The Serpent of Their Agonies

Exploitation as Structural Determinant of Mental Illness

Seth J. Prins,[a,b] *Sarah McKetta,*[c] *Jonathan Platt,*[c] *Carles Muntaner,*[d] *Katherine M. Keyes,*[c] *and Lisa M. Bates*[c]

Background: Social stratification is a well-documented determinant of mental health. Traditional measures of stratification (e.g., socioeconomic status) reduce dynamic social processes to individual attributes downstream of mechanisms that generate stratification. In this study, we measure one process theorized to generate and reproduce social stratification—economic exploitation—and explore its association with mental health.

Methods: Data are from the 1983 to 2017 waves of the Panel Study of Income Dynamics, a nationally representative cohort study (baseline N = 3059). We operationalized "unconcealed exploitation" as the percentage of individuals' labor income they were hypothetically not paid for productive hours. We ascertained psychologic distress and mental illness with the Kessler-6 (K6) scale.

Results: We fit inverse probability-weighted marginal structural models and found that for each unit increase in unconcealed exploitation, psychologic distress increased by 1.6 points (95% confidence interval = 0.71, 2.5) on the K6 scale and the odds of mental illness tripled (odds ratio = 3.0, 95% confidence interval = 1.5, 6.1). Results were not driven entirely by overwork and were robust to different inverse probability-weighted estimation strategies and sensitivity analyses.

Conclusions: Exploitation is associated with mental illness. Focusing on exploitation rather than its consequences (e.g., socioeconomic status), shifts attention to a structural process that may be a more appropriate explanatory mechanism, and a more pragmatic intervention target, for mental illness.

Keywords: Income; Labor; Mental disorders; Psychologic distress; Social class; Social problems; Workplace

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From the [a]Department of Epidemiology, Columbia University, New York, NY; [b]Department of Sociomedical Sciences, Columbia University, New York, NY; [c]Department of Epidemiology, Columbia University, New York, NY; and [d]Lawrence S Bloomberg Faculty of Nursing, University of Toronto, Toronto, ON, Canada.
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Data for this analysis come from publicly available sources, and code required to replicate the analysis is available at https://github.com/DPHRC/PSID-Exploitation.

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Correspondence: Seth J. Prins, Columbia University, 722 W 168 St, Room 521, New York, NY 10032. E-mail: seth.j.prins@columbia.edu.

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Social stratification is a determinant of physical and mental health; there is an established social gradient in almost all health outcomes.[1–6] Epidemiologic research has traditionally examined the health effects of social stratification using indicators of socioeconomic status (SES),[7] typically income, education, and occupational prestige rankings. These measures, and the stratificationist framing generally, have been criticized for conceptualizing social class as an individual attribute rather than a social relation.[7–13] Traditional measures of SES are the downstream outcomes of dynamic social processes, and do not shed light on the mechanisms generating social stratification in the first place. As such, the stratification perspective neglects pathways that are not fully explained by SES.[13] In this article, we measure one social process theorized to both generate and reproduce social stratification: economic exploitation. We estimate the association between economic exploitation and mental illness using inverse probability-weighted (IPW) marginal structural models (MSM) in a large, nationally representative longitudinal sample.

Exploitation occurs in employment relations when workers, who do not own productive property and must sell their labor to people who do, are paid less than the full value of the goods or services they produce.[14,15] Owners of productive assets (or their representatives, e.g., upper management) exclude workers from access to certain productive resources, control workers' labor process, and appropriate the fruits of their labor.[15–17] This social class relation between workers and owners is mutually antagonistic, because the material abundance of owners, who represent a small minority of the population, causally depends on the material deprivation of workers, who represent the majority of the population.[15]

Since the Industrial Revolution, common wisdom has held that exploitation causes distress and suffering and harms workers' health and well-being. Marx, quoting Engels, described exploitation as "the serpent of [workers'] agonies," noting that while it appears that workers are free to sell their labor, they are really forced to sell it, and that "the vampire will not let go 'while there remains a single muscle, sinew, or drop of blood left to be exploited'" (10, p. 395).

