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Life-course trajectories of employment quality and health in the U.S.: a multichannel sequence analysis

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Abstract

The organization of employment in the U.S. has changed dramatically since the 1970s, causing decreased power and security for workers across many dimensions of the employment relationship. Multidimensional employment-quality (EQ) measures can be used to capture these changes and test their association with health. However, most public-health EQ studies have used cross-sectional, unidimensional data. We addressed these limitations using a longitudinal, multidimensional EQ measure and data on 2,779 1985–2017 Panel Study of Income Dynamics respondents. First, using a multichannel sequence-analysis approach, we identified gender-specific clusters of mid-career (ages 29–50) EQ trajectories based on respondents' employment stability, material rewards, working-time arrangements, collective organization, and power relations. Next, we examined cross-cluster variation in respondent characteristics. Finally, we estimated the gender-specific associations between cluster-membership and post-sequence-analysis-period prevalence of poor/fair self-rated health (SRH) and moderate mental illness (Kessler-K6 5). We identified five clusters among women and seven among men. Respondents in poor-EQ clusters were disproportionately people of color and less-educated; they also tended to report worse health. For example, among women, the prevalence of poor/fair SRH and moderate mental illness was lowest among standard-employment-relationship-like-non-union workers and the becoming self-employed, and greatest among minimally-attached, returning-to-the-labor-force, and precariously-employed workers. Meanwhile, among men, the prevalence of the outcomes was lowest among stably-high-wage workers and the wealthy self-employed, and greatest among exiting-the-labor-force and precariously-employed workers. Given the potential role of EQ in health inequities, researchers and practitioners should consider EQ in their work.

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Keywords

United States; employment quality; work quality; health inequities; health disparities; precarious employment; precariousness; sequence analysis

1. Introduction

The organization of employment in the U.S. has changed dramatically since the 1970s, driven by economic and political forces like recessions, transformations in industrial production, and shifts in the power balance between employers and workers (Ahonen et al., 2018; Vosko, 2010). One important trend concerns the decline in jobs resembling the standard employment relationship (SER), ideally characterized by permanent, full-time employment with secure wages and benefits and some worker control over the labor process (Kalleberg, 2009). Although the SER was never common for people of color or white women (Branch and Hanley, 2018; Cranford et al., 2003), nor has it been typical in capitalism historically (Quinlan, 2012), it remains the model for many workplace regulations and thus is a useful standard from which to evaluate modern employment arrangements (Van Aerden et al., 2014). To reduce costs, employers have increasingly de-standardized the employment relationship by eroding worker power and security, employment-protection policies, and other labor regulations (Benach et al., 2014). Among the poor and working class, this has contributed to stagnant wages, plummeting labor-union density, and weakening fringe benefits and hours stability (Benach et al., 2014; Kalleberg and Vallas, 2018). Meanwhile, employment conditions have improved for upper-class workers, causing increased inequality across social classes (Kalleberg, 2013). Socioeconomic inequities in health have grown concomitantly (Bor et al., 2017), suggesting a connection between shifting employment relations and health inequities.

Historically, occupational-health researchers have focused on the risks of workplace physical hazards like chemicals (Quinlan et al., 2001). Others have focused on the risks of workplace psychosocial hazards; for example, studies using the Job-Demand-Control model have associated adverse outcomes with psychological demands like pressure to complete work tasks quickly (Quinlan et al., 2001). Although these approaches have produced important insights, they focus on the nature of work tasks themselves while neglecting key health-related aspects of the worker-employer relationship (Peckham et al., 2019).

To address the limitations of traditional approaches, researchers have re-conceptualized their work-health models (Benach et al., 2014). For example, recent studies have focused on the health harms of growing employment instability caused by factors like temporary work contracts (Benach et al., 2014). However, de-standardization has also affected other dimensions of the employment relationship, like material rewards and power relations (Benach et al., 2014). Moreover, de-standardization has created a variety of non-standard employment arrangements that deviate from the SER in unique ways and thus have unique implications for worker health (Van Aerden et al., 2014). Consequently, unidimensional contract-type measures may not adequately capture the range of employment dimensions and arrangements relevant to health (Julià et al., 2017).

Multidimensional measures can address these limitations. However, most public-health studies using multidimensional measures have relied on cross-sectional data, which cannot address changes in employment over the life course. Moreover, most of these studies have been European-Union-based, which may not generalize to the U.S.-context, given the regions' political and economic differences (Kim et al., 2012). To address these gaps, we used a multidimensional "employment-quality" (EQ) measure and U.S.-based longitudinal data to construct detailed EQ trajectories and examine the associations between EQ, self-rated health (SRH), and mental illness.

1.1. Employment quality

EQ is a multidimensional construct characterizing the health-related terms and conditions of the worker-employer relationship (Julià et al., 2017; Van Aerden et al., 2014). Researchers have identified seven key EQ dimensions, which include contractual (e.g., wages and benefits) and relational (e.g., power relations) aspects of employment: 1) *employment stability* refers to the continuity of workers' employment; 2) *material rewards* refers to the wage and non-wage benefits of an employment arrangement; 3) *workers' rights* refers to workers' labor rights, like protection from discrimination; 4) *working-time arrangements* refers to the regularity and length of workers' working hours; 5) *training and employment opportunities* refers to the opportunities available to workers to advance their skills and position in the workplace; 6) *collective organization* refers to whether workers have institutions, like unions, which they can use to advance their class interests at the workplace, industry, and societal levels; and 7) *interpersonal power relations* refers to the division of decision-making power between workers, supervisors, managers, and owners. These dimensions are interrelated; for example, workers with greater collective organization (e.g., unionization) can demand greater material rewards (e.g., higher wages).

