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Differential employment quality and educational inequities in mental health: A causal mediation analysis

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Abstract

Background—In the United States inequities in mental distress between those more and less educated have widened over recent years. Employment Quality, a multidimensional construct reflecting the relational and contractual features of employer–employee relationships, may mediate this inequity throughout adulthood, yet no study has examined the extent of this mediation in the United States, or how it varies across racialized and gendered populations.

Methods—Using information on working-age adults from the 2001-2019 Panel Study of Income Dynamics, we construct a composite measure of employment quality via principal component analysis. Using this measure and the parametric mediational g-formula, we then estimate randomized interventional analogues for natural direct and indirect effects of low baseline educational attainment (≤High School: No/Yes) on end-of-follow-up prevalence of moderate mental distress (Kessler-6 Score ≥5: No/Yes) overall and within subgroups by race and gender.

Results—We estimate that low educational attainment would result in a 5.3% greater absolute prevalence of moderate mental distress at end of follow-up (randomized total effect: 5.3%, 95% CI: 2.2%, 8.4%), with approximately 32% of this effect mediated by differences in employment quality (indirect effect: 1.7%, 95% CI: 1.0%, 2.5%). The results of subgroup analyses across race and gender are consistent with the hypothesis of mediation by employment quality, though not when selecting on full employment (indirect effect: 0.6%, 95% CI: −1.0%, 2.6%).

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Conflicts of Interest:
None declared.

Data and Computing Code Availability:
All data supporting the findings of this study are publicly available from the Panel Study of Income Dynamics, though per Conditions of Use authors cannot make data available directly. The code used throughout our analyses, as well as a simplified general-use template script and accompanying dataset for performing the parametric mediational g-formula in R are available at: https://github.com/kblaikie/PSID_education_eq_k6.

Conclusions—We estimate that approximately one third of US educational inequities in mental distress may be mediated by differences in employment quality.

Keywords

education; employment quality; mental health; health disparities; mediation analysis; g-formula

Introduction

Educational attainment is a social determinant of mental distress, with those less educated at greater risk of depression, anxiety, and suicide.[1,2] In recent years, educational inequities in the prevalence of mental distress and depression have widened,[3-6] with depression becoming more prevalent among those least educated in particular. Understanding the factors responsible for this inequity is important for improving population mental health.

In keeping with broader neoliberal health policy,[7] interventions addressing educational inequities in mental distress have focused on changing individual health behaviors.[8] These interventions have had limited success in reducing inequities, however, chiefly benefiting those more educated.[8] Conceptualizing education as a fundamental cause of health[9] may explain this ineffectiveness, in that education improves access to resources that can be used to overcome structural barriers to health and prevent the onset of mental health disorders.[10,11] Behavioral interventions often ignore these barriers, and so may fail to address the underlying causes of poor health for those less educated. A more effective approach would prioritize interventions and policies which address the structural factors mediating educational inequities in mental distress,[7,12,13] such as employment quality.[14-17]

Employment quality is a multi-dimensional construct shaped by the contractual and relational aspects of the employer–employee relationship, with better employment quality reflecting better work arrangements and benefits. Building on theoretical work by Rodgers[18] and following the conceptual model developed by Van Aerden *et al.*[19] and Julia *et al.*,[20] the dimensions of employment quality are: 1) employment stability, 2) material rewards, 3) workers' rights & social protections, 4) working time arrangements, 5) collective organization, 6) employability opportunities, and 7) interpersonal power relations. Employment quality is an emerging and under-studied structural determinant of health, in which those with poorer employment quality experience worse mental health outcomes.[14,15,20] Employment quality may also mediate educational inequities in mental health,[16,17] given those less educated typically have worse employment quality through lower wages, fewer benefits, and greater psychosocial stress.[10,21-23] With rising precarious employment[24] and declines in the 'Standard Employer Relationship',[25] characterized by permanent, full-time employment with good wages and benefits and regular working hours, understanding how employment quality mediates educational inequities in mental distress may be important for developing policies which address these inequities. Potential employment quality-modifying interventions include minimum-wage legislation, anti-discrimination laws, unionization, and Medicaid expansion.[15]

This study evaluates how employment quality mediates the effect of educational attainment on mental distress in the United States (US). Most research on this topic has focused on employment quality in the European Union (EU),[26,27] but for many reasons the construct may operate differently in the US. Compared to the EU, US employees typically work longer hours and enjoy fewer worker protections and guaranteed benefits.[28] Simultaneously, the US has a weaker social safety net,[29] meaning factors associated with poor employment quality including financial insecurity and lack of employer-provided health insurance may have a greater influence on mental distress in the US.

As systemic racism and sexism impact education and employment, we also examine differences in the mediating effect of employment quality within subgroups by race, ethnicity, and gender. Racially minoritized groups, particularly Latinx and non-Hispanic Black populations, have lower educational attainment than non-Hispanic whites[30] due to inequitable access to education and education-supporting material resources. Women and racially minoritized people likewise face inequities in employment through discrimination in hiring, workplace practices,[31-33] and occupational segregation,[34,35] with both groups more likely to be segregated into jobs with poorer employment quality.[21,24,36-38] Thus, we hypothesize that the effect of education on mental distress mediated by employment quality will vary across subpopulations.