A rich history of scholarship finds empirical evidence for this intuition; however, most research has focused on workplace organization or the psychosocial consequences of exploitation, for example, alienation and powerlessness. Alienation of workers from the products of their labor diminishes self-efficacy and creates a sense of powerlessness and self-estrangement,[18–20] while jobs with imbalances between demand and autonomy and effort and reward are associated with increases in depression, anxiety, and drug and alcohol use disorders.[21–27]

Yet the psychosocial dimensions of working conditions may also stem from workplace domination, for example, stressful, hostile, or interpersonally strained workplace environments. Thus, while psychosocial measures are consistent with exploitation, they may capture an amalgam of factors and not adequately isolate exploitation as an exposure. If direct measures of exploitation were also associated with mental health, this would strengthen confidence in relational class theory and suggest more fundamental targets for intervention.

Direct or objective measures of exploitation, however, are typically unavailable. Exploitation is built into—and concealed in—all wages and salaries to the extent that workers are not paid the full value of the commodities or services they produce. This concealment makes exploitation exceedingly difficult to measure: for every individual, we would need to know not only their remuneration but also the ratio of their employers' revenues divided by the sum of their capital outlays and expenditures on wages. We know of no population data that contain this individual-level information in addition to mental health outcomes.

Nonetheless, it is also typical for workers to be exploited beyond levels concealed in wages and salaries. This type of unconcealed exploitation is easier to measure by examining unpaid hours of work, which vary widely within labor markets. Consider a full-time worker whose annual salary is $50,000. If a standard full-time work year contains 2080 hours (40 hours per week), this means they make $24/hour. But if that worker actually works an average of 60 hours per week, their actual income drops to $16/hour. In this example, their employer appropriates the equivalent of 33% of the worker's hourly pay toward profit—a rate of unconcealed exploitation of 33%. For workers paid hourly, this phenomenon takes the form of overt wage theft (e.g., unpaid overtime hours). Despite numerous labor laws prohibiting it, wage theft is rampant. In 2014, up to $50 billion in wages were stolen in the United States[28]—more than triple the $14.3 billion lost to all property crime.[29]

Unconcealed exploitation is an individual-level indicator of the "productivity-to-pay gap."[30,31] Since 1973, productivity in the United States increased over six-fold relative to wages, which largely remained flat.[32,33] Instead of working fewer hours for the same output/standard of living, the average American full-time work week is over 40 hours.[34] Meanwhile, the fruits of workers' increased productivity accrued entirely to large business owners, top managers, and corporate profits: since 1989, the top 1%'s wealth increased by $21 trillion, while the bottom 50%'s wealth decreased by $900 billion.[35]

We attempt to capture these dynamics and approximate individual-level rates of unconcealed exploitation, and determine whether they are associated with psychologic distress and mental illness.

METHODS

Data

Data are from the 1983 to 2017 waves of the Panel Study of Income Dynamics36 (PSID). The PSID is an ongoing prospective cohort study that enrolled a representative national probability sample of US households in 1968.[36] The original sample was formed from an oversample of 1872 low-income households and a nationally representative sample of 2930 households, totaling approximately 18,000 individuals.[36] These families were interviewed annually until 1997 and biennially thereafter.[36] Since 1973 the majority of interviews have been conducted by telephone, with computer-assisted telephone technology since 1993.[36] Between 1983 and 2017, response rates ranged from 88% to 94.3%.[37,38] In 1983 the sample comprised 6852 families (20,327 individuals). In 2017, the sample comprised 9607 families (26,445 individuals[38]).

We restricted the sample to heads of household, as they were the only respondents administered the mental health assessment. We further restricted the sample to those who worked at least full-time (2080 hours/year) and were not in the top 1% of wage earners nationally each year. We excluded the latter because they were the only group whose earnings increased over the 40-year period in which the productivity-to-pay gap grew across the rest of the labor market.[33] We also excluded full-time workers who reported earning less than 75% of the federal minimum wage in the respective survey wave, as we assumed these individuals experienced unique or extreme circumstances (sensitivity models including these individuals did not yield appreciably different estimates—see eTables S3 and S4; http://links.lww.com/EDE/B748). Finally, we restricted data to 1983–2017 because 1983 was the earliest first year of participation for respondents who could subsequently respond to the mental health assessment, which was first administered in 2003.

PSID data are publicly available and de-identified; nonetheless, our analysis was approved by the Institutional Review Board at Columbia University.