In public health, the EQ construct has developed alongside the precarious-employment (PE) construct (Julià et al., 2017). EQ and PE share theoretical orientations, including their focus on multidimensionality and worker-employer power relations. However, although more widely-used, PE has drawbacks. First, there is little consensus on PE measurement. For example, despite the construct's emphasis on multidimensionality, researchers frequently operationalize PE using unidimensional employment-stability measures (Kim et al., 2008). Moreover, researchers across disciplines conceptualize and measure PE at different levels, including at the employment-relationship level (e.g., business owner), job-level (e.g., janitorial work), and social-class or demographic levels (e.g., undocumented workers) (Campbell and Price, 2016). Thus, PE's meaning frequently differs across studies (Kreshpaj et al., 2020). Second, PE constructs often rely on objective *and* subjective measures of the employment relationship. For example, the widely-used Employment Precariousness Scale (EPRES) combines objective measures like wages with subjective measures like whether workers feel easily replaceable (Vives et al., 2010). However, responses to subjective measures often depend on circumstances external to the employment relationship, such as family-level (e.g., family income) or macro-level (e.g., unemployment rate) factors. Thus, PE constructs may not measure the employment relationship alone. Finally, multidimensional PE measures, including EPRES, often aggregate the dimensions into a composite linear score ranging from "least precarious" to "most precarious" (Vives et al.,

2010). Nonetheless, PE may not be reducible to a continuum, as certain combinations of health-harming employment conditions may interact nonlinearly (Van Aerden et al., 2014).

Given these limitations, the EQ construct may have advantages over the PE construct. Unlike PE, EQ: 1) focuses exclusively on characteristics of the employment relationship, 2) excludes subjective measures, and 3) is typically measured using typological approaches (e.g., cluster-based) rather than linear scores (Julià et al., 2017; Peckham et al., 2019; Van Aerden et al., 2014). The latter point may allow the EQ construct to characterize a broader spectrum of employment arrangements, as it does not focus on distinguishing “precarious” employment from “non-precarious” employment. Rather, the EQ construct conceptualizes PE as an accumulation of adverse EQ conditions, with PE representing but one possible arrangement (Julià et al., 2017). Indeed, recent studies using the EQ construct have revealed substantial heterogeneity in modern employment arrangements and emphasized that their associations with health may depend on the specific configuration of EQ dimensions (Peckham et al., 2019; Van Aerden et al., 2017, 2016).

1.2. EQ and health

Many studies have identified associations between EQ/PE and health (Benach et al., 2014); the conceptual model in Appendix A1 displays hypothesized pathways. Although being a worker (rather than an employer) in a capitalist society is essentially risky because working conditions are always vulnerable to cost-cutting degradation (Eisenberg-Guyot and Prins, 2019), certain employment arrangements may be more perilous than others. First, poor EQ caused by employment instability or inadequate material rewards may prevent workers from obtaining health-promoting necessities like healthcare that are often accessible with SER-like employment. Material deprivation can also independently contribute to psychological distress (Julià et al., 2017). Second, poor EQ may expose workers to occupational hazards like toxic chemicals and job strain (Benach et al., 2014). Compared with SER workers, workers with poor EQ may receive less training, be less familiar with hazards, and be more reluctant to refuse dangerous tasks and report hazardous conditions due to inadequate workplace rights and power (Quinlan et al., 2001). They may also face greater demands and have less control over the labor process (Benach et al., 2014). For example, piecework employees may face heightened pressure to increase output (Brisson et al., 1989), while non-managerial workers may have little autonomy and face antagonism from superiors (Muntaner et al., 2015). Finally, workers with poor EQ may have little control over their personal and professional lives (Julià et al., 2017; Kalleberg, 2018); for example, nonstandard working-time arrangements and employment instability may contribute to feelings of powerlessness and insecurity and independently harm relationships (Lewchuk et al., 2008) and sleep (Mai et al., 2019). Moreover, unstably-employed workers may be unable to build the workplace social connections that buffer employment-related stressors (Clarke et al., 2007).

Given low social mobility in the U.S. (Bor et al., 2017), most workers' EQ may change little over their lifetimes, suggesting poor-EQ's health effects may accumulate (Amick et al., 2016), manifesting most strongly in later life. Even among the upwardly mobile, earlier-life exposure to poor EQ may harm later-life health, while among the downwardly mobile, later-

life exposure to poor EQ may counteract the salutary effects of good earlier-life EQ (Amick et al., 2016).

1.3. Variation in the distribution of EQ and in the EQ-health relationship

The prevalence of poor EQ and the EQ-health relationship may vary by place (Benach et al., 2014; Kim et al., 2012). For example, workers in states with laws that hinder labor organizing may struggle to build sufficient power to improve their working conditions, while workers in states with weaker labor standards, like low minimum wages, may have access to lower-quality employment (Benach et al., 2014; Kalleberg and Vallas, 2018). Meanwhile, employment-related material deprivation may be less harmful in states with stronger social-welfare protections, as workers can obtain certain necessities from public programs (Kalleberg, 2018; Kim et al., 2012). This suggests European studies may not generalize to the U.S., given differences between U.S. and European labor markets and welfare states (Kim et al., 2012).

The prevalence of poor EQ may also vary across genders and racialized groups, as might the EQ-health relationship. For example, relative to men, women are often segregated into lower-quality employment, face more employment-related discrimination and harassment, and are burdened with greater domestic-labor responsibilities (Cranford et al., 2003; Quinn and Smith, 2018). Although this suggests EQ may produce worse health among women, in heterosexual couples, the gendered division of labor means that couples' material well-being may depend most heavily on men's EQ (Ferguson et al., 2019), suggesting the EQ-health relationship may actually be stronger among men. Meanwhile, people of color, particularly women of color, are often segregated into the lowest-quality employment and face the most employment-related racism, discrimination, and harassment (Bailey et al., 2017; Gee and Ford, 2011). Moreover, they may lack certain material resources like wealth (Bailey et al., 2017; Gee and Ford, 2011) that mitigate employment-related deprivation. Thus, the burden of EQ-related morbidity and the EQ-health relationship may be greater among people of color than among white people.

1.4. Aims

To our knowledge, no U.S.-based studies have used a longitudinal, multidimensional EQ measure to examine the EQ-health association. We addressed this gap using Panel Study of Income Dynamics (PSID) data and a multichannel sequence-analysis approach. Our study had three aims: 1) to identify gender-specific clusters of early-to-mid-career EQ trajectories, 2) to examine how socioeconomic and demographic factors varied across EQ-trajectory clusters, and 3) to analyze the gender-specific associations between EQ-trajectory cluster and later-life prevalence of poor/fair SRH and moderate mental illness.

