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Wage theft and life expectancy inequities in the United States: A simulation study

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ABSTRACT

Wage theft – employers not paying workers their legally entitled wages and benefits – costs workers billions of dollars annually. We tested whether preventing wage theft could increase U.S. life expectancy and decrease inequities therein. We obtained nationally representative estimates of the 2001–2014 association between income and expected age at death for 40-year-olds (40 plus life expectancy at age 40) compiled from tax and Social Security Administration records, and estimates of the burden of wage theft from several sources, including estimates regarding minimum-wage violations (not paying workers the minimum wage) developed from Current Population Survey data. After modeling the relationship between income and expected age at death, we simulated the effects of scenarios preventing wage theft on mean expected age at death, assuming a causal effect of income on expected age at death. We simulated several scenarios, including one using data suggesting minimum-wage violations constituted 38% of all wage theft and caused 58% of affected workers' losses. Among women in the lowest income decile, mean expected age at death was 0.17 years longer in the counterfactual scenario than observed (95% confidence interval [CI]: 0.11–0.22), corresponding to 528,685 (95% CI: 346,018-711,353) years extended in the total 2001–2014 age-40 population. Among men in the lowest decile, the estimates were 0.12 (95% CI: 0.07–0.17) and 380,502 (95% CI: 229,630-531,374). Moreover, among women, mean expected age at death in the counterfactual scenario increased 0.16 (95% CI: 0.06–0.27) years more among the lowest decile than among the highest decile; among men, the estimate was 0.12 (95% CI: 0.03–0.21).

1. Introduction

1.1. Overview

United States (U.S.) employers steal tens of billions of dollars annually from workers by failing to pay them their legally entitled wages and benefits (Cooper and Kroeger, 2017; Fine et al., 2020; Bernhardt et al., 2009; Galvin, 2016). The total value of this wage theft is greater than is lost to all recorded property theft (FBI National Press Office, 2020). Fallout from the COVID-19 pandemic may intensify wage theft, as recessions may increase employer offenses (Fine et al., 2020). Women, Black, Hispanic, and undocumented workers will likely be disproportionately targeted (Fine et al., 2020). Given wage theft's considerable burden among lower-income workers (Cooper and Kroeger, 2017; Fine et al., 2020; Bernhardt et al., 2009) and the direct and graded relationship between income and life expectancy (Bor et al., 2017; Chetty et al., 2016), wage theft may decrease life expectancy for affected workers and worsen life expectancy inequities, inequities which have grown in recent decades (Bor et al., 2017; Chetty et al., 2016) and which the COVID-19 pandemic may have intensified (Chen et al., 2021; Woolf et al., 2021; Friedman et al., 2021.; Feldman and Bassett, 2021). Nonetheless, despite calls for public-health research on wage theft (Minkler et al., 2014), no studies have examined its effects on life expectancy and inequities therein. Our study fills this gap.

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1.2. Wage theft

Wage theft occurs when employers fail to pay the wages and benefits they legally owe workers (Cooper and Kroeger, 2017; Bernhardt et al., 2009; Minkler et al., 2014). Wage theft is a problem globally (Foley and Piper, 2021), although we focus on the U.S.-context. Among the most common types in the U.S. are (Cooper and Kroeger, 2017; Bernhardt et al., 2009; Minkler et al., 2014):

- *Minimum-wage violations*: not paying eligible workers the minimum wage.
- *Contract violations*: not paying workers the amount an employment contract outlines.
- *Overtime violations*: not paying eligible workers time-and-a-half for weekly hours over 40.
- *Off-the-clock violations*: forcing workers to work outside paid shifts.
- *Meal-break violations*: forcing workers to work during meal breaks.
- *Tipped-job violations*: not paying tipped workers the proper minimum wage or stealing tips.
- *Misclassification*: misclassifying employees as independent contractors.
- *Illegal deductions*: illegally deducting equipment damages or losses from workers' pay.

Comprehensive estimates regarding the prevalence and cost (i.e., burden) of all types of wage theft are unavailable, as violations are seldom reported and public data are limited (Cooper and Kroeger, 2017; Galvin, 2016). Nonetheless, Cooper and Kroeger estimated that 4% of minimum-wage-eligible workers in the 10 most populous U.S. states experienced minimum-wage violations annually from 2013 to 2015, including 17% of low-wage workers, who typically had 24% of their incomes stolen (Cooper and Kroeger, 2017). Other types of wage theft are also harmful. For example, a 2008 study by Bernhardt et al. in Chicago, Los Angeles, and New York City estimated that 68% of low-wage workers had experienced some form of wage theft in the previous week; among the 25% who had worked over 40 hours, 76% were not paid the legally required overtime rate (Bernhardt et al., 2009). Wage theft is especially common among women, racialized, and undocumented workers, who are segregated into precarious, low-wage, and hyper-exploited sectors and disproportionately targeted for wage theft within workplaces (Cooper and Kroeger, 2017; Fine et al., 2020; Bernhardt et al., 2009; Minkler et al., 2014; Laster Pirtle, 2020; Fernandez-Esquer et al., 2021; Benach et al., 2014). Indeed, Cooper and Kroeger estimated that workers who were Black and Hispanic or women were over 40% more likely than those who were non-Hispanic white or men to experience minimum-wage violations (Cooper and Kroeger, 2017). Moreover, they estimated non-citizens had a nearly 70% greater risk than citizens (Cooper and Kroeger, 2017).