Measures

Outcomes

The outcomes of interest are psychologic distress and mental illness, both measured by the K6 Scale.[39,40] The K6 is a commonly used six-question scale (see online supplementary material; http://links.lww.com/EDE/B748) developed to estimate the prevalence of serious mental illness as defined by US federal agencies.[39] Serious mental illness is defined as at least one 12-month Diagnostic and Statistical Manual IV disorder other than a substance use disorder (e.g., major depressive disorder, bipolar disorder, generalized anxiety disorder) with serious impairment.[39,40] The K6 reliably distinguishes individuals with and without serious mental illness in an adult general population sample using a scale cut-point of 13 or greater (receiver operating characteristic area under the curve: 0.86).[39] A cut-point of $5 \leq$ K6 < 13 (receiver operating characteristic area under the curve: 0.82) also reliably identifies respondents with moderate mental illnesses, defined as mental distress necessitating mental health treatment and causing functional impairment.[41] We present findings for the continuous K6 score (a general measure of psychologic distress) and "mental illness," which combines moderate and serious mental illness at a cutoff of ≥5. The K6 was administered in 2003, and then from 2007 to 2017.

Exposure

We defined unconcealed exploitation as:

$$\frac{Income_{40\ hours/week} - Income_{Actual\ hours/week}}{Income_{40\ hours/week}}$$

Where

- $Income_{40\ hours/week}$ is an individual's hourly earnings based on a 40-hour work week. This variable is the quotient of individuals' total self-reported annual labor income divided by 2080 hours (52 weeks at 40 hours per week). Total annual labor income, asecertained in each survey wave, is the sum of wages and salaries, bonuses, overtime, tips, commissions, professional practice or trade, additional job income, and miscellaneous labor income.
- $Income_{Actual\ hours/week}$ is an individual's hourly total labor income based on the number of hours they actually worked. Total work hours, ascertained in each survey wave, is the product of self-reported total weekly work hours on all jobs and self-reported number of weeks worked, plus overtime work hours.

The ratio can be interpreted as the percentage of their wage or salary that individuals were hypothetically not paid for productive hours, assuming constant output per hour and the same pay rate for every hour worked (after accounting for tips, bonuses, overtime, and commissions). An alternate operationalization of this measure, where overtime hours do not contribute to $Income_{40\ hours/week}$ but do contribute to $Income_{Actual\ hours/week}$, did not appreciably alter our findings (see eTables S5 and S6; http://links.lww.com/EDE/B748).

We chose 40 hours per week as the cutoff for full-time employment for two reasons. First, 40 hours per week is the cut-point after which the Fair Labor Standards Act of 1938 (29 U.S.C. § 203) requires overtime pay for nonexempt occupations. Second, labor movements across the world have fought for an 8-hour workday (equivalent to 40 hours per week today) since the beginning of the Industrial Revolution.[42,43]

Time-invariant Baseline Confounders

Because time-varying outcome data are only available for the years 2003, 2007–2017, we created summary baseline measures for covariates ascertained between 1983 and 2003, to account for confounding that occurred temporally before the primary exposure. These measures include mean annual overtime hours; number of changes in employment status, industry, and occupation; mean hours worked at an extra job; mean income from an extra job, interest, overtime, and a spouse; mean years covered by a union, self-employed, and working an extra job; whether the respondent self-reported ever being depressed or having a drug problem before age 17; whether their modal job was hourly or salaried; modal occupation; racialized group membership; and sex.

Time-varying Confounders

Indicators that varied between 2003 and 2017 include age; year; annual overtime hours; annual work hours; income from interest, overtime, and a spouse; total labor income; years worked an extra job; alcohol frequency; being covered by a union; grades of education completed; whether primary job is hourly or salaried; occupation, and whether the home is owned or rented.

All baseline and time-varying confounders were selected based on theory and were tested for bivariate associations in the data.

Analysis

An individual's exposure to time t exploitation likely affects time $t + 1$ confounders, which are on the pathway to subsequent exploitation and mental illness. It is also possible that time $t - 1$ mental illness is a common cause of entering a more exploitative job and mental illness at time t. Furthermore, both exploitation and mental illness may influence selection into particular occupations and increase loss to follow-up. To address these issues, we estimated MSM for the cumulative effect of exploitation on mental health outcomes with stabilized inverse probability of exposure weights (IPEW) and stabilized inverse probability of censoring weights (IPCW).[44,45] All analyses were conducted in R version 4.0.2.