2. Methods

2.1. Data

The PSID is a panel survey that enrolled a nationally-representative probability sample of U.S. families in 1968 (McGonagle et al., 2012). PSID interviewed these "core" families and subsequent "split-off" families annually until 1997 and biennially thereafter; core families

and related split-off families constitute “family clans” (McGonagle et al., 2012). Our analyses used data on family “heads” and heads’ “partners” from the 1985–2017 survey waves; non-heads/partners did not have data on all variables of interest and several EQ variables were not asked until 1984 (McGonagle et al., 2012). From 1985–1997, we excluded survey waves in even years to align with the survey’s post-1997 structure with the survey’s structure post-1997. We also excluded the 1990–1995 “Latino sample” because of its limited follow-up.

2.2. Sample and missing data

First, to focus on early-to-mid-career EQ and ages with the greatest labor-force participation (U.S. Bureau of Labor Statistics, 2019), we restricted our sample of respondents ages 18 (n=31,298) to those observed at least once between ages 29–31 and at least once between ages 48–50 (n=2,913). Next, because our sequence-analysis approach required that respondents’ sequences were equal lengths (Studer et al., 2011), we restricted our sample of 29-to-50-year-olds to those observed 9 waves between those ages (n=2,789). When respondents missed a wave or had missing values in variables of interest, we carried their values forwards from the prior wave (or backwards from a subsequent wave, if necessary). 90% of respondents were observed every wave during follow-up, and no respondents missed more than two total waves; in observed waves, variables had 4% missingness. After implementing the above procedures, we removed 10 respondents with remaining missingness in variables of interest. Our final sample in the sequence analyses and SRH analyses included 2,779 respondents. In the mental-illness analyses, we only included non-proxy respondents (n=2,055) because proxy respondents did not have mental-health measurements. Appendix A2 compares those excluded from our analyses with those included.

2.3. EQ measure

To create our EQ measure, we first classified respondents’ current employment status as “unemployed”, “not in the labor force (NILF)” (i.e., “student”, “retired/disabled”, “keeping house”, or “other”), “poor self-employed” (total household wealth below the age-specific median of self-employed respondents), “wealthy self-employed” (total household wealth at or above the age-specific median of self-employed respondents), or “employed as a wage laborer”. Appendix A3 contains wealth-measure details. We differentiated the self-employed from wage-laborers because the self-employed were not asked certain EQ questions and they may have a different social class than wage-laborers (Eisenberg-Guyot and Prins, 2019); we differentiated the poor self-employed from the wealthy self-employed to separate those in the working class (e.g., gig workers with little power/autonomy) from those in the upper classes (e.g., business owners with substantial power/autonomy). We included “unemployed”, “NILF”, “poor self-employed”, and “wealthy self-employed” as categories in each of the EQ variables. Next, among employed wage-laborers, we analyzed five of seven EQ dimensions: *employment stability*, *material rewards*, *working-time arrangements*, *collective organization*, and *interpersonal power relations*. PSID did not have consistent measures of *employment opportunities* or *workers’ rights*. Guided by prior studies (Julià et al., 2017; Peckham et al., 2019; Van Aerden et al., 2014), we measured the dimensions as follows:

1. *Employment stability*: whether respondents were ever unemployed/temporarily laid off in the past year (yes/no). Respondents' current employment status also proxied this dimension.
2. *Material rewards*: respondents' annual labor income (in age-specific quartiles in 2017 dollars) and whether respondents had any employer-based health insurance (yes/no). PSID did not have consistent data on employer-based health insurance from 1984–1997. To address missingness, we used data from 1999–2017 to impute respondents' health-insurance status from 1984–1997 (Appendix A4).
3. *Working-time arrangements*: respondents' annual hours worked (categorized into three age-specific groups: quartile 1 (low), quartiles 2–3 (medium/standard), and quartile 4 (high)).
- 4–5. *Collective organization and interpersonal power relations*: respondents' labor-union-membership status (yes/no), as well as respondents' self-employment status, which proxied *interpersonal power relations* because the wealthy self-employed may have considerable decision-making power and autonomy.

2.4. Health outcomes

From 1985–2017, PSID measured respondents' SRH (“Would you say your health in general is...?”); we dichotomized the variable as poor/fair versus good/very good/excellent to improve reliability (Zajacova and Dowd, 2011). From 2001–2017, save 2005, PSID administered the Kessler-K6 (K6) to non-proxy respondents. The K6 is a six-question scale (range 0–24) designed to estimate the prevalence of serious mental illness (Kessler et al., 2010). We dichotomized K6 as ≤ 5 or > 5 , which reliably identifies those with and without moderate mental illness (Kessler et al., 2010).

2.5. Effect modifiers, confounders, and other covariates

We treated gender as a potential effect-modifier of the EQ-health relationship. Potential confounders included respondents' age, race, education, region of residence, marital status, childhood wealth, whether respondents had a disability that limited the type/amount of work they could perform, and baseline (i.e., measured at ages 29–31) dichotomized SRH. Descriptively, we also examined respondents' family income, occupation, and industry. We addressed inconsistencies in occupation codes using Autor et al.'s and NIOSH's crosswalks and classified the resulting occupations into seven categories (Autor and Dorn, 2013; National Institute for Occupational Health and Safety, 2019); we addressed inconsistencies in industry codes using IPUMS's crosswalks and classified the resulting industries into nine categories (Minnesota Population Center, n.d.). Tables 1 and 2 display how covariates were operationalized.

2.6. Statistical methods

2.6.1. Multichannel sequence analysis—Sequence analyses measure the similarity of individuals' life-course trajectories (i.e., “sequences”) of states (e.g., union-member) in a variable (e.g., labor-union membership) and cluster together individuals with similar trajectories (Barban and Billari, 2012; Gabadinho et al., 2011; Studer et al., 2011). Although

typical sequence-analysis approaches assess one variable, multichannel approaches can assess several simultaneously (Gabadinho et al., 2011). Our multichannel approach, conducted using R's "TraMineR" (Gabadinho et al., 2020) and "cluster" (Rousseeuw et al., 2019) packages, proceeded in several steps.