1.3. Income, wage theft, and life expectancy

Research consistently associates increased income with increased life expectancy (Bor et al., 2017; Chetty et al., 2016; Dowd et al., 2011; Bosworth, 2018). For example, Chetty et al. estimated that the average inequity in life expectancy at age 40 between the highest and lowest household income percentiles from 2001 to 2014 was 10.1 years among women and 14.6 years among men (Chetty et al., 2016). Moreover, Chetty et al. (Chetty et al., 2016) (and others (Bor et al., 2017; Dowd et al., 2011)) estimated that the association between income and life expectancy was strongest at lower incomes, as increased income may most strongly improve access to necessities among lower-income people. Research suggests the association between increased income and increased life expectancy is mostly causal, although confounding and reverse causation may contribute (Muennig, 2008; Kröger et al., 2015; Lindahl, 2005).

Thus, preventing wage theft – i.e., increasing take-home incomes for lower-income workers by eliminating theft by higher-income employers – could extend life expectancy for lower-income workers and mitigate life expectancy inequities. This aligns with relational theories regarding the inversely interdependent nature of the worker-employer relationship (Muntaner et al., 2015). That is, because employers' profits inversely relate to labor costs, their relative abundance of wealth and health often causally depends on workers' deprivation (Muntaner et al., 2015). Thus, redistributing resources from employers to workers, i.e., to those who benefit most from increased income, could mitigate life expectancy inequities.

1.4. Objectives

Using nationally representative data on the association between income and expected age at death (Chetty et al., 2016) (a measure described below) and wage-theft estimates developed from Current Population Survey (CPS) data (Cooper and Kroeger, 2017) and other sources (Bernhardt et al., 2009), we estimated the effects of preventing wage theft on expected age at death and inequities therein. We constructed several counterfactual scenarios in which wage theft was prevented, assuming varying wage-theft burdens.

2. Methods

2.1. Software and code

We used R version 4.1.0 (R Core Team, 2020). Our code is on Github: https://github.com/Critical-Social-Epi/wage_theft_life_expectancy.

2.2. Data

2.2.1. Income and expected age at death

We used data on the 2001–2014 association between income and expected age at death from Chetty et al., described elsewhere (Chetty et al., 2016). Briefly, for every U.S. individual with a valid social security number from 1999 to 2014, the authors merged household income data from tax records with mortality data from Social Security Administration death records (excluding $0 incomes) (Chetty et al., 2016). The authors lagged income by two years for those 63 and younger; for those over 63, the authors measured income at 61 because income at older ages is often affected by retirement (Chetty et al., 2016). Using these records, the authors estimated race-ethnicity-adjusted period expected age at death for 40-year-olds (hereafter referred to as expected age at death) within income percentiles and genders (women/men) (Chetty et al., 2016). Period expected age at death for 40-year-olds equals 40 plus period life expectancy at age 40, which is the mean length of life for a hypothetical 40-year-old who experiences mortality rates at each subsequent age equal to those observed in a given period (Chetty et al., 2016). The aggregated dataset (200 rows, with one row for each gender-income-percentile) is publicly available (along with the corresponding income value in dollars at each gender-income-percentile) (Chetty et al., 2016).

2.2.2. Minimum-wage violations

Estimating the burden of all types of wage theft is challenging. However, data are available regarding the burden of minimum-wage violations, compiled by Cooper and Kroeger (Cooper and Kroeger, 2017). These data are described elsewhere (Cooper and Kroeger, 2017), align with other estimates (Fine et al., 2020; Bernhardt et al., 2009; Galvin, 2016; Eastern Research Group, 2014), and are among the most timely and thorough available. Briefly, the authors used data on 2013–2015 CPS respondents living in the 10 most populous states – CA, FL, GA, IL, MI, NY, NC, OH, PA, and TX – where over half the workforce resides (Cooper and Kroeger, 2017). From these data, the authors identified minimum-wage-eligible workers, i.e., those covered by state or federal minimum-wage laws (88% of all workers) (Cooper and

Kroeger, 2017). From this group, the authors identified workers whose reported weekly earnings and hours equated to hourly wages below their state's minimum wage (Cooper and Kroeger, 2017). The CPS has drawbacks, including income overreporting among low earners, bunching of reported wages at round numbers, and underrepresentation of Hispanic and undocumented workers (Cooper and Kroeger, 2017; Galvin, 2016; Eastern Research Group, 2014; Bollinger, 1998). Nonetheless, it contains among the best publicly available wage data. Thus, using these data, the authors estimated the prevalence of minimum-wage violations and the average annual underpayment for those experiencing minimum-wage violations (assuming the weekly underpayment applied to the entire year) overall and by binary gender (women/men), family income (total income from all sources for related family members sharing a housing unit), and state (Cooper and Kroeger, 2017). Assuming the weekly underpayment applied to the entire year is a strong assumption – also made in other studies (Bernhardt et al., 2009; Eastern Research Group, 2014) – because affected workers may not work for an entire year. However, the authors' approach may otherwise be conservative because: 1) it did not incorporate city/county minimum wages, which must equal or exceed state minimum wages, and 2) hourly wage estimates for non-hourly workers included earnings from bonuses, overtime, and commissions, which minimum-wage laws do not count towards hourly earnings (Cooper and Kroeger, 2017). Moreover, the authors' estimates were robust to sensitivity analyses addressing measurement error (Cooper and Kroeger, 2017).