Methods

Causal Mediation Analysis in Complex Longitudinal Settings

Until recently, methodologic limitations have impeded research on the relationship between education, employment quality, and mental health. Each factor is time-varying, changing as individuals age, transition between jobs, and experience periods of poor mental health. The relationship between factors is also bi-directional and interactive, with poor employment quality worsening mental health and poor mental health predisposing individuals to precarious employment, particularly if less educated. These features imply time-varying confounding and exposure–mediator interaction, which compromise traditional adjustment-based mediation techniques. Factors affected by education such as marital status also likely confound the relationship between employment quality and mental distress, implying exposure-induced mediator–outcome confounding. In this context the total effect (TE) of educational attainment cannot easily be decomposed into parts mediated by employment quality (the indirect effect) and independent of employment quality (the direct effect)[39] using either Controlled Effect[40] or Natural Effect (NE) estimands,[39,40] the latter of which are unidentifiable in the presence of exposure-induced mediator–outcome confounding.[40-42] Further explanation for why is given in eAppendix 1.

Recently several approaches have been developed to address these methodological barriers. Randomized interventional analogues of NE are one set of estimands that allow effect decomposition through relaxing the identifiability assumption of no exposure-caused mediator–outcome confounding.[43-46] Further, unlike NE these estimands do not rely on untestable ‘cross-world’ assumptions.[47] Our study uses the parametric mediational g-formula[46] to estimate randomized, interventional analogues of the Total Effect (rTE), pure Natural Direct Effect (rPNDE) and total Natural Indirect Effect (rTNIE), defined as below:

$$rTE = E[Y_{a,Ga}] - E[Y_{a^*,Ga^*}], \quad rPNDE = E[Y_{a,Ga^*}] - E[Y_{a^*,Ga^*}], \quad rTNIE = E[Y_{a,Ga}] - E[Y_{a,Ga^*}]$$

The rTE represents the average difference in outcomes Y expected had everyone experienced counterfactual exposure a (vs. exposure a*) and a random mediator value drawn from the mediator distribution G under exposure a, G_a (vs. exposure a*, G_{a*}). The rPNDE represents the average difference in outcomes Y expected had everyone experienced counterfactual exposure a (vs. exposure a*) and a random mediator value drawn from the mediator distribution G_{a*}. The rTNIE represents the average difference in outcomes Y expected had everyone experienced counterfactual exposure a and some random mediator value drawn from the counterfactual mediator distribution G_a (vs. mediator distribution G_{a*}). Where identifiability assumptions are met, these estimands sum to the rTE and in the absence of exposure-induced mediator–outcome confounding, the mediational g-formula reduces to Pearl's mediation formula estimating the TE, PNDE and TNIE.[40]

Study Population

We used participant information from the Panel Study of Income Dynamics (PSID), a nationally representative study of US households established in 1968.[48] Administered annually from 1968-1997 and biennially thereafter, PSID collects information on participant employment, income, and wealth. Health information has additionally been collected since 1984, with mental health assessed since 2001.

We restricted our analyses to 2001-2019, when mental health data were available. We further restricted our analysis to all eligible respondents aged 30-60 years old with known gender, nativity, race and ethnicity, educational attainment, and parental wealth, who were employed by someone other than themselves for at least one survey assessment at which their mental health was recorded.

For each eligible participant, information from up to five consecutive survey waves (totaling 10 years of follow-up) were retained for the primary analysis, including at least one wave where participants were employed. As individuals with poor employment quality are more likely to experience precarious employment,[49,50] eligible participants could be temporarily unemployed or 'not in the labor force' for up to four of five assessments to avoid introducing selection bias. We excluded individuals ever exclusively self-employed during follow-up, theorizing that employment quality is defined and operates differently in that cohort. A flow diagram describing the generation of our study cohort and longitudinal loss-to-follow-up is provided in eAppendix 2.

Exposure

Using information on respondents' highest levels of educational attainment, we created an indicator for baseline educational attainment ≤12 years (i.e., equivalent to high school completion or less) or a GED versus >12 years,[51] defining baseline as the earliest record contributing towards a participant's follow-up period. We dichotomized at this threshold on the educational gradient as completion of secondary education or equivalent is associated with large discontinuities in mental health.[52] We treated education as time-fixed, as it typically remains unchanged after age 30.

Mediator

We conceptualized employment quality as a multi-dimensional construct shaped by contractual and relational dimensions of the employer–employee relationship.[20,53] Using information on multiple employment quality indicators (Table 2, eAppendix 3), we created a composite employment quality score via a Principal Component Analysis (PCA)-based approach used previously in the employment quality literature.[21,54,55] This approach reduces information from multiple correlated employment quality characteristics into a smaller number of uncorrelated principal components, each explaining distinct portions of the shared data variance.[56] To create our employment quality score, principal components with eigenvalues ≥1 (N=3) were summed, weighting each by the proportion of the shared data variance they explained. Data were used for all PSID respondents aged 30-60 and employed by someone other than themselves between 1984-2019, with 1984 the earliest year data was collected for all PCA variables. Those unemployed or not in the labor force had missing employment quality information imputed as in eAppendix 3, with their employment quality score subsequently imputed through multiple imputation (MI), conceptualizing them as lacking the same health-promoting resources as those employed with poor employment quality.[57,58] We also created a simpler linear employment quality score, described under SensitivityAnalyses. Participant characteristics by employment status and employment quality quartile are reported in eAppendix 4.