First, we stratified the data by gender, given hypothesized gender differences in EQ and in the EQ-health relationship (Cranford et al., 2003; Quinn and Smith, 2018); we conducted the steps described below separately by gender.

Second, using the data available for respondents from ages 29–31 to 48–50, we constructed employment-history sequences of each of the five EQ measures. Because only employed wage-laborers could have values for the EQ measures, we included "unemployed", "NILF", "poor self-employed", and "wealthy self-employed" as possible states in the measures.

Third, we combined respondents' sequences of each variable (called "channels") into a single multistate sequence. To this end, for each respondent at each age, we combined the individual states observed for each of the EQ measures into a single "multistate" (e.g., for a currently-employed wage-laborer at age 50, no past-year unemployment/high labor income/health insured/moderate working hours/union member).

Fourth, using dynamic Hamming distances (DHD), we generated a pairwise dissimilarity matrix that minimized the total 'cost' of transforming each respondent's longitudinal multistate sequence into every other respondent's longitudinal multistate sequence (Studer et al., 2011). We created the dissimilarity matrix by summing the transformation costs of each channel in the multistate sequence. When calculating transformation costs, DHD permits substitutions (e.g., at age-50, substituting "labor-union non-member" for "labor-union member") but not insertions/deletions, thus preserving states' life-course timing (Studer et al., 2011). The cost of a given substitution is inversely proportional to the probability of the state transition at that age in the data (e.g., the cost of substituting quartile-4 income for quartile-1 income is greater than the cost of substituting quartile-2 income for quartile-1 income, because quartile-2 to quartile-1 transitions are more common) (Studer et al., 2011).

Finally, we performed a hierarchical cluster analysis on the dissimilarity matrix using Ward's method, which separated respondents into EQ-trajectory clusters by grouping together respondents who shared low cost values (and thus had similar sequences) (Studer et al., 2011). We considered four-to-ten-cluster solutions to approximate the range in prior research (Julià et al., 2017; Peckham et al., 2019; Van Aerden et al., 2014); we chose the final number after considering the clusters' interpretability, sample sizes, and silhouette values (which measure how similar observations are to observations within their cluster relative to observations outside their cluster) (Rousseeuw, 1987).

2.6.2. EQ-trajectory clusters and health—To estimate the prevalence of the health outcomes among each cluster relative to the prevalence among the reference cluster at the last observed wave of the sequence-analysis period and each observed wave thereafter, we used gender-stratified log-linear Poisson generalized estimating equations (GEE) with family-clan-level exchangeable correlation structure and cluster-robust standard errors

(Højsgaard et al., 2019). To estimate the total magnitude of health inequities across clusters, we ran minimally-adjusted models that included only age and year as covariates (specified as 3-knot restricted cubic splines to allow for nonlinearity). We also ran fully-adjusted models that additionally included race, baseline education, baseline region, baseline marital status, childhood SES, baseline work disability, and baseline SRH. In sensitivity analyses, we excluded those with baseline work disabilities to address reverse causation (i.e., poor health harming respondents' EQ).

3. Results

3.1. Women

3.1.1. Sequence-analysis and clustering diagnostics—Of 1,605 women in the sample, 1,575 had unique EQ sequences. Thus, average silhouette widths (ASW) across the cluster solutions were low (range: 0.10–0.28) (Appendix A5). We chose a five-cluster solution (ASW=0.24) because the four-cluster solution lacked typologies found in prior research (e.g., a precariously-employed cluster), while six-to-ten-cluster solutions had low ASWs and clusters with small sample sizes.

3.1.2. Overview of EQ-trajectory clusters—Figure 1 displays the distribution of the EQ variables at each age by cluster among women; Appendix A6a displays the information in table format.

1. **SER-like-non-union** workers (n=745) had low probabilities of current unemployment and NILF, were distributed across labor-income quartiles, almost always had employer-based health insurance, were infrequently union members (although were union members more often than respondents in most other clusters), had low/moderate working hours, and had somewhat low past-year unemployment.
2. The **becoming self-employed** (n=122) tended to begin follow-up as wage laborers or NILF but moved into poor or wealthy self-employment as they aged. While employed as wage laborers, they tended to have low/moderate labor incomes, working hours, and probabilities of union membership, but had decent access to employer-based health insurance and low past-year unemployment.
3. **Precariously-employed** workers (n=216) had higher probabilities of current unemployment than respondents in any other cluster. When employed, they concentrated in labor-income quartile 1, often lacked employer-based health insurance, were rarely union members, had somewhat low working hours, and had high past-year unemployment.
4. **Returning-to-the-labor-force** workers (n=212) tended to begin follow-up NILF but moved into the labor force as they aged. While employed as wage laborers, they concentrated in labor-income quartiles 1–2 and had low/moderate working hours, but more often than workers in most other clusters, had employer-based health insurance, were union members, and lacked past-year unemployment.

5. **Minimally-attached** workers (n=310) had moderate levels of wage-labor employment at the beginning of follow-up, but tended to become NILF as they aged. While in the labor force, they had high probabilities of current unemployment, and while employed as wage laborers, they concentrated in labor-income quartile 1 and had poor employer-based health-insurance access, low probabilities of union membership, low working hours, and high probabilities of past-year unemployment.

3.1.3. Demographic and socioeconomic characteristics of EQ-trajectory clusters—Women of color concentrated in the precariously-employed and minimally-attached clusters (Table 1). Relative to respondents in other clusters, respondents in these clusters tended to have lower education levels, family incomes, and marriage rates, and greater childhood poverty. They were also more often from the South. Meanwhile, respondents in the becoming-self-employed cluster tended to have higher socioeconomic status (SES) than respondents in other clusters, including less childhood poverty and greater education levels, family incomes, and probabilities of managerial/professional occupations.