Leveraging Cooper and Kroeger's data (Cooper and Kroeger, 2017), we used simultaneous equations (Hasselman, 2018; BBC, 2022) to estimate the prevalence of minimum-wage violations within family income and gender subgroups (we used simultaneous equations because the estimates were stratified separately by income and gender). We assumed the ratio of the prevalence of minimum-wage violations among women versus men held within income strata (1.40), as did the proportion of women versus men within income strata (0.47) (Cooper and Kroeger, 2017). We also assumed the average annual underpayment within income strata was equal across genders, which the authors (Cooper and Kroeger, 2017) suggest is approximately true, income aside.

2.3. Primary analyses

2.3.1. Statistical approach

First, to model the association between income and expected age at death, we fit a linear model to Chetty et al.'s 2001–2014 data (Chetty et al., 2016), with expected age at death as the dependent variable and gender, household income (in dollars), and their interaction as predictors, weighted by the frequency counts provided by Chetty et al. (Chetty et al., 2016) We specified income as a 7-knot restricted cubic spline to accommodate nonlinearity (Harrell, 2021).

Second, we simulated a large population (n = 1,408,185, 1/1000th Chetty et al.'s (Chetty et al., 2016) underlying sample),[1] with income and counts of respondents in each gender-income stratum as observed in Chetty et al.'s data (Chetty et al., 2016), and expected age at death in each stratum as predicted by the linear model.

Third, we predicted expected age at death in a counterfactual population in which wage theft was prevented. To do so, we repeated steps one and two, but at each income percentile, we created an income variable that included workers' stolen wages and used that to predict expected age at death for each respondent. We predicted expected age at death in three counterfactual scenarios (described below).

Fourth, we estimated the difference in mean expected age at death in the observed versus counterfactual scenarios overall and within income deciles (deciles of the observed data). We also multiplied these mean differences by the total 2001–2014 age-40 U.S. population in a given stratum (Ruggles et al., 2021) to estimate the total years of expected age at death extended by our scenarios. Finally, we estimated difference-in-differences (DiD) by subtracting the difference in the observed versus counterfactual scenarios within the highest decile from the difference in the lowest decile.

We calculated standard errors (SEs) for estimates of mean expected age at death for a given gender under a given scenario overall and within income deciles as follows (Altman and Bland, 2005):

$$SE_{Scenario} = \frac{weighted\ mean\left(SE_{Chetty}\right)}{\sqrt{n}}$$

where *weighted mean* is weighted by the frequency counts provided by Chetty et al. (Chetty et al., 2016), SE_{Chetty} is a vector of SEs provided by Chetty et al. (Chetty et al., 2016) for expected age at death at a given set of income percentiles, and n is the vector's length (100 when calculating SEs for overall estimates; 10 when calculating SEs for decile estimates). We calculated SEs for the difference in mean expected age at death across scenarios (e.g., scenario 1 versus observed) as follows (Altman, 2003):

$$SE_{Difference} = \sqrt{\left(SE_{Scenario\ 1}\right)\hat{}2 + \left(SE_{Observed}\right)\hat{}2}$$

Likewise, we calculated SEs for the DiD as follows (Altman, 2003):

$$SE_{DiD} = \sqrt{\left(SE_{Difference\ in\ lowest\ decile}\right)\hat{}2 + \left(SE_{Difference\ in\ highest\ decile}\right)\hat{}2}$$

2.3.2. Wage-theft-prevention scenarios

We evaluated three scenarios, varying assumptions about wage theft's burden. In scenario one, we assumed total wage theft among each gender and household income stratum was only as prevalent and costly as Cooper and Kroeger's estimates (Cooper and Kroeger, 2017) regarding minimum-wage violations alone. However, Bernhardt et al. estimated (Bernhardt et al., 2009) that while 26% of low-wage workers had experienced minimum-wage violations in the previous week – contributing to 58% of their total stolen wages – 68% had experienced *any* type of wage theft. Moreover, Bernhardt et al.'s estimate of the average annual cost of all wage theft for affected workers approximated Cooper and Kroeger's estimate (Cooper and Kroeger, 2017) regarding minimum-wage violations alone ($2936 and $3300, respectively, in 2016 dollars). Thus, we ran additional scenarios. In scenario two, we assumed total wage theft was 2.62 times (68%/26%) as prevalent as Cooper and Kroeger's estimates (Cooper and Kroeger, 2017) regarding minimum-wage violations alone, but only equally costly for affected workers, while in scenario three, we assumed total wage theft was 2.62 times as prevalent *and* 1.72 times (1/58%) as costly. We believe these scenarios provide plausible bounds on wage theft's effects, not precise estimates.