Outcome

PSID has collected information since 2001 (except for 2005) on the mental health of non-proxy respondents through the Kessler-6: a standardized measure for assessing non-specific mental distress validated among diverse groups.[59,60] The Kessler-6 has been used to assess serious and moderate mental distress, defined as scores ≥13 and ≥5 respectively,[61,62] and is predictive of DSM-IV depression and anxiety disorder diagnoses.[63] In our analysis we assessed moderate mental distress at end-of-follow-up using this ≥5 threshold, which is indicative of clinically relevant functional and social impairment requiring treatment.[62] We also assess severe mental distress at end-of-follow-up using the ≥13 threshold in eAppendix 6.

Confounders

We accounted for multiple factors thought to confound the exposure–mediator, mediator–outcome, or exposure–outcome relationship (Figure 1). Time-fixed factors included baseline survey year, age (years), gender (man vs. woman), race and ethnicity (defined under Effect Modifiers), migrant background (grew up in US vs. outside US), work-limiting disability status (no vs. yes), self-reported childhood socioeconomic status (SES) (growing up 'poor' vs. 'average or well-off'), census region ('Northeast', 'Midwest', 'West'. 'South'), and occupational category (coded following Autor and Dorn's[64] typology of census occupation codes). Time-varying factors included current unemployment or not in the labor force status (unemployed/not in the labor force vs. employed), self-reported health ('excellent or very good' vs. 'good, fair, or poor'), and marital status ('married or cohabiting' vs. 'not married or cohabiting'), as well as one-wave lagged mediator (employment quality) and outcome (Kessler-6) values.

Effect Modifiers

Gender, race and ethnicity are important modifiers of the relationship between educational attainment, employment quality, and mental distress. To accommodate sample size constraints, we collapsed race (white, Black, Native American or Alaska Native, Native Hawaiian or Pacific Islander, Asian, Other) and ethnicity (Hispanic/Latinx vs. not Hispanic/Latinx) into an indicator for belonging to one or more racially or ethnically minoritized groups versus none, using those non-Hispanic white as referent. We repeated all analyses within subgroups 'non-Hispanic white', 'racially and/or ethnically minoritized', 'women', and 'men', modeling exposure-modifier and mediator-modifier interaction in each case.

Statistical Methods

Parametric Mediational G-Formula and Causal Contrasts under Study—Using the parametric mediational g-formula approach developed by Lin *et al.*[46] we estimate the expected difference in end-of-follow-up prevalence of moderate mental distress under 10-year exposure–mediator histories of low versus high educational attainment and consequent employment quality (rTE). We decompose this effect into population average direct effects (rPNDE) and employment quality-mediated indirect effects (rTNIE), representing the effect of everyone having low educational attainment (vs. high) for a consecutive 10-year period while experiencing employment quality comparable to that expected under high educational attainment (rPNDE), and the effect of everyone having employment quality comparable to that expected under low educational attainment (vs. high) for a consecutive 10-year period while all counter-to-fact having low educational attainment (rTNIE). Effects are presented using prevalence ratios (PR) and prevalence differences (PD). Moment-based bootstrap confidence intervals (CI) for these effects were constructed following the 'MI Boot' approach proposed by Schomaker and Heumann,[65] with 200 bootstrap repetitions. The steps to our approach as implemented including CI limit construction are described in eAppendix 5.

As with the parametric g-formula, the mediational g-formula implicitly adjusts for loss-to-follow-up assuming that it is ignorable conditional on measured covariates.[66,67] As such, mediational g-formula findings reflect the entire study population including those lost-to-follow-up, despite their mental health at end-of-follow-up being unobserved. In evaluating model performance, observed prevalences of moderate mental distress at end-of-follow-up were compared against those simulated under the natural course, representing the outcome prevalence expected in the whole study population, simulating each covariate from baseline to end-of-follow-up without intervention. In the absence of model misspecification, the natural course should provide similar outcome prevalences to those observed,[67,68] except where loss-to-follow-up is meaningful.[69] The robustness of our findings and comparability of rTE and TE estimates were evaluated through multiple analyses described under Sensitivity Analyses and in eAppendix 6, alongside full covariate model specifications.

Missing Data—Variables treated as fixed were carried over from complete participant records. For all other missing data, multiple imputation by chained equations (MICE) was performed with 25 iterations using the '*mice*'[70] and '*miceadds*'[71] R packages, using predictive mean matching clustering by individual for employment quality and Kessler-6 imputation models and linear discriminant analysis for all other models. Each imputation model included all analysis variables presented in Table 1 and employment quality component variables in Table 2. To have as many imputation datasets as the percentage of incomplete cases (37%),[72] we created 40 imputed datasets. MI was performed separately within educational strata,[73] with exposure stratum-specific imputed datasets merged post-imputation.

Sensitivity Analyses—All analyses were repeated: (1) among respondents fully employed throughout follow-up; (2) under eight- and twelve-year follow-up periods; and (3) using a linear employment quality measure,[24,74,75] in which employment quality dimensions are assigned 0-1 scores and overall employment quality is the unweighted sum of these scores (operationalized as in eAppendix 3). Each sensitivity analysis differs in-part from primary analyses, where respondents could be unemployed during follow-up, were followed over 10 years, and had their employment quality assigned using a PCA-based approach. We deliberately repeated our analyses selecting on full employment despite its potential to introduce bias, as employment-based selection is common in the employment quality literature[16] and relevant to our inclusion of those unemployed/not in the labor force in primary analyses.