3.1.4. EQ-trajectory clusters and health—Figure 2 displays results from the GEE models of cluster membership, SRH, and mental illness among women; Appendix A7a displays the results in table format. The prevalence of poor/fair SRH during follow-up was 18.2%. In the minimally-adjusted model, the becoming self-employed had a similar prevalence of poor/fair SRH to SER-like-non-union workers (prevalence ratio [PR]: 1.01, 95% confidence interval [CI]: 0.63, 1.64); the estimate was similar in the fully-adjusted model. Meanwhile, in the minimally-adjusted model, minimally-attached (PR: 2.60, 95% CI: 2.02, 3.36), returning-to-the-labor-force (PR: 1.54, 95% CI: 1.11, 2.14), and precariously-employed (PR: 1.23, 95% CI: 0.85, 1.77) workers had a greater prevalence of poor/fair SRH than SER-like-non-union workers. In the fully-adjusted model, only minimally-attached (PR: 1.95, 95% CI: 1.51, 2.53) and returning-to-the-labor-force (PR: 1.51, 95% CI: 1.09, 2.09) workers had a meaningfully greater prevalence.

The prevalence of moderate mental illness during follow-up was 24.9%. In the minimally-adjusted model, the becoming self-employed had a similar prevalence of mental illness to SER-like-non-union workers (PR: 1.09, 95% CI: 0.74, 1.62); the estimate was similar in the fully-adjusted model. Meanwhile, in the minimally-adjusted model, minimally-attached (PR: 2.26, 95% CI: 1.84, 2.78), precariously-employed (PR: 1.34, 95% CI: 1.03, 1.75), and returning-to-the-labor-force (PR: 1.21, 95% CI: 0.89, 1.63) workers had a greater prevalence of mental illness than SER-like-non-union workers. In the fully-adjusted model, only minimally-attached (PR: 1.88, 95% CI: 1.53, 2.32) workers had a meaningfully greater prevalence.

Excluding those with baseline work disabilities did not meaningfully affect the estimates (Appendix A8a).

3.2. Men

3.2.1. Sequence-analysis and clustering diagnostics—Of 1,174 men in the sample, 1,140 had unique EQ sequences. Thus, average silhouette widths (ASW) across the

cluster solutions were low (range: 0.16–0.18) (Appendix A5). We chose a seven-cluster solution (ASW=0.16) because four-to-six-cluster solutions lacked typologies found in prior research (e.g., precariously-employed and stably-high-wage clusters), while sample sizes were too small in eight-to-ten-cluster solutions.

3.2.2. Overview of EQ-trajectory clusters—Figure 3 displays the distribution of the EQ variables at each age by cluster among men; Appendix A6b displays the information in table format.

1. **SER-like-non-union** workers (n=367) had low probabilities of current unemployment and NILF, concentrated in labor-income quartiles 2–3, tended to have employer-based health insurance, were rarely union members, had moderate/high working hours, and had moderate past-year unemployment.
2. **SER-like-union** workers (n=183) had very low probabilities of current unemployment and NILF, concentrated in labor-income quartiles 3–4, almost always had employer-based health insurance, had high union membership, more moderate working hours than SER-like non-union workers, and moderate past-year unemployment.
3. **Stably-high-wage** workers (n=286) resembled SER-like-union workers in terms of their current unemployment and NILF, as well in their access to employer-based health-insurance. However, they tended to have higher incomes and working hours and lower union membership and past-year unemployment.
4. The **wealthy self-employed** (n=103) often began follow-up as wage-laborers, but moved into wealthy self-employment as they aged. They were similar to SER-like-union and stably-high-wage workers in terms of their probabilities of current unemployment and NILF, and when employed as wage-laborers, resembled stably-high-wage workers across all EQ variables.
5. The **poor self-employed** (n=69) tended to begin follow-up as wage-laborers but moved into poor self-employment as they aged. They had higher probabilities of current unemployment and NILF than the wealthy self-employed, and when employed as wage-laborers, resembled SER-like-non-union workers in terms of their incomes, union membership, working hours, and past-year unemployment, but more often lacked employer-based health insurance.
6. **Precariously-employed** workers (n=98) had higher probabilities of current unemployment than respondents in other clusters. When employed as wage-laborers, they concentrated in labor-income quartiles 1–2, tended to lack employer-based health insurance, were rarely union members, had low/moderate working hours, and had high past-year unemployment.
7. **Exiting-the-labor-force** workers (n=68) tended to begin follow-up in the labor force but became NILF as they aged. While in the labor force, they had high probabilities of current unemployment, and while employed as wage laborers, they had similar incomes and working hours to SER-like-non-union workers and

higher probabilities of union membership, but more often lacked employer-based health insurance and had past-year unemployment.

3.2.3. Demographic and socioeconomic characteristics of EQ-trajectory clusters

—Men of color concentrated in more-precarious clusters, especially in the precariously-employed and exiting-the-labor-force clusters (Table 2). Relative to respondents in other clusters, respondents in these clusters tended to have lower education levels, family incomes, and marriage rates, and greater childhood poverty. Along with those in the SER-like-non-union cluster, they were also more often from the South. Meanwhile, respondents in the stably-high-wage and wealthy-self-employed-employed clusters tended to have higher SES than respondents in other clusters, including less childhood poverty and greater education levels, family incomes, and probabilities of managerial/professional occupations.

3.2.4. EQ-trajectory clusters and health

—Figure 4 displays results from the GEE models of cluster membership, SRH, and mental illness among men; Appendix A7b displays the results in table format. The prevalence of poor/fair SRH during follow-up was 14.2%. In the minimally-adjusted model, stably-high-wage workers (PR: 0.40, 95% CI: 0.25, 0.63), the wealthy self-employed (PR: 0.50, 95% CI: 0.30, 0.84), and SER-like-union workers (0.78, 95% CI: 0.52, 1.18) had a lower prevalence of poor/fair SRH than SER-like-non-union workers. In the fully-adjusted model, only stably-high-wage workers (PR: 0.52, 95% CI: 0.30, 0.87) and the wealthy-self-employed (PR: 0.63, 95% CI: 0.36, 1.12) had a meaningfully lower prevalence. Meanwhile, in the minimally-adjusted model, the poor self-employed had a similar prevalence of poor/fair SRH to SER-like-non-union workers (PR: 1.12, 95% CI: 0.64, 1.93); the estimate was similar in the fully-adjusted model. Finally, in the minimally-adjusted model, exiting-the-labor-force (PR: 2.87, 95% CI: 2.09, 3.94) and precariously-employed (PR: 1.58, 95% CI: 1.05, 2.37) workers had a greater prevalence of poor/fair SRH than SER-like-non-union workers. In the fully-adjusted model, exiting-the-labor-force workers still had a much greater prevalence (PR: 2.49, 95% CI: 1.84, 3.38), but precariously-employed workers only had a somewhat greater prevalence (PR: 1.26, 95% CI: 0.85, 1.87).

