the sense in which the model is proposed as an alternative interpretation of the data. Second, the variance of the error among those who are assumed to misreport their wage rates can be chosen to fit moments that relate to the dispersion in observed wages both above and below the minimum. We choose this parameter to match the mass we observe at wage rates that are between the minimum wage itself (non-inclusive) and $2 below the minimum wage. Having selected the variance parameter in this way, we can then ask whether data simulated to match underpayment also match the degree of positive spillovers.

For our empirical analyses, the wage data come from the Outgoing Rotation Groups (ORG) of the Current Population Survey (CPS) from 2011–2019. We focus on individuals who are hourly wage workers and who have responded to the relevant survey questions such that their wage rates need not be imputed. Our data on minimum wage rates are the data underlying our complementary analysis of the employment effects of minimum wage changes enacted from 2011-2019 (Clemens and Strain, 2021).

Table 1 reports a mix of regression analyses and simulation output. The regressions are straightforward panel regressions in which the explanatory variable of interest is the effective minimum wage, while the covariates include sets of fixed effects for state, time, and respondent age and education level. The outcomes describe an individual's wage rate relative to the minimum wage. In the first two columns, the outcome variables are the moments of the data that our simulations were parameterized to match, namely an indicator for whether an individual makes exactly the minimum wage and an indicator for whether an individual makes up to $2 per hour below the minimum wage.

As shown in the first panel of Table 1, we do observe a pattern of relatively symmetric spillovers and underpayment when we analyze a sample that pools all individuals ages 16 to 65. A straightforwardly parameterized version of the AMS model of measurement error would thus appear to have the potential to underlie the observed patterns of spillovers and underpayment in this pooled sample. Indeed, the accompanying simulation output reveals this to be the case. The simulation output falls within the 95 percent confidence interval for all seven of the regression estimates describing changes in the wage distribution following real-world minimum wage increases.

The findings for the pooled sample, however, mask asymmetric degrees of underpayment relative to spillovers for *both* younger workers and older workers. Specifically, underpayment occurs primarily in the wages paid to those ages 16–25, as shown in Panel 2, while positive spillovers accrue almost entirely to those ages 26–65, as shown in Panel 3.

A model of symmetric measurement error does not provide a strong alternative interpretation of the data. If the simulated data for young workers (Panel 2) are made to fit the degree of self-reported subminimum wage payment following minimum wage increases, then they also dramatically overstate the positive spillovers observed in the data. Contrary to common readings of AMS, a symmetric measurement error model is thus unable to rationalize the pattern of underpayment and spillovers in the data. This in turn suggests that noncompliance with minimum wage regulation may be more common than many economists realize, which points to a potentially fruitful avenue for further research.

The simulated data (calibrated, once again, to match the observed incidence of subminimum wage payment) also understate the positive spillovers realized by workers ages 26 to 65. This can be seen in Panel 3, where simulated data fit better than in the case of younger workers, but nonetheless fail to match the degree of positive spillovers non-trivially. This is consistent with evidence from Cengiz *et al.* (2019), whose findings on the spillovers received by incumbent low-wage workers support the view that these spillovers are a real feature of the data. The evidence we present bolsters the case for interpreting both spillovers to incumbent workers and increases in subminimum wage payment to younger workers as real effects of minimum wage increases rather than as artifacts of measurement error.

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Table 1. Relationship Between Minimum Wage Increases and Moments of the Wage Distribution in CPS Data As Compared with Data Simulated Using the Autor, Manning, and Smith Model of Measurement Error

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hourly Wage Relative to Effective Minimum	Same as min	$2 less	$2 more	$1 less	$1 more	$1–2 less	$1–2 more
Panel A: Ages 16–65							
Effective Minimum Wage	0.0194***	0.0189***	0.0191***	0.0152***	0.0169***	0.0036***	0.0022
	(0.0048)	(0.0026)	(0.0056)	(0.0026)	(0.0024)	(0.0002)	(0.0034)
Simulation Output							
Parameters chosen to match columns 1 and 2	0.0193	0.0184	0.0266	0.0148	0.0196	0.0036	0.0070
Observations	409,121	409,121	409,121	409,121	409,121	409,121	409,121
Panel B: Ages 16–25							
Effective Minimum Wage	0.0372***	0.0380***	0.0046	0.0300***	0.0167***	0.0080***	-0.0122**
	(0.0107)	(0.0048)	(0.0087)	(0.0051)	(0.0046)	(0.0009)	(0.0047)
Simulation Output							
Parameters chosen to match columns 1 and 2	0.0377	0.0379	0.0330	0.0274	0.0283	0.0105	0.0047
Observations	96,095	96,095	96,095	96,095	96,095	96,095	96,095
Panel C: Ages 26–65							
Effective Minimum Wage	0.0136***	0.0124***	0.0231***	0.0101***	0.0161***	0.0022***	0.0069**
	(0.0030)	(0.0022)	(0.0054)	(0.0021)	(0.0023)	(0.0002)	(0.0033)
Simulation Output							
Parameters chosen to match columns 1 and 2	0.0138	0.0124	0.0180	0.0074	0.0106	0.0050	0.0074
Observations	313,026	313,026	313,026	313,026	313,026	313,026	313,026

Notes: Panels A, B, and C in the table report regression results examining the effect of minimum wage increases on the probability that individuals ages 16–65, 16–25, 26–65, report wages within several specified intervals above and below the minimum wage. The samples are from the CPS Outgoing Rotation Groups and include all people who are employed, paid by the hour, do not have imputed wage rates. The outcome in column 1 takes a value of 1 if the wage is equal to the minimum wage. The outcome in columns 2 and 3 take a value of 1 if the wage is within $2 of the minimum wage, below and above, respectively. The outcome in columns 4 and 5 take a value of 1 if the wage is within $1 of the minimum wage, below and above, respectively. The outcome in columns 6 and 7 take a value of 1 if the wage is within $1 and $2 of the minimum wage, below and above, respectively. All specifications include state and time fixed effects. Age and education controls consist of a dummy variable for each education group and age. Standard errors are clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The simulation output in Panel A, B, and C in the table reports the same moments of the data as the regression results, but for simulated rather than actual data. Key parameters are chosen to match the moments described in columns 1 and 2.