PCA was performed in Stata MP Version 17,[76] with all other analyses performed in R Version 4.1.2[77] using RStudio IDE.[78]

Results

Respondent Characteristics

Our primary sample included 8581 respondents. Respondents were predominantly women (58%) and non-Hispanic white (53%), with a mean baseline age of 37.9 years (SD: 8.2) (Table 1). 24% of respondents reported moderate mental distress (Kessler-6 score ≥5) at end-of-follow-up. Respondents with low baseline educational attainment (40%) were more likely to be racially and/or ethnically minoritized (56% vs. 41%), to have had low childhood SES (31% vs. 19%), to be currently unemployed or not in the labor force (16% vs. 10%), and to report moderate mental distress at end-of-follow-up (29% vs. 21%), and were less likely to rate their general health as very good or excellent (46% vs. 63%) or to be married (58% vs. 65%).

Employment Quality Score and Characteristics

Respondents had a mean PCA-derived employment quality score of −0.2 (SD: 0.6, Range: −2.2, +2.8), with longer prior-year unemployment associated with lower (worse) employment quality scores and all other employment quality indicators associated with higher scores (Table 2). Those less educated at baseline reported lower employment quality (Mean (SD): −0.4 (0.5) vs. −0.1 (0.5)), longer prior-year unemployment, and lower (worse) values for all variables associated with better employment quality, except annual hours worked and union membership where groups were similar (Table 2). Non-Hispanic whites had higher mean employment quality overall (Mean (SD): −0.1 (0.5) vs. −0.3 (0.6)), with smaller within-group differences by baseline education (difference in mean employment quality by education: 0.23 vs. 0.29). Men had higher mean employment than women (Mean (SD): 0.1 (0.5) vs. −0.3 (0.6)), with larger within-group differences in mean employment quality by baseline education (0.32 vs. 0.27).

Natural Course Simulations

The mean observed prevalence of moderate mental distress at end-of-follow-up in the primary analysis population (24%, 4124 lost-to-follow-up) was similar to that simulated under the natural course in the whole study population (24%), suggesting parametric models were not grossly misspecified (eAppendix 7 Table 1).

Primary Analyses using Multiply Imputed Datasets

Compared to a counterfactual population where all respondents had high educational attainment over a 10-year period, a population with low educational attainment would have a 24% greater relative prevalence (PR rTE: 1.24, 95% CI: 1.09, 1.40) and 5.3% greater absolute prevalence (PD rTE: 5.3%, 95% CI: 2.2%, 8.4%) of moderate mental distress at end-of-follow-up (eAppendix 7 Table 2, Figure 2). The direct component of this effect where both populations experienced employment quality comparable to that under more education (rPNDE) would have resulted in a 16% greater relative prevalence (PR rPNDE: 1.16, 95% CI: 1.01, 1.32) and 3.5% greater absolute prevalence (PD rPNDE: 3.5%, 95% CI: 0.4%, 6.7%), while the indirect component mediated by differences in employment quality expected under less (vs. more) educational attainment (rTNIE) would have resulted in a 7% greater relative prevalence (PR rTNIE: 1.07, 95% CI: 1.04, 1.10) and 1.7% greater absolute prevalence (PD rTNIE: 1.7%, 95% CI: 1.0%, 2.5%), explaining approximately 32% of the rTE.

Secondary Analyses by Gender and Race and Ethnicity

The randomized total effect (rTE) of low educational attainment would result in a greater prevalence of moderate mental distress at end-of-follow-up in all subpopulations, with estimated rTE ranging from 27%-33% greater relative prevalence (for those female and male respectively) and 5.7%-6.6% greater absolute prevalence (for those male and racially and/or ethnically minoritized respectively) (eAppendix 7 Table 2, Figure 2). Mediated effects through population differences in employment quality (rTNIE) would have likewise increased prevalence in all subpopulations, with estimated rTNIE ranging from 8%-15% greater relative prevalence (for those male and racially and/or ethnically minoritized versus non-Hispanic white respectively), and 1.8%-3.5% greater absolute prevalence (for those male and non-Hispanic white respectively), explaining between 32%-58% of rTEs across subpopulations (for those male and racially and/or ethnically minoritized versus non-Hispanic white respectively).

Sensitivity Analyses

Fully Employed—Restricting to respondent records where individuals were fully employed, observed moderate mental distress at end-of-follow-up was markedly less prevalent (15% vs. 24%, 7075 vs. 4124 lost-to-follow-up). Within this cohort, the estimated rTE of low educational attainment was consistent with no effect on the relative prevalence (PR rTE: 1.16, 95% CI: 0.92, 1.42) or absolute prevalence (PD rTE: 3.1%, 95% CI: −1.3%, 7.5%) of moderate mental distress at end-of-follow-up (eAppendix 7 Table 3, Figure 3). Similarly, meaningful employment quality-mediated effects were not indicated on the relative scale (PR rTNIE: 1.03, 95% CI: 0.95, 1.13) or absolute scale (PD rTNIE: 0.6%, 95% CI: −1.0%, 2.6%).

Linear Employment Quality Score—Linear and PCA-derived employment quality scores were highly correlated in primary and fully employed samples (rho: 0.91 and 0.86 respectively). Using the linear employment quality score, the estimated rTE of low educational attainment was 5.3% greater absolute prevalence of moderate mental distress at end-of-follow-up (PD rTE: 5.3%, 95% CI: 2.2%, 8.4%), with the direct effect causing 4.0% greater prevalence (PD rPNDE: 4.0%, 95% CI: 0.9%, 7.1%), and employment quality-mediated indirect effect causing 1.2% greater prevalence (PD rTNIE: 1.2%, 95% CI: 0.6%, 1.9%) (eAppendix 7 Table 3).