Inverse Probability of Exposure and Censoring Weights

To construct the IPEW denominator, we fit a linear model regressing our measure of exploitation on all time-invariant and time-varying covariates (lagged by 1 year), in addition to 1-year-lagged exploitation. We weighted this model with PSID's individual longitudinal weights to account for sampling probabilities and informative attrition. We created a vector of predicted values from this model for every respondent, and then input this vector into R's normal probability density function. The resulting values represent the predicted probability that an individual was exploited at the level they were actually exploited. We followed the same procedure to construct the IPEW numerator, but only included time-invariant confounders and lagged exploitation in the model. The estimated stabilized IPEW ranged from 0.82 to 1.2 with a mean of 0.97 and a SD of 0.02 (Table 1). These weights are

TABLE 1. Distribution of Inverse Probability of Exposure and Censoring Weights

Analysis	Weight	Mean	SD	Min	Max
Exploitation, normal distribution	Exposure	0.97	0.02	0.82	1.2
	Censoring	0.75	0.65	0.00	9.2
Exploitation, quantile binning	Exposure[a]	1.2	1.4	0.11	10
	Censoring[b]	1.0	0.15	0.71	2.0
Exploitation, normal distribution, hourly only [c]	Exposure	0.99	0.02	0.86	1.2
	Censoring	1.1	0.40	0.00	15
Exploitation, normal distribution, salary only[c]	Exposure	0.96	0.02	0.81	1.2
	Censoring	1.1	0.52	0.00	7.2
Overwork hours per week, normal distribution[c]	Exposure	0.98	0.02	0.74	1.5
	Censoring[b]	1.0	0.29	0.71	11

[a]Truncated at 99th percentile
[b]Truncated at 99.5th percentile.
[c]Sensitivity analysis.
Max indicates maximum; Min, minimum.

reasonably stable, as the mean is close to one and the range is not extreme.[44,45]

Inspection of a standardized residuals plot (eFigure S1; http://links.lww.com/EDE/B748) of the exposure conditional on covariates suggested heteroskedasticity due to zero-inflation. To address the possibility that IPEW modeled with linear regression was misspecified, we additionally constructed stabilized weights estimated with the quantile binning approach, by converting the exploitation variable into deciles. Using R package "nnet,"[46] we fit a multinomial regression model for the denominator of the weights as described in Naimi et al,[47] to estimate the probability of being in a given decile. The numerator of the weights is the marginal probability of falling into a decile, or 1/10. See Table 1 for weight distribution.

We constructed stabilized IPCW by creating a missingness indicator for the K6 and fitting a logistic model regressing this indicator on all covariates (denominator model) and only time-invariant covariates (numerator model), accounting for PSID's individual longitudinal sampling weights. Stabilized IPCW represent the inverse probability that a respondent remained uncensored. Examination of the stabilized IPCW revealed a small number of outliers (0.5% of observations) with extremely high inverse probabilities of remaining uncensored. We thus truncated the weights[44] by assigning the value of the weight at the 99.5th percentile to any observation greater than that value. Table 1 shows that the truncated stabilized IPCW achieved good stability, as the mean is close to 1 and the range is narrow. Our final stabilized weights are the product of the IPEW, IPCW, and PSID individual longitudinal sampling weights.

Marginal Structural Models

We fit MSM with R package "survey,"[48,49] which enabled us to incorporate our final stabilized weights and estimate complex sample variance based on PSID's dynamic complex design. Standard errors were estimated using Taylor series linearization. We fit two models, a logistic model for the effect of exploitation on the dichotomous mental illness variable, and a linear model for the effect of exploitation on the K6 scale. Both models controlled for all time-invariant covariates used to stabilize the inverse probability weights, as stabilization creates exchangeability conditional on those variables.[44]

Sensitivity Analyses

Because hourly workers are eligible for overtime pay and salaried workers typically are not, we also examined the effects of exploitation for these two types of wage earners separately. The distribution of weights for this approach is shown in Table 1, and results are presented in Table 2.

Finally, given that our measure of exploitation is collinear with overwork, we were concerned that observed associations between unconcealed exploitation and mental health might be driven entirely by overwork, defined as work hours per week over 40. Overwork might be harmful for mental health even if workers are paid for every hour. To explore this possibility, we fit MSM for the effect of overwork hours on both mental health outcomes. These models were weighted by stabilized IPEW and IPCW for overwork hours (Table 1), created with the same steps as above.