The prevalence of moderate mental illness during follow-up was 18.7%. In the minimally-adjusted model, stably-high-wage workers (PR: 0.42, 95% CI: 0.27, 0.63), the wealthy self-employed (PR: 0.68, 95% CI: 0.40, 1.16), and SER-like union workers (0.72, 95% CI: 0.45, 1.15) had a lower prevalence of mental illness than SER-like-non-union workers; estimates were similar in the fully-adjusted model. Meanwhile, in the minimally-adjusted model, the poor self-employed (PR: 1.12, 95% CI: 0.64, 1.99) and precariously-employed workers (PR: 1.05, 95% CI: 0.64, 1.71) had a similar prevalence of mental illness to SER-like-non-union workers; estimates were similar in the fully-adjusted model. Finally, in the minimally-adjusted model, exiting-the-labor-force workers had a greater prevalence of poor/fair SRH than SER-like-non-union workers (PR: 1.62, 95% CI: 1.04, 2.52; the estimate was similar in the fully-adjusted model).

Excluding those with baseline work disabilities did not meaningfully affect the estimates (Appendix A8b).

4. Discussion

Using a multichannel sequence-analysis approach and a multidimensional EQ measure, we identified clusters of early-to-mid-career EQ trajectories among women and men in the U.S. and examined their associations with SRH and mental illness. As in prior studies (Cranford et al., 2003; Quinn and Smith, 2018), women tended to have worse EQ than men. For example, even at a seven-cluster solution, there were no stably-high-wage or wealthy-self-employed clusters among women, whereas among men, such clusters emerged at a 5-cluster solution. Moreover, women in most clusters tended to have less labor-force attachment during follow-up than their male counterparts, likely because of gender inequities in domestic-labor responsibilities (Quinn and Smith, 2018). Across clusters and within genders, health followed expected patterns, with those in better-EQ clusters (e.g., SER-like-non-union among women and stably-high-wage among men) tending to report better health than those in more-precarious clusters (e.g., minimally-attached among women and exiting-the-labor-force among men). Among women and men, people of color and the less-educated concentrated in more-precarious clusters, suggesting EQ may contribute to racial and educational inequities in health.

The better health among male stably-high-wage workers and male wealthy self-employed respondents is unsurprising given their considerable employment stability and material rewards throughout follow-up. Moreover, their occupational and educational credentials (and the wealthy self-employed's assets) may have afforded them training/employment opportunities, decision-making power, and job autonomy, buffering harms from long working hours and labor-union non-membership. Meanwhile, among women and men, the worse health among those with less labor-force attachment may be related to their lack of income while NILF and poor EQ while employed. Moreover, given their high levels of baseline disability, some less-attached workers may have been segregated into lower-quality employment or forced out of the labor force because of pre-existing illness, a possibility not entirely accounted for by our adjustment for baseline SRH and disability status.

Prior research broadly supports our findings. For example, several cross-sectional analyses using multidimensional EQ measures have found similar health patterns across EQ clusters (Peckham et al., 2019; Van Aerden et al., 2017, 2016). In a U.S.-based study, Peckham et al. found more-precarious workers reported worse SRH and mental health than SER-like workers, while stably-high-wage workers reported better health (Peckham et al., 2019). Meanwhile, Giudici et al., using a longitudinal single-channel sequence-analysis approach and an EQ measure based on respondents' labor-force status and working-time arrangements, found that Swiss workers with intermittent unemployment/inactivity and little labor-force attachment reported worse SRH and mental health than those with stabler employment and greater labor-force attachment, findings similar to ours (Giudici and Morselli, 2019). Likewise, Devillanova et al., using a similar approach and measure to Giudici et al., found unstably-employed Italian workers reported worse SRH than stably-employed workers, while among the stably-employed, professional workers reported better SRH than others (Devillanova et al., 2019). Finally, although few prior EQ studies have differentiated the wealthy self-employed from the poor self-employed, our findings on the self-employed do align with those of prior social-class studies, which have often found that

self-employed respondents with more assets report better health than those with fewer (Muntaner et al., 2015).

Our results demonstrate the usefulness of multidimensional, longitudinal EQ measures in occupational-health research. Because workers across several clusters differed on only one or two EQ measures, or differed on EQ measures at certain ages but not at others, studies using single-dimensional EQ measures and/or cross-sectional data may have grouped these distinct workers together, overlooking their unique trajectories and health outcomes. Although multidimensional, longitudinal approaches can distinguish these subtypes, to our knowledge, our study is the first U.S.-based one to employ such an approach. Additionally, our longitudinal data allowed us to estimate the cumulative associations between EQ and health over the life course – which may be stronger than cross-sectional associations – and to mitigate reverse causation.