Different Follow-Up Length Analyses—Analyses following participants over eight and 12 years showed slightly higher rTE estimates than obtained following participants over 10 years. These larger estimated effects operated through pathways independent of employment quality, with employment quality-mediated effects near-equivalent across analyses (eAppendix 7 Table 3).

Discussion

This study is to our knowledge the first to examine how multidimensional employment quality mediates educational inequities in mental distress. Our results provide strong evidence for lower education causally increasing prevalence of mental distress among working-age adults, consistent with prior literature.[1,79-81] Importantly, we estimate that roughly one-third of educational inequities in mental distress may result from negative effects of lower education on employment quality. We also find that selection on employment greatly reduces total and employment quality-mediated effect estimates, highlighting the importance of considering selection bias when estimating effects of employment-dependent factors on health.

Our findings are also consistent with prior research examining employment-based mediation of educational inequities in mental health. Using the parametric g-formula, Milner *et al.*[16] examined whether income, occupational skill, and employment status mediate educational disparities in mental health in Australia. They estimated that these factors jointly mediated 40% of the cumulative effect of low educational attainment on mental health over a 3-year period, and that selection on employment eliminated any mediating effects of employment variables. Separately, Qui, Bures, and Shehan[82] conducted a traditional mediation analysis evaluating whether psychosocial job demands mediate educational inequities in depression among women and men in the US, finding job demands only mediated educational inequities among women. Though not directly comparable, our results assessing mediation by employment quality similarly estimated proportionally larger mediating effects for women compared to men.

Counter to expectations, we identified smaller proportions of educational inequities in moderate mental distress were mediated by employment quality for those racially and/or ethnically minoritized (32%) compared to non-Hispanic white (58%). An artefactual explanation for this finding could be that non-differential mediator misclassification is more prevalent among those racially and/or ethnically minoritized, where non-differential mediator misclassification would bias employment quality-mediated effects, on average, towards the null while amplifying non-employment quality-mediated effects.[83,84] For example, our employment quality measure did not account for shift worked and on-the-job training opportunities, though racially minoritized groups are more likely to work night shifts[85] and report fewer on-the-job training and advancement opportunities.[86,87] Separately, better employment quality may simply provide fewer protections for those racially and/or ethnically minoritized. This would be consistent with the 'diminishing returns hypothesis'[88,89] which suggests that high-SES confers fewer health benefits for racially minoritized groups due to structural racism and discrimination,[31] life-course effects of childhood adversity,[90] and status incongruence.[91]

Several limitations of our work are important to acknowledge. Though we account for many confounding factors, the causal interpretation of our results depends on the completeness of our causal model, which may be threatened by unmeasured confounding, such as by parental occupation or educational quality. Non-differential mediator misclassification could likewise be present due to unmeasured employment quality indicators, or because our PCA-derived employment quality measure only accounted for 54% of the shared variance across indicators, though results were comparable in analyses using PCA-derived and linear employment quality measures. Relatedly, though unemployed individuals were retained in our primary analysis to mitigate selection bias, any inaccuracy in the employment quality scores imputed for those unemployed could introduce misclassification bias as well. Separately, selection bias could have been introduced if loss-to-follow-up in our study was not ignorable conditional on measured covariates. Though analyses requiring different lengths of follow-up provided comparable employment quality-mediated effect estimates, this is still a possible concern as 48% of primary analysis respondents were lost-to-follow-up. Other limitations are that rNIE estimands can indicate mediation in the absence of true mediating effects,[92] that our end-of-follow-up outcome may be sensitive to the episodic nature of mental distress, that we cannot discount exposure misclassification among those educated outside the US (7.3% of individuals), and that secondary analyses must be interpreted with caution, given sample-size limitations prohibited disaggregating racialized groups or considering strata defined intersectionality by race, ethnicity, and gender. Finally, as we conceptualize employment quality as an inherently multi-dimensional construct and operationalize it as-such, our effect estimates must be interpreted as compound effects that do not reflect a single real-world entity which could be intervened on.

Our study builds on existing literature in important ways. Using longitudinal data, we account for reverse causation in the relationship between education, employment quality, and mental distress more fully than previous studies. Using the mediational g-formula, we likewise better account for time-varying confounding, exposure–mediator interaction, and exposure-induced mediator–outcome confounding, while unbiasedly decomposing educational inequities in mental distress into parts mediated and not mediated by employment quality. Through sensitivity analyses and natural course comparisons we further show that our results are not sensitive to the causal Markov-1 assumption, assumed causal ordering of covariates, specific choice of employment quality measure, or length of follow-up assessed, and likely not subject to gross model misspecification.[67,93] Finally, by using a multi-dimensional employment quality measure, our study demonstrates how employment holistically shapes mental distress clearer than prior studies assessing individual employment indicators, and may serve as an applied example of how social causes can be assessed using methods appropriate in complex causal settings.