2.3.3. Assumptions

Even given the scenarios' validity, our primary analyses relied on strong assumptions. First, we assumed the relationship between income and expected age at death estimated by Chetty et al. (Chetty et al., 2016) is causal. Second, we assumed preventing wage theft would have affected expected age at death solely through the direct, individual-level effects of increased income, e.g., no spillover or contextual-level effects, no loss of means-tested benefits, and no uniquely harmful effects of wage theft beyond income loss (e.g., from the stress of feeling cheated). Third, we assumed income itself – rather than income rank – affected expected age at death. Fourth, we assumed those at the top of the income distribution would not have lost income or wealth if wage theft had been prevented (a minor assumption, as the weak income/life-expectancy association at higher incomes (Chetty et al., 2016) means those losses would not

[1] Simulating a large population allowed us to return stolen wages to a fraction of respondents in each gender-income stratum and estimate mean life expectancy in the simulated population under a given wage-theft-prevention scenario, which is just a weighted average of respondents' predicted life expectancies. The exact size of the simulated population is unimportant, as our standard errors were not a function of the size of the simulated population.

have affected expected age at death). Finally, we assumed Cooper and Kroeger's estimates (Cooper and Kroeger, 2017) applied to the same populations as Chetty et al.'s (Chetty et al., 2016), including within subgroups.

2.4. Sensitivity analyses

First, we examined whether using locally estimated scatterplot smoothing (LOESS) (Cleveland, 1979) to model the association between income and expected age at death would alter our estimates, as LOESS more precisely captured the association in the data. Primary analyses used a restricted cubic spline because the spline curve's shape was more theoretically plausible.

Second, we examined whether using Chetty et al.'s (Chetty et al., 2016) data from 2014 alone would alter our estimates, as 2014 data better aligned with our 2013–2015 wage-theft data . Primary analyses used pooled 2001–2014 data to improve precision.

Finally, to relax the assumption regarding the causal relationship between income and expected age at death, we ran analyses assuming increased income would only affect expected age at death for half of respondents. To do so, we used the approach described previously, but for each scenario, we kept half of respondents' incomes as observed rather than returning their stolen wages.

2.5. Ethical compliance

Our study used publicly available, deidentifed data and thus was exempt from IRB review.

3. Results

3.1. Income and expected age at death

Our linear model fit to Chetty et al.'s (Chetty et al., 2016) data had an adjusted R-squared of 0.995, suggesting it stronglycaptured the association between income and expected age at death. Using this model, among women, we estimated that expected age at death at the 1st ($452) and 100th ($2,010,515) household income percentiles was 80.3 years (95% confidence interval [CI]: 80.2, 80.4) and 88.9 years (95% CI: 88.7, 89.0), respectively; among men, we estimated that expected age at death at the 1st ($372) and 100th ($2,072,218) household income percentiles was 74.6 years (95% CI: 74.5, 74.7) and 87.4 years (95% CI: 87.2, 87.5), respectively (Fig. 1). We also estimated the association between income and expected age at death was strongest at lower incomes. Indeed, among women, a household-income increase from $452 to $17,507 was associated with a two-year increase in expected age at death, the same as a household-income increase from $123,732 to $2,010,515. Patterns were similar among men.

3.2. Minimum-wage violations

Minimum-wage violations were most common among women and lower-income people, particularly lower-income women (Table 1). For example, drawing from Cooper and Kroeger (Cooper and Kroeger, 2017), we estimated that 10% of women and 7% of men with family incomes under $10,000 experienced minimum-wage violations annually, costing them $3500, while just 3% of women and 2% of men with family incomes of at least $150,000 experienced minimum-wage violations annually, costing them $3700.

3.3. Effects of wage-theft-prevention scenarios

The wage-theft-prevention scenarios - primarily scenarios two and three - were associated with increases in mean expected age at death overall, with stronger associations among those with lower incomes and women, and substantial associations across the total age-40 population

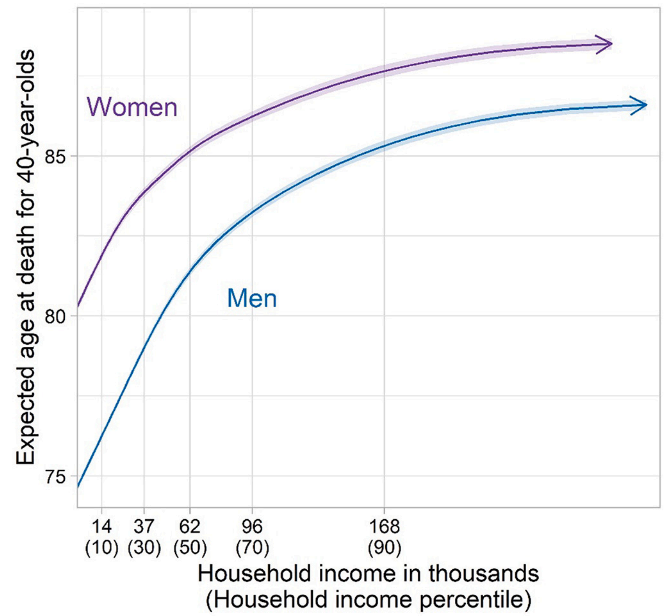

Fig. 1. Modeled association between household income and expected age at death for 40-year-olds in the U.S.
Notes: Estimates generated from linear model fit to Chetty et al.'s (Chetty et al., 2016) 2001–2014 data with expected age at death as the dependent variable and gender, household income, and their interaction as predictors, with household income specified as a 7-knot restricted cubic spline. Standard errors estimated from Chetty et al.'s (Chetty et al., 2016) data using the approach described in the main text. Income displayed in thousands of 2016 dollars.