Despite its strengths, our study had limitations. First, we restricted our sample to those observed for two decades; although measured characteristics of included and excluded respondents did not differ substantially (Appendix A2), those excluded had somewhat lower SES, less health insurance, and poorer health. Thus, the identified clusters – and their relationship with health – may not represent those in the broader U.S. population. Second, EQ changed substantially over the years under study, particularly during the Great Recession (Kalleberg and Vallas, 2018). Unfortunately, we were unable to address such secular trends in our analyses – e.g., by stratifying the sequence analyses by time period – because of sample-size limitations and the limited variation between respondents in calendar years of follow-up (no sequences were constructed using data from earlier than 1985–2005 or later than 1997–2017). Third, our analyses produced clusters with considerable within-cluster EQ heterogeneity due to the length of follow-up and the many possible states at each wave. Although we believe our results are still useful because of our descriptive focus and the theoretical coherence of the identified clusters, the clusters were likely somewhat unstable, which demonstrates the difficulty of analyzing longitudinal, multidimensional EQ measures. Fourth, PSID lacked data on the *employment opportunities* and *workers' rights and social protections* dimensions. These unmeasured dimensions correlate with measured dimensions, but not perfectly. For example, certain lower-paid workers may have training opportunities that help them advance into less-precarious employment over time, while certain higher-paid workers may lack training opportunities and thus be stuck in dead-end employment (Julià et al., 2017; Peckham et al., 2019). Thus, our clusters may have had unmeasured EQ heterogeneity. However, to our knowledge, no longitudinal U.S.-based datasets contain more complete mid-career EQ data. Finally, our analyses relied on self-reported health outcomes. Although SRH and the K6 have high reliability and validity, they can suffer from misclassification, particularly SRH among racialized and lower-SES respondents (Dowd and Zajacova, 2007; Zajacova and Dowd, 2011).

5. Conclusion

We identified five EQ-trajectory clusters among women and seven among men, which differed in employment stability, material rewards, working-time arrangements, collective organization, and interpersonal power relations. The prevalence of poor/fair SRH and

moderate mental illness varied considerably across clusters, with respondents in worse-EQ clusters, who were disproportionately from racialized and less-educated populations, reporting worse health than others. Given the potential role of EQ in health inequities, as well as the responsiveness of EQ to policy and organizing, public-health researchers and practitioners should consider EQ in their work.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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- Identified employment-quality trajectory clusters using multidimensional measure
- Estimated association between clusters, self-rated health, and mental illness
- Found five clusters among women and seven clusters among men
- Those with poor employment quality often people of color and less-educated
- Adverse health outcomes more common among those with poor employment quality

Figure 1.

Distribution among women of each EQ variable at each age by cluster from multichannel sequence analysis conducted on sample of 1605 Panel Study of Income Dynamics respondents. Notes: unemp: unemployed; NILF: not in the labor force; S-E: self-employed.

Figure 2.

Prevalence among women of poor/fair self-rated health (SRH) or moderate mental illness (Kessler K6>5) among each cluster relative to the prevalence among SER-like non-union workers at the last observed wave of the sequence-analysis period and each wave thereafter. X-axis plotted on log scale. Notes: Estimates from Poisson generalized estimated equations with family-clan-level exchangeable correlation structure and cluster-robust standard errors run on Panel Study of Income Dynamics data. SRH analyses included 6117 observations, 1605 respondents, and 1000 family clans. Mental-health analyses included 4450 observations, 1296 respondents, and 860 family clans. Minimally-adjusted models adjusted for age and year. Fully-adjusted models additionally adjusted for race, baseline education, baseline region, baseline marital status, childhood wealth, baseline work disability, and baseline SRH.

Figure 3.

Distribution among men of each EQ variable at each age by variable from multichannel sequence analysis conducted on sample of 1174 Panel Study of Income Dynamics respondents. Gaps in figure due to zero cells. Notes: unemp: unemployed; NILF: not in the labor force; S-E: self-employed.

Figure 4.

Prevalence among men of poor/fair self-rated health (SRH) or moderate mental illness (Kessler K6>5) among each cluster relative to the prevalence among SER-like non-union workers at the last observed wave of the sequence-analysis period and each wave thereafter. X-axis plotted on log scale. Notes: Estimates from Poisson generalized estimated equations with family-clan-level exchangeable correlation structure and cluster-robust standard errors run on Panel Study of Income Dynamics data. SRH analyses included 4582 observations, 1174 respondents, and 811 family clans. Mental-health analyses included 2651 observations, 759 respondents, and 572 family clans. Minimally-adjusted models adjusted for age and year. Fully-adjusted models additionally adjusted for race, baseline education, baseline region, baseline marital status, childhood wealth, baseline work disability, and baseline SRH.

Table 1

Descriptive statistics of women in Panel Study of Income Dynamics sample (n = 1605) at baseline (unless otherwise noted) stratified by cluster.

	SER ^a -like non-union	Becoming self-employed	Precariously employed	Returning to the LF ^b	Minimally attached
n	745	122	216	212	310
Person of color	334 (45)	29 (24)	130 (60)	47 (22)	166 (54)
Education					
<HS	55 (7)	7 (6)	52 (24)	21 (10)	87 (28)
HS	278 (37)	38 (31)	80 (37)	84 (40)	111 (36)
Some college	227 (30)	37 (30)	57 (26)	59 (28)	74 (24)
College+	185 (25)	40 (33)	27 (12)	48 (23)	38 (12)
Income 1 ^c	6 [4, 9]	8 [5, 11]	4 [2, 6]	7 [4, 10]	4 [2, 7]
Income 2 ^c	9 [6, 14]	11 [6, 18]	4 [2, 9]	9 [5, 15]	4 [1, 8]
Married ^d	523 (70)	98 (80)	115 (53)	188 (89)	206 (66)
Childhood wealth ^e					
Poor	184 (25)	24 (20)	67 (31)	45 (21)	98 (32)
Average	358 (48)	62 (51)	82 (38)	108 (51)	125 (40)
Well off	203 (27)	36 (30)	67 (31)	59 (28)	87 (28)
Region					
Midwest	174 (23)	36 (30)	53 (25)	61 (29)	68 (22)
Northeast	124 (17)	27 (22)	30 (14)	46 (22)	32 (10)
South	344 (46)	37 (30)	110 (51)	61 (29)	160 (52)
West	103 (14)	22 (18)	23 (11)	44 (21)	50 (16)
Occupation ^f					
Managerial	64 (9)	24 (20)	4 (2)	6 (3)	8 (3)
Operators	72 (10)	4 (3)	15 (7)	2 (1)	24 (8)
Production	20 (3)	5 (4)	2 (1)	2 (1)	1 (0)
Professional	145 (19)	23 (19)	24 (11)	17 (8)	29 (9)
Services	91 (12)	11 (9)	45 (21)	15 (7)	29 (9)
Sales	283 (38)	24 (20)	57 (26)	21 (10)	48 (15)
NILF	47 (6)	28 (23)	28 (13)	145 (68)	149 (48)
Unemployed	22 (3)	3 (2)	41 (19)	4 (2)	22 (7)
Industry ^g					
Construction	11 (1)	5 (4)	1 (0)	2 (1)	3 (1)
FIRE	69 (9)	5 (4)	8 (4)	6 (3)	12 (4)
Manufacturing	112 (15)	9 (7)	17 (8)	3 (1)	29 (9)
Public admin.	44 (6)	1 (1)	1 (0)	1 (0)	3 (1)
Services	305 (41)	46 (38)	76 (35)	29 (14)	57 (18)
Transport	41 (6)	5 (4)	9 (4)	2 (1)	6 (2)