In summary, our study highlights the importance of employment quality in addressing educational inequities in mental distress in the US. While not interpretable as ‘interventional effects’ due to the various ways employment quality could be intervened on, we estimate that employment quality accounts for a third of educational inequities in mental distress, supporting the enactment of employment quality-improving and education-promoting policies. In identifying which dimensions of employment quality are most relevant to mental health, further research could consider path-specific mediation analyses allowing for mediator–mediator interaction.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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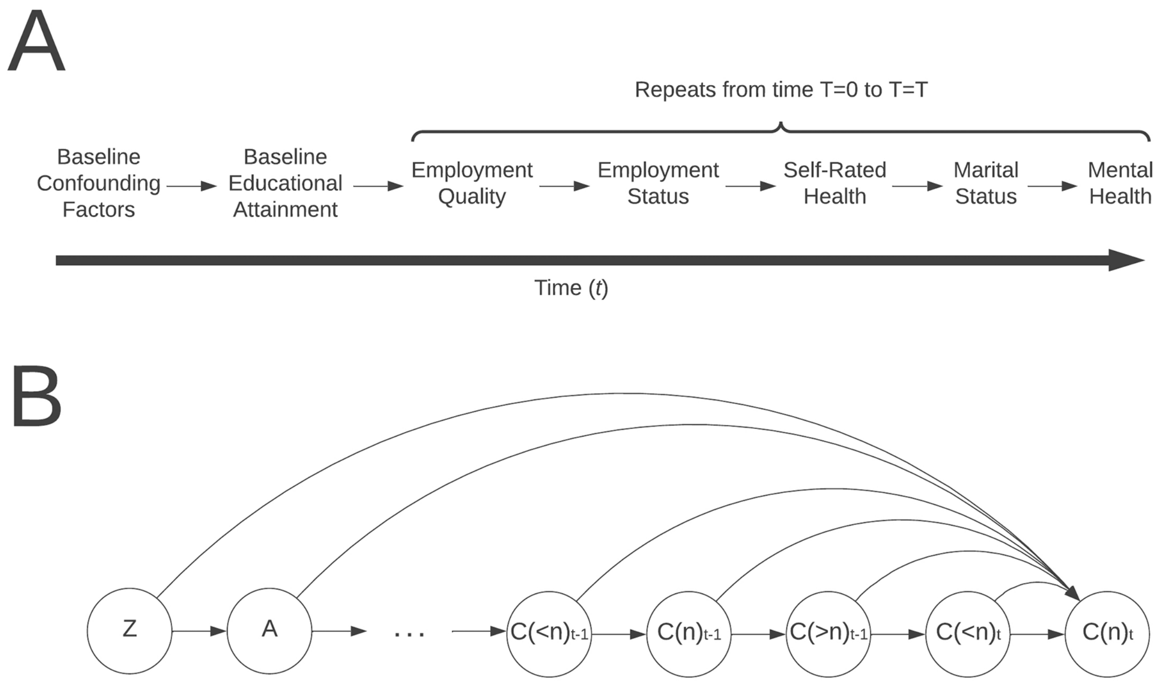

FIGURE 1.

Chronological covariate order and causal Directed Acyclic Graph (DAG) assumed in primary mediational g-formula analyses. (A) Chronological covariate order assumed, with post-exposure covariates at each time-point *t* repeating in the same order from T=0 to T=T. (B) Causal DAG assumed for each nth chronologically ordered post-exposure covariate C at time *t*, $C(n)_t$. For each $C(n)_t$, a Markov-1 assumption is made such that $C(n)_t$ is assumed independent of all covariates observed at T<t-1 other than baseline confounding factors, Z, and baseline educational attainment, A, conditional on all covariates observed at T=*t*-1 and causally antecedent (<n) covariates at T=*t*. Baseline confounding factors, Z, includes survey year, age, gender, collapsed race and ethnicity, migrant background, disability status limiting ability to work, self-reported childhood socioeconomic status, census region, and occupational category.

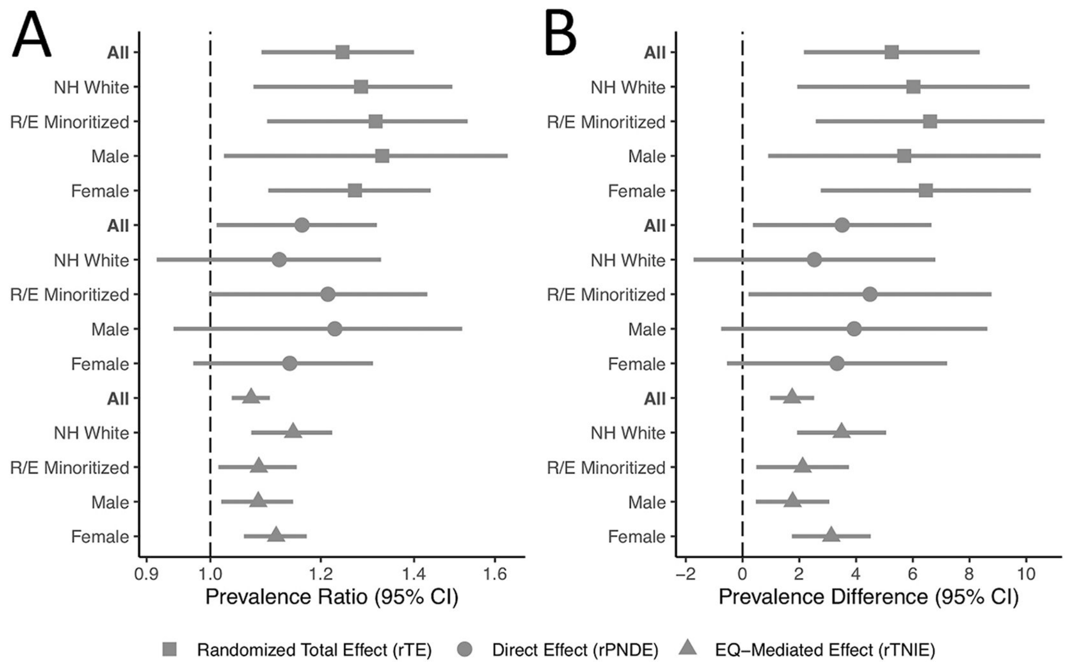

FIGURE 2.