Table 1
Estimated prevalence of minimum-wage violations by gender and family income in the U.S., as well as the estimated average annual underpayment among those experiencing minimum-wage violations.

Family income	Prevalence of minimum-wage violations	Average annual underpayment
Women		
<$10,000	0.10	$3500
$10,000–$24,999	0.09	$3200
$25,000–$39,999	0.06	$3200
$40,000–$59,999	0.05	$3300
$60,000–$99,999	0.04	$3200
$100,000–$149,999	0.03	$3200
$150,000+	0.03	$3700
Men		
<$10,000	0.07	$3500
$10,000–$24,999	0.06	$3200
$25,000–$39,999	0.04	$3200
$40,000–$59,999	0.03	$3300
$60,000–$99,999	0.03	$3200
$100,000–$149,999	0.02	$3200
$150,000+	0.02	$3700

Notes: Estimates based on Cooper and Kroeger's[1] data regarding minimum-wage violations among minimum-wage-eligible workers in the 10 most population U.S. states from 2013 to 2015. Because Cooper and Kroeger's estimates were stratifed separately by family income and gender, we used simultaneous equations to estimate the prevalence of minimum-wage violations within gender-income subgroups. We assumed the average annual underpayment within family income strata was equal across genders. Income displayed in 2016 dollars.

(Table 2, Fig. 2).

For example, among women in the lowest income decile, mean expected age at death was 0.04 (95% CI: −0.02, 0.10), 0.10 (95% CI: 0.04,

Table 2
Estimates regarding effects of wage-theft-prevention scenarios on expected age at death for 40-year-olds in the U.S. overall and within the lowest and highest household income deciles.

		Expected age at death			Difference[b]			Years extended[c]		
	Scenario[a]	Estimate	Lower	Upper	Estimate	Lower	Upper	Estimate	Lower	Upper
Overall										
Women	Observed	84.93	84.91	84.95	–	–	–	–	–	–
Women	Scenario 1	84.94	84.93	84.96	0.01	−0.01	0.03	333,163	−363,395	1,029,721
Women	Scenario 2	84.96	84.94	84.97	0.03	0.01	0.05	871,072	174,513	1,567,630
Women	Scenario 3	84.98	84.96	84.99	0.05	0.02	0.07	1,471,717	775,159	2,168,275
Men	Observed	81.28	81.27	81.30	–	–	–	–	–	–
Men	Scenario 1	81.29	81.28	81.30	0.01	−0.01	0.03	294,502	−298,906	887,911
Men	Scenario 2	81.31	81.29	81.32	0.02	0.01	0.04	770,457	177,048	1,363,866
Men	Scenario 3	81.32	81.31	81.34	0.04	0.02	0.06	1,317,428	724,019	1,910,837
Lowest household income decile										
Women	Observed	81.16	81.12	81.20	–	–	–	–	–	–
Women	Scenario 1	81.20	81.16	81.24	0.04	−0.02	0.10	119,848	−62,819	302,516
Women	Scenario 2	81.26	81.22	81.30	0.10	0.04	0.16	309,916	127,248	492,583
Women	Scenario 3	81.33	81.29	81.37	0.17	0.11	0.22	528,685	346,018	711,353
Men	Observed	75.48	75.44	75.51	–	–	–	–	–	–
Men	Scenario 1	75.50	75.47	75.54	0.03	−0.02	0.08	84,130	−66,742	235,003
Men	Scenario 2	75.55	75.51	75.58	0.07	0.02	0.12	220,652	69,780	371,524
Men	Scenario 3	75.60	75.57	75.63	0.12	0.07	0.17	380,502	229,630	531,374
Highest household income decile										
Women	Observed	88.29	88.23	88.35	–	–	–	–	–	–
Women	Scenario 1	88.29	88.23	88.35	0.00	−0.08	0.09	1995	−267,775	271,766
Women	Scenario 2	88.29	88.23	88.35	0.00	−0.08	0.09	5088	−264,683	274,859
Women	Scenario 3	88.29	88.23	88.35	0.00	−0.08	0.09	8622	−261,149	278,392
Men	Observed	86.35	86.30	86.40	–	–	–	–	–	–
Men	Scenario 1	86.35	86.30	86.40	0.00	−0.07	0.07	1641	−226,620	229,903
Men	Scenario 2	86.35	86.30	86.40	0.00	−0.07	0.08	4314	−223,948	232,576
Men	Scenario 3	86.35	86.30	86.41	0.00	−0.07	0.08	7304	−220,957	235,566

Notes: Mean predicted expected age at death for 40-year-olds in observed and counterfactual scenarios generated from linear model fft to Chetty et al.'s (Chetty et al., 2016) 2001–2014 data, with expected age at death as the dependent variable and gender, household income, and their interaction as predictors, with household income specifed as a 7-knot restricted cubic spline. Standard errors estimated from Chetty et al.'s (Chetty et al., 2016) data using the approach described in the main text.