RESULTS

eTable S1; http://links.lww.com/EDE/B748 presents summary statistics for all time-invariant baseline covariates. The sample was predominantly male (83%), reflecting gendered disparities in who identified as head of household, and white (62%). Table S2; http://links.lww.com/EDE/B748 presents summary statistics for covariates that varied between 2003 and 2017. The sample was predominantly paid hourly (45%), home-owning (61%), and educated beyond high school (61%). Respondents worked on average 2586 hours/year (50 hours/week). The mean income from labor was $59,150 (median: $45,881). The mean level of unconcealed exploitation was 17%. The distribution of the exploitation variable was right-skewed (eFigure S2; http://links.lww.com/EDE/B748), reflecting a high frequency of respondents with zero

TABLE 2. Results from IPW Marginal Structural Models for the Effect of Exploitation and Overwork Hours on Psychologic Distress and Mental Illness

	Psychologic Distress[a]		Mental Illness[b]	
Exposure	Beta	95% CI	OR	95% CI
Exploitation, normal distribution	1.6	0.71, 2.5	3.0	1.5, 6.1
Exploitation, quantile binning	1.4	0.43, 2.4	2.7	1.4, 5.5
Exploitation, normal distribution, hourly only[c]	3.6	1.4, 8.8	2.4	1.3, 4.6
Exploitation, normal distribution, salary only[c]	5.8	1.8, 19	2.7	1.2, 6.2
Overwork hours per week, normal distribution[c]	1.0	0.52, 1.6	2.0	1.4, 2.9

[a]K6 scale, unit change.
[b]$5 \leq$ K6 < 13, yes/no.
[c]Sensitivity analysis.
OR indicates odds ratio.

or near zero exploitation. The mean K6 score was 3.0, and 23% of respondents had any mental illness (K6 ≥ 5). eFigures S3–S10; http://links.lww.com/EDE/B748 display descriptive statistics for the time-varying covariates over the study period, and eFigure S11; http://links.lww.com/EDE/B748 displays the unweighted bivariate association between the K6 scale and unconcealed exploitation.

Table 2 presents MSM results for primary and sensitivity analyses. For every percentage point increase in unconcealed exploitation, respondents' psychologic distress increased by 1.6 points (95% confidence interval [CI] = 0.71, 2.5) on the K6 scale and the odds of mental illness tripled (odds ratio = 3.0, 95% CI = 1.5, 6.1). When estimated with weights constructed using quantile binning, each percentage point increase in unconcealed exploitation was associated with a 1.4 point (95% CI = 0.43, 2.4) increase on the K6 scale and 2.7 times higher (95% CI = 1.4, 5.5) odds of mental illness.

Table 2 shows that there was an association between overwork hours alone and psychologic distress and mental illness, but these estimates were smaller than those of unconcealed exploitation. An hour of overwork per week was associated with a 1.0 point (95% CI = 0.52, 1.6) increase on the K6 and 2.0 times higher (95% CI = 1.4, 2.9) odds of mental illness.

Table 2 also includes results from analyses stratified by hourly/salary wages. (these estimates are not directly comparable to each other or to those from the IPW-MSM for the full sample, as exposure and censoring weights were re-estimated and stabilized for each subsample). For hourly workers, for every percentage point increase in unconcealed exploitation, psychologic distress increased by 3.6 points (95% CI = 1.4, 8.8), and the odds of mental were 2.4 times higher (95% CI = 1.3, 4.6). For salaried workers, an increase in exploitation was associated with a 5.8 point (95% CI = 1.8, 19) increase in psychologic distress and 2.7 times the odds (95% CI = 1.2, 6.2) of mental illness.

DISCUSSION

In a nationally representative cohort followed from 1983 to 2017, unconcealed exploitation, measured as the percentage of labor income workers were hypothetically not paid for productive hours, was associated with increased psychologic distress and mental illness. Findings were not completely driven by overwork: sensitivity models found smaller associations between overwork hours alone and psychologic distress and mental illness. Results are consistent with the hypothesis that unconcealed exploitation has had harmful consequences for population mental health.

Findings are consistent with our expectations from a rich history of theory and research on labor and mental health. Results provide suggestive evidence of a direct effect of unconcealed exploitation on mental health. Because total exploitation (concealed and unconcealed) is by definition larger than unconcealed exploitation, exploitation likely damages workers' mental health.