Randomized total, direct, and indirect effect from mediational g-formula of the association between low education and poor mental health mediated through employment quality (EQ) overall and by gender, race, and ethnicity within an inconsistently employed cohort. (A) Prevalence ratios and 95% confidence intervals (B) Prevalence differences and 95% confidence intervals. NH White: Non-Hispanic White. R/E Minoritized: Racially and/or Ethnically Minoritized. CI: Confidence Interval. rTE: Randoimzed Total Effect. rPNDE: Randomized Pure Natural Direct Effect. rTNIE: Randomized Total Natural Indirect Effect.

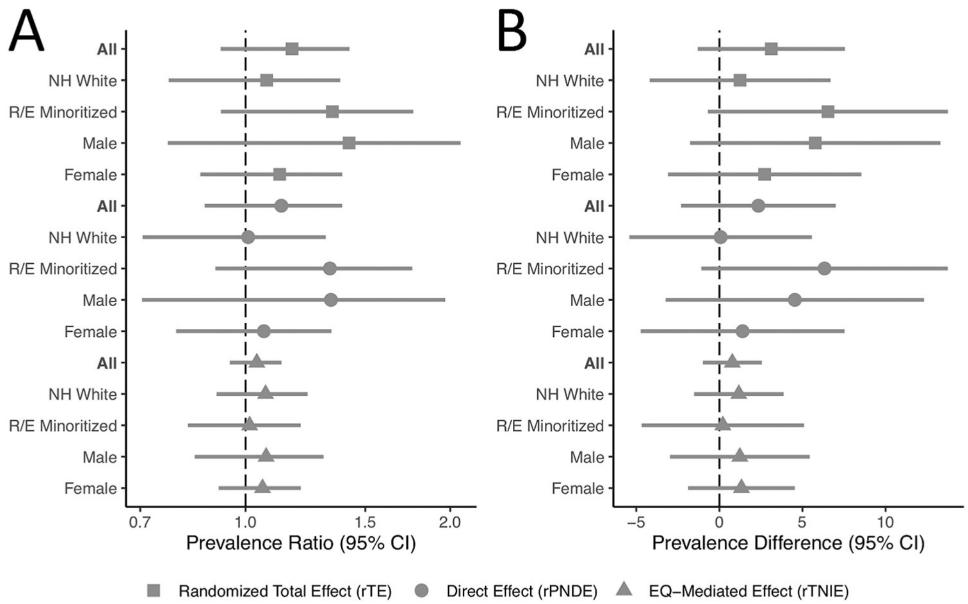

FIGURE 3.

Randomized total, direct, and indirect effect from mediational g-formula of the association between low education and poor mental health mediated through employment quality (EQ) overall and by gender, race, and ethnicity within a consistently employed cohort. (A) Prevalence ratios and 95% confidence intervals (B) Prevalence differences and 95% confidence intervals. NH White: Non-Hispanic White. R/E Minoritized: Racially and/or Ethnically Minoritized. CI: Confidence Interval. rTE: Randomized Total Effect. rPNDE: Randomized Pure Natural Direct Effect. rTNIE: Randomized Total Natural Indirect Effect.

TABLE 1.

Participant Characteristics, by Baseline Educational Attainment, and by Employment Quality Quartile, Panel Study of Income Dynamics 2001-2019.

Measure		Overall	Baseline Education Attainment	
			≤High School	>High School
	N (Observations)	8581 (42905)	3460 (17300)	5121 (25605)
Baseline year				
	Mean (SD)	2006.8 (6.3)	2005.9 (6.0)	2007.5 (6.4)
	Median [IQR]	2005 [2001, 2013]	2003 [2001, 2011]	2007 [2001, 2013]
Baseline age (years)				
	Mean (SD)	37.9 (8.2)	38.8 (8.2)	37.3 (8.2)
	Median [IQR]	35 [31, 44]	37 [31, 45]	33 [31, 43]
Gender, N (%)				
	Men	3590 (42)	1484 (43)	2106 (41)
	Women	4991 (58)	1976 (57)	3015 (59)
Race & Ethnicity, N (%)				
	Non-Hispanic white	4562 (53)	1540 (45)	3022 (59)
	Racially or Ethnically Minoritized	4019 (47)	1920 (56)	2099 (41)
Grew up in US, N (%)				
	No	629 (7.3)	334 (9.7)	295 (5.8)
	Yes	7952 (93)	3126 (90)	4826 (94)
Childhood SES (Poor), N (%)				
	No	6526 (76)	2381 (69)	4145 (81)
	Yes	2055 (24)	1079 (31)	976 (19)
Baseline Education, N (%)				
	≤High School	3460 (40)	3460 (100)	0 (0)
	>High School	5121 (60)	0 (0)	5121 (100)
Baseline Disability Limits Work, N (%)				
	No	7876 (92)	3141 (91)	4735 (93)
	Yes	705 (8.2)	319 (9.2)	386 (7.5)
Baseline Region, N (%)				
	Midwest	2116 (25)	907 (26)	1209 (24)
	Northeast	1148 (13)	385 (11)	763 (15)
	South	3756 (44)	1581 (46)	2175 (43)
	West	1561 (18)	587 (17)	974 (19)
Baseline Occupation, N (%)				
	Technical sales, admin support	2173.6 (25)	777.3 (23)	1396.3 (27)
	Professional specialty	1634.2 (19)	158 (4.6)	1476.2 (29)
	Services	1263.1 (15)	708 (21)	555.1 (11)
	Operators, fabricators, laborers	1004.4 (12)	702.3 (20)	302 (5.9)
	Managerial	807 (9.4)	198 (5.7)	609 (12)
	Precision production, craft and repair	682.4 (8.0)	407.4 (12)	275 (5.4)