[a] Scenario 1 assumed wage theft was as prevalent and costly as Cooper and Kroeger's estimates (Cooper and Kroeger, 2017) regarding minimum-wage violations alone; scenario two assumed it was 2.62 times as prevalent but only as costly; scenario three assumed it was 2.62 times as prevalent and 1.72 times as costly.

[b] Difference in mean predicted expected age at death in given scenario versus in observed scenario.

[c] Total years of expected age at death extended in given scenario versus in observed scenario among 2001–2014 U.S. 40-year-olds in given stratum.

0.16), and 0.17 (95% CI: 0.11, 0.22) years longer in scenarios one, two, and three, respectively, than in the observed data, corresponding to 119,848 (95% CI: −62,819, 302,516), 309,916 (95% CI: 127,248, 492,583), and 528,685 (95% CI: 346,018, 711,353) years extended in the total age-40 population in that decile (3,169,777 people). However, among women in the highest income decile, mean expected age at death was not meaningfully longer in any of the scenarios than in the observed data. The DiD in mean expected age at death in the lowest versus highest deciles was 0.04 (95% CI: −0.07, 0.14), 0.10 (95% CI: −0.01, 0.20), and 0.16 (95% CI: 0.06, 0.27) across the scenarios (Table 3).

Among men in the lowest income decile, mean expected age at death was 0.03 (95% CI: −0.02, 0.08), 0.07 (95% CI: 0.02, 0.12), and 0.12 (95% CI: 0.07, 0.17) years longer in scenarios one, two, and three, respectively, than in the observed data, corresponding to 84,130 (95% CI: −66,742, 235,003), 220,652 (95% CI: 69,780, 371,524), and 380,502 (95% CI: 229,630, 531,374) years extended in the total age-40 population in that decile (3,084,277 people). However, among men in the highest income decile, mean expected age at death was not meaningfully longer in any of the scenarios than in the observed data. The DiD in mean expected age at death in the lowest versus highest deciles was 0.03 (95% CI: −0.06, 0.12), 0.07 (95% CI: −0.02, 0.16), and 0.12 (95% CI: 0.03, 0.21) across the scenarios (Table 3).

3.4. Sensitivity analyses

Using LOESS to model the association between income and expected age at death strengthened our estimates (Appendix A.1). For example, among women in the lowest income decile, mean expected age at death was 0.18 (95% CI: 0.13, 0.24) years longer in scenario three than in the observed data; among men, the estimate was 0.14 (95% CI: 0.09, 0.19).

Using Chetty et al.'s (Chetty et al., 2016) data from 2014 alone also strengthened our estimates, albeit with imprecision, as the association between income and expected age at death strengthened from 2001 to 2014 (Appendix A.2). For example, among women in the lowest income decile, mean expected age at death was 0.27 (95% CI: −0.10, 0.64) years longer in scenario three than in the observed data; among men, the estimate was 0.17 (95% CI: −0.13, 0.46) (Appendix A.3).

Relaxing the assumption regarding the causal relationship between income and expected age at death diminished our estimates (Appendix A.4). Specifically, when we assumed increased income would only affect expected age at death for half of respondents, the estimate of the difference in mean expected age at death in scenario three relative to the observed data decreased to 0.08 (95% CI: 0.03, 0.14) among women in the lowest income decile. Among men, the estimate was 0.06 (95% CI: 0.01, 0.11). Nonetheless, the estimates still corresponded to tens of thousands of years of expected age at death extended in the total age-40 population.

4. Discussion

4.1. Summary of results

Using nationally representative data on the association between income and expected age at death (Chetty et al., 2016) and wage-theft