A large body of literature has previously established strong estimated effects of psychosocial workplace conditions on mental health. The extent to which those psychosocial factors mediate the relationship between exploitation and mental health remains unclear empirically and we plan to explore these pathways in future research. Furthermore, findings are consistent with past research confirming that the relationship between labor-related exposures and mental health are not appreciably due to social drift into occupations with particular characteristics.[22]

Focusing explicitly on exploitation, rather than consequences of exploitation such as income inequality or SES, shifts attention to a structural process that generates social and economic inequality. This structural process may be a more appropriate explanatory mechanism for mental illness. Moreover, it may be a more effective intervention target, because it acknowledges the relational nature of workers' labor income and owners' profits: to pay workers fairly for every hour they work, owners and their representatives must accrue less.

Since the 1990s, the prevalence of depression and death by suicide have increased substantially among adults in the United States,[50,51] while educational attainment has increased,[31] and real wages have remained flat.[32] Recent research has identified broad trends (e.g., declines in unions, despair, and increasing income inequality) as drivers of these patterns.[52–54] Here, we offer a potential explanatory mechanism through which these processes may operate. Declines in union power may enable employers to extract more work hours from employees without accompanying increases in pay, which in turn increases population income inequality, when profits from increased productivity accrue entirely to owners and executives. Exploitation may also act as an effect modifier of other causes of psychiatric distress or disorder.

Challenges for Causal Inference

There is an ongoing debate over the use of methods like IPW-MSM for estimating counterfactual realized causal effects versus Potential Outcomes intervention effects.[55–57] A realized causal effect is the effect an exposure did have in the past, whereas an intervention effect is the hypothetical effect that an intervention to change the exposure would have in the future.[55,57] Employing these models to test our theory about exploitation, we interpret our findings as follows: if there are no unmeasured sources of non-exchangeability, the use of IPW-MSM in this context provides evidence that there was an effect of exploitation on mental health outcomes over the study period; that is, we used these models for causal identification.[55,58] Based on our theoretical expectations, the alternative explanations we ruled out in our sensitivity analyses, and by accounting for time-varying confounding, we are confident that our findings reflect more than spurious associations. That said, as with all analyses of observational data, there may be unmeasured sources of non-exchangeability that would reduce our confidence in the precision of our estimates.

Even if there were no unmeasured sources of non-exchangeability, our results could not be interpreted as an intervention effect because we do not posit an intervention mechanism. Although it is easy to imagine a world in which labor laws or mass strikes ensured that individuals were paid for every hour they worked, the sociohistorical context in which our sample was exploited is not the same as it is today or would be in the future. Moreover, laws, strikes, or even a randomized controlled trial in an experimental sample would undoubtedly create changes in myriad other factors likely to alter the relationship between exploitation and mental health. Such an intervention would almost certainly violate the Stable Unit Treatment Variance Assumption. Nonetheless, understanding how political-economic processes influence mental health can provide evidence to help push systems in a particular direction, even if we are unable to isolate the effects of a single intervention target.

Limitations

Our findings should be interpreted in light of the following limitations. First, as noted, heads of household are the primary survey respondent. Virtually all men in the sample were heads of household versus 40% of women, and those women were likely to be widowed or divorced. Therefore, women who are or were married are overrepresented in the PSID relative to other large surveys. As such, our findings may not be fully generalizable to single women. Second, additional intersectional social relations are implicated in exploitation, in particular racialization, racism, gendering, and sexism, which select individuals into occupations and influence domination and exploitation at work.[59,60] These factors warrant more in-depth analysis, based on theory-informed indicators of these intersecting and sometimes mutually constitutive processes. Third, as noted, our measure captures only unconcealed exploitation above and beyond endemic levels inherent to wage labor. Thus our current findings may be conservative. Fourth, while the full sample is weighted to be nationally representative, subsets of the data may not be nationally representative of those subsets. Finally, IPEW were somewhat sensitive to model specification, in addition to decisions about bias-variance tradeoffs, for example, truncation. However, the fact that weights estimated with quantile binning, which makes no distributional assumptions,[47] produced results of similar magnitude increases our confidence in the robustness of our findings.

CONCLUSIONS

Unconcealed exploitation was associated with higher psychologic distress and mental illness in a nationally representative sample followed from 1983 to 2017, controlling for time-varying confounding. Results were not driven entirely by overwork and were robust to different IPW estimation strategies. If the exploitation inherent in wage labor is the serpent of workers' agonies, then unconcealed exploitation may represent the painful tightening of the snake's coils. But today, as when the analogy was first drawn, there are popular and pragmatic social actions readily available to reduce or even eliminate what may be a structural determinant of mental health.

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