Measure		Overall	Baseline Education Attainment	
			≤High School	>High School
	Farming, forestry, fishing	56 (0.7)	46 (1.3)	10 (0.2)
	Military	57 (0.7)	9 (0.3)	48 (0.9)
	Unemployed or NILF	903.4 (11)	454 (13)	449.4 (8.8)
Unemployed or NILF, N (%) [a]				
	No	28220 (87)	11206 (84)	17014 (90)
	Yes	4116 (13)	2142 (16)	1974 (10)
Self-Rated Health, N (%) [a]				
	Poor/Fair/Good	14299.2 (44)	7176.6 (54)	7122.6 (38)
	Very Good/Excellent	18036.8 (56)	6171.4 (46)	11865.5 (63)
Married or Cohabitating, N (%) [a]				
	No	12234 (38)	5640 (42)	6594 (35)
	Yes	20102 (62)	7708 (58)	12394 (65)
Kessler-6 Score				
	Mean (SD)	3.2 (3.7)	3.5 (4.1)	2.9 (3.3)
	Median [IQR]	2 [0, 4.8]	2 [0, 5.6]	2 [0, 4]
	<5, N (%) [a]	24186.7 (75)	9467.9 (71)	14718.8 (78)
	≥5, N (%) [a]	8149.3 (25)	3880.2 (29)	4269.2 (23)

[a]Numbers and percentages refer to the number of observations, rather than participants. SD: Standard Deviation. IQR: Inter-Quartile Range. NILF: Not in Labor Force. SES: Socioeconomic Status. Note: Data presented represent the average summary across multiply imputed datasets. Data on 'Unemployment or NILF' status, 'Self-Rated Health', 'Married or Cohabiting', and 'Kessler-6 Score' rows represent average survey assessment summaries across analysis years.

TABLE 2 .

Employment Quality Indicators Overall and by Baseline Educational Attainment, Panel Study of Income Dynamics 2001-2019.

Measure		Overall	Baseline Educational Attainment	
			≤High School	>High School
	N Observations (%)	32336 (100)	13340 (41)	18996 (59)
PCA Employment Quality Score				
	Mean (SD)	−0.2 (0.6)	−0.4 (0.5)	−0.1 (0.5)
	Median [IQR]	−0.1 [−0.6, 0.3]	−0.3 [−0.7, 0.1]	0.1 [−0.4, 0.3]
Linear Employment Quality Score				
	Mean (SD)	2.8 (1.3)	2.5 (1.4)	3.0 (1.3)
	Median [IQR]	3.2 [2.0, 4.0]	2.8 [1.5, 3.5]	3.5 [2.4, 4.0]
Union Membership, N (%)				
	No	28223.3 (87)	11698.2 (88)	16525.2 (87)
	Yes	4112.7 (13)	1641.8 (12)	2470.8 (13)
Employer-provided HI, N (%)				
	No	8381.4 (26)	4886.4 (37)	3495.1 (18)
	Yes	23954.6 (74)	8453.6 (63)	15501.0 (82)
Salaried Employment, N (%)				
	No	21291.3 (66)	11102.7 (83)	10188.6 (54)
	Yes	11044.7 (34)	2237.3 (17)	8807.4 (46)
Extra Overtime Pay, N (%)				
	No	6842.9 (21)	3461.4 (26)	3381.5 (18)
	Yes	25493.1 (79)	9878.6 (74)	15614.5 (82)
Pension Contributions, N (%)				
	No	16444.4 (51)	8269.5 (62)	8174.9 (43)
	Yes	15891.6 (49)	5070.4 (38)	10821.1 (57)
Annual Work Hours (1000s)				
	Mean (SD)	1.9 (0.8)	1.8 (0.9)	1.9 (0.8)
	Median [IQR]	2.0 [1.6, 2.3]	2.0 [1.5, 2.2]	2 [1.7, 2.3]
Past Year Unemployment (months)				
	Mean (SD)	0.3 (1.4)	0.4 (1.6)	0.2 (1.2)
	Median [IQR]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
Employment Tenure Z-Score				
	Mean (SD)	−0.3 (1.0)	−0.3 (1.0)	−0.2 (1.0)
	Median [IQR]	−0.6 [−1.1, 0.4]	−0.7 [−1.1, 0.3]	−0.5 [−1.0, 0.5]
Total Labor Income Z-Score				
	Mean (SD)	0.2 (1.1)	−0.2 (0.6)	0.4 (1.3)
	Median [IQR]	−0.1 [−0.4, 0.4]	−0.2 [−0.6, 0.1]	0.1 [−0.3, 0.7]

PCA: Principal Component Analysis. SD: Standard Deviation. IQR: Inter-Quartile Range. HI: Health Insurance. Note: Data presented represent the average summary across multiply imputed datasets.