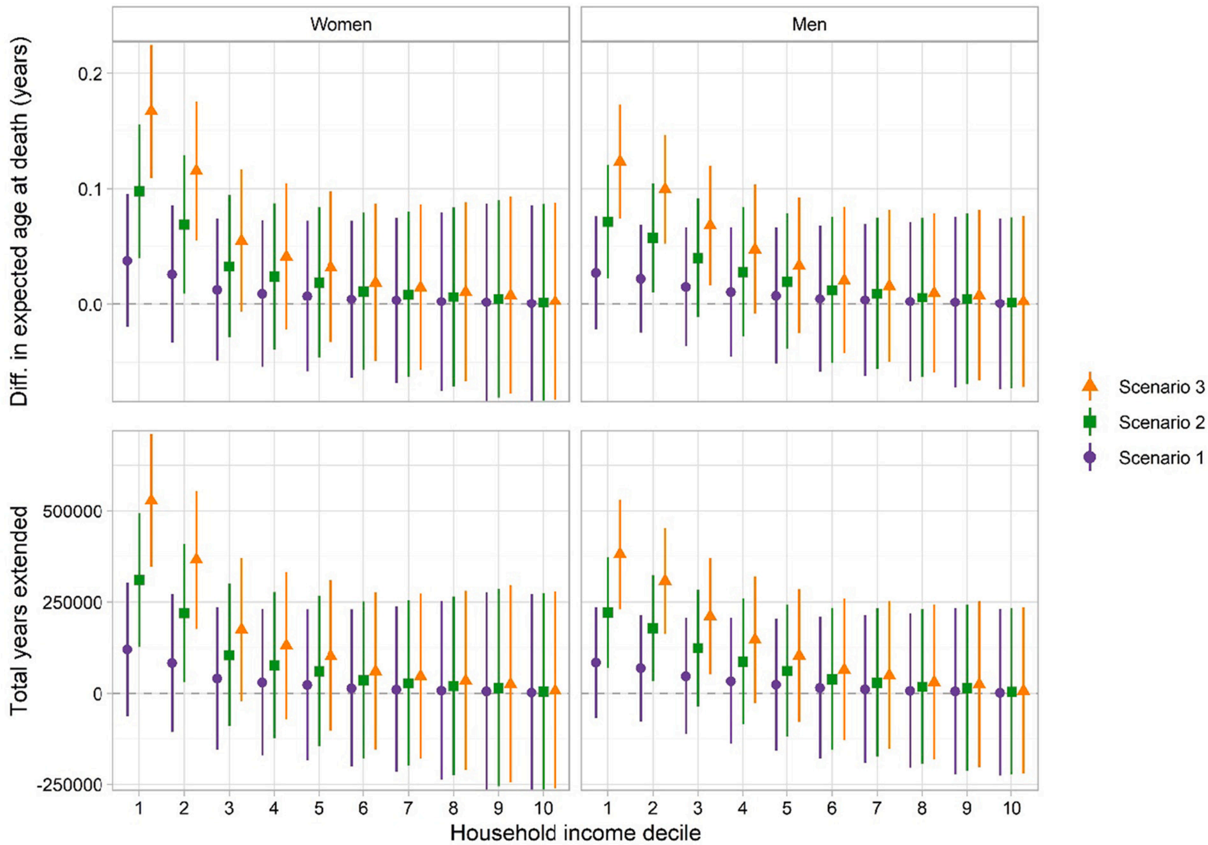

Fig. 2. Estimates regarding effects of wage-theft-prevention scenarios on expected age at death for 40-year-olds in the U.S. within household income deciles (decile 1 = lowest income).

Notes: Top panel displays differences in mean predicted expected age at death in given scenario versus in observed scenario, while bottom panel displays total years of expected age at death extended in given scenario versus in observed scenario among 2001–2014 U.S. 40-year-olds in given stratum. Predicted age at death generated from linear model fitted to Chetty et al.'s (Chetty et al., 2016) 2001–2014 data, with age at death as the dependent variable and gender, household income, and their interaction as predictors, with household income specified as a 7-knot restricted cubic spline. Standard errors estimated from Chetty et al.'s (Chetty et al., 2016) data using the approach described in the main text. Scenario 1 assumed wage theft was as prevalent and costly as Cooper and Kroeger's estimates (Cooper and Kroeger, 2017) regarding minimum-wage violations alone; scenario two assumed it was 2.62 times as prevalent but only as costly; scenario three assumed it was 2.62 times as prevalent and 1.72 times as costly.

Table 3
Difference-in-differences (DiD) estimates comparing the effects of the scenarios in the lowest versus highest U.S. household income deciles.

		DiD in expected age at death[b]			DiD in total years extended[c]		
	Scenario[a]	Estimate	Lower	Upper	Estimate	Lower	Upper
Women	Scenario 1	0.04	−0.07	0.14	117,853	−207,944	443,650
Women	Scenario 2	0.10	−0.01	0.20	304,828	−20,969	630,625
Women	Scenario 3	0.16	0.06	0.27	520,064	194,267	845,861
Men	Scenario 1	0.03	−0.06	0.12	82,489	−191,127	356,105
Men	Scenario 2	0.07	−0.02	0.16	216,338	−57,278	489,955
Men	Scenario 3	0.12	0.03	0.21	373,198	99,581	646,814

Notes: DiD estimates calculated by subtracting the difference in mean predicted expected age at death or total years extended in the observed versus counterfactual scenarios within the highest decile from the difference in the lowest decile. Mean predicted expected age at death for 40-year-olds in observed and counterfactual scenarios generated from linear model fft to Chetty et al.'s (Chetty et al., 2016) 2001–2014 data, with expected age at death as the dependent variable and gender, household income, and their interaction as predictors, with household income specffed as a 7-knot restricted cubic spline. Standard errors estimated from Chetty et al.'s (Chetty et al., 2016) data using the approach described in the main text.

[a] Scenario 1 assumed wage theft was as prevalent and costly as Cooper and Kroeger's estimates (Cooper and Kroeger, 2017) regarding minimum-wage violations alone; scenario two assumed it was 2.62 times as prevalent but only as costly; scenario three assumed it was 2.62 times as prevalent and 1.72 times as costly.

[b] Difference in mean predicted expected age at death in the observed versus counterfactual scenarios within the highest decile subtracted from the difference in the lowest decile.

[c] Difference in total years of expected age at death extended in the observed versus counterfactual scenarios within the highest decile subtracted from the difference in the lowest decile.

estimates developed from CPS data (Cooper and Kroeger, 2017) and other sources (Bernhardt et al., 2009), we estimated the effects on expected age at death, and inequities therein, of counterfactual scenarios in which wage theft was prevented. The scenarios were associated with increases in mean expected age at death overall, with stronger associations among those with lower incomes and women, and hundreds of thousands of years of expected age at death extended in the total age-40 population. Our estimates suggest preventing wage theft could have eliminated up to 10% of the observed (Chetty et al., 2016) increase in inequities in expected age at death between the highest and lowest household income deciles from 2001 to 2014 (Appendix A.5). Nonetheless, due to imprecision, estimates from scenarios assuming smaller burdens of wage theft or weaker effects of increased income on expected age at death were compatible with small or adverse effects of wage-theft prevention on expected age at death.

If our assumptions are valid, our estimates – particularly from scenario three – indicate preventing wage theft *would have* reduced inequities in expected age at death over follow-up (Schwartz et al., 2016; Prins et al., 2021). Because we did not investigate specific anti-wage-theft interventions, we do not regard our estimates as indicating how inequities *would be affected in the future* by a hypothetical anti-wage-theft intervention (Schwartz et al., 2016; Prins et al., 2021), a topic that should be investigated. For example, treble-damages policies – employer penalties 3× the value of wages stolen – can reduce minimum-wage violations (Galvin, 2016); thus, such policies may mitigate inequities in expected age at death. More broadly, policy and organizing to increase worker power, such as those promoting labor-union membership, may also reduce wage theft (Cooper and Kroeger, 2017; Fine et al., 2020) and have salutary effects on other health-promoting factors (Eisenberg-Guyot et al., 2021). Finally, alleviating the strength of the association between income and mortality – by decommodifying necessities and expanding public-health programs (Chetty et al., 2016; Montez et al., 2016) – may also mitigate the harmful effects of wage theft. Indeed, preliminary – albeit highly imprecise – analyses suggested weaker effects of the scenarios in New York City than Detroit (Appendix A.6), findings driven by Detroit's steeper income/life-expectancy gradient (Chetty et al., 2016). The austerity measures implemented in Detroit may have strengthened this gradient, particularly cuts to social programs (Laster Pirtle, 2020; Peck, 2012).

Our analysis builds on research documenting the adverse health effects for workers of *unconcealed* exploitation, which includes blatant, often illegal theft of workers' wages by employers (Prins et al., 2021). *Concealed* exploitation, meanwhile, is a feature of the worker-employer relationship because workers produce more value for their employers than they are paid in wages, even in the absence of labor-law violations (Prins et al., 2021; Marx, 1990). Such concealed exploitation may be especially acute for workers often excluded from policies like minimum-wage laws, such as gig, agricultural, tipped, and domestic workers (Bernhardt et al., 2009; Galvin, 2016; Fernandez-Esquer et al., 2021). Thus, the total effects of all forms of exploitation on inequities in expected age at death likely greatly exceed our estimates regarding the effects of unconcealed exploitation alone (Prins et al., 2021).

4.2. Limitations

Our study had limitations. First, although our estimates were generally robust across specifications and we used among the best data available, our analyses relied on strong data and modeling assumptions, discussed previously. Because our estimates' magnitude depended strongly on these assumptions and on assumptions regarding wage theft's burden, we regard our analyses as providing plausible bounds on wage theft's effects, not precise estimates.

Second, Cooper and Kroeger (Cooper and Kroeger, 2017) only reported the burden of minimum-wage violations across broad family-income categories. Thus, we assumed the burden did not vary within such categories, a strong assumption since it may vary more smoothly with income. Future research should estimate wage theft's burden across finer categories.

Finally, we lacked data on the association between income and expected age at death by racialized group membership, immigration status, or occupation, preventing us from stratifying our analyses by such factors. Nonetheless, wage theft is more common among certain racialized groups, like Black, Hispanic, and undocumented workers (Cooper and Kroeger, 2017; Bernhardt et al., 2009), and among certain occupations, like childcare workers (Cooper and Kroeger, 2017; Bernhardt et al., 2009). Thus, preventing wage theft could reduce inequities across these exploited and oppressed social locations, which future should explore. Nonetheless, because minoritized and oppressed workers are segregated into lower-income households (Manduca, 2018; Bailey et al., 2017), our analyses do suggest that preventing wage theft could mitigate racialized and occupational inequities.

5. Conclusion

Our study brings visibility to wage theft as an important but obscured contributor to life expectancy inequities. Policies and organizing to prevent wage theft may mitigate burgeoning life expectancy inequities and have salutary spillover effects on worker power.

Declaration of Competing Interest

The authors declare that they have no known competing ffnancial interests or personal relationships that could have appeared to infiuence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2022.107068.

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