	SER ^a -like non-union	Becoming self-employed	Precariously employed	Returning to the LF ^b	Minimally attached
Trade	92 (12)	19 (16)	32 (15)	20 (9)	27 (9)
NILF	47 (6)	28 (23)	28 (13)	144 (68)	148 (48)
Unemployed	22 (3)	3 (2)	42 (19)	4 (2)	22 (7)
Disability ^h	33 (4)	6 (5)	8 (4)	15 (7)	44 (14)

Cells for categorical variables show counts and percentages. Cells for continuous variables show medians and quartiles 1 and 3.

^aStandard employment relationship.

^bLabor force.

^cTotal family income in tens of thousands of 2017 dollars at baseline (1) and at the end of follow-up (2).

^dMarried or cohabiting with a partner.

^eFamily's wealth when respondent was growing up.

^fOperators is operates, fabricators, and laborers. Production a precision production, craft, and repair. Sales is technical, sales, and administrative support. NILF is not in the labor-force. Excludes 1 respondent with a farming, forestry, and fishing occupation. 0 respondents had a military occupation.

^gFIRE is finance, insurance, and real estate. Transport is transportation, communications, and other public utilities. Trade is wholesale and retail trade. NILF is not-in-the-labor-force. Excludes 9 respondents in agriculture, forestry, and fishing and mining industries. 0 respondents were in military industry.

^hRespondent had disability that limited the type or amount of work they could do.

Table 2

Descriptive statistics of men in Panel Study of Income Dynamics sample (n = 1174) at baseline (unless otherwise noted) stratified by cluster.

	SER ^a -like non-union	SER ^a -like union	Stably high-wage	Wealthy self- employed	Poor self- employed	Precariously employed	Exiting the labor force
n	367	183	286	103	69	98	68
Person of color	154 (42)	67 (37)	42 (15)	10 (10)	17 (25)	56 (57)	33 (49)
Education							
<HS	65 (18)	9 (5)	9 (3)	2 (2)	15 (22)	32 (33)	23 (34)
HS	165 (45)	89 (49)	50 (17)	28 (27)	30 (43)	42 (43)	29 (43)
Some college	88 (24)	51 (28)	68 (24)	27 (26)	17 (25)	19 (19)	14 (21)
College+	49 (13)	34 (19)	159 (56)	46 (45)	7 (10)	5 (5)	2 (3)
Income 1 ^b	5 [4, 7]	7 [6, 9]	9 [7, 11]	10 [6, 13]	5 [4, 7]	3 [2, 5]	4 [2, 6]
Income 2 ^b	8 [5, 11]	11 [8, 15]	16 [12, 21]	15 [10, 26]	7 [3, 10]	3 [2, 7]	3 [1, 6]
Married ^c	279 (76)	150 (82)	237 (83)	88 (85)	56 (81)	64 (65)	43 (63)
Childhood wealth ^d							
Poor	99 (27)	46 (25)	30 (10)	10 (10)	12 (17)	33 (34)	21 (31)
Average	157 (43)	74 (40)	154 (54)	50 (49)	40 (58)	37 (38)	22 (32)
Well off	111 (30)	63 (34)	102 (36)	43 (42)	17 (25)	28 (29)	25 (37)
Region							
Midwest	91 (25)	56 (31)	79 (28)	34 (33)	21 (30)	21 (21)	23 (34)
Northeast	54 (15)	39 (21)	68 (24)	15 (15)	13 (19)	5 (5)	10 (5)
South	164 (45)	50 (27)	87 (30)	33 (32)	29 (42)	54 (55)	29 (43)
West	58 (16)	38 (21)	52 (18)	21 (20)	6 (9)	18 (18)	6 (9)
Occupation*							
Farming	11 (3)	0 (0)	0 (0)	13 (13)	5 (7)	5 (5)	2 (3)
Managerial	31 (8)	4 (2)	58 (20)	27 (26)	11 (16)	5 (5)	4 (6)
Operators	110 (30)	53 (29)	19 (7)	3 (3)	12 (17)	26 (27)	15 (22)
Production	67 (18)	46 (25)	34 (12)	21 (20)	21 (30)	12 (12)	6 (9)
Professional	30 (8)	19 (10)	85 (30)	22 (21)	6 (9)	8 (8)	2 (3)
Services	32 (9)	26 (14)	8 (3)	1 (1)	5 (7)	16 (16)	13 (19)
Sales	52 (14)	29 (16)	68 (24)	11 (11)	4 (6)	9 (9)	4 (6)
NILF	12 (3)	3 (2)	12 (4)	3 (3)	4 (6)	4 (4)	8 (12)
Unemployed	22 (6)	3 (2)	2 (1)	2 (2)	1 (1)	10 (10)	14 (21)
Industry ^f							
Agriculture	13 (4)	1 (1)	1 (0)	14 (14)	5 (7)	4 (4)	1 (1)
Construction	21 (6)	16 (9)	15 (5)	24 (23)	13 (19)	11 (11)	4 (6)
FIRE	5 (1)	3 (2)	29 (10)	4 (4)	2 (3)	1 (1)	1 (1)
Manufacturing	113 (31)	45 (25)	74 (26)	11 (11)	10 (14)	16 (16)	11 (16)
Public admin.	25 (7)	28 (15)	21 (7)	2 (2)	1 (1)	17 (17)	3 (4)
Services	58 (16)	32 (17)	55 (19)	25 (24)	16 (23)	15 (15)	8 (12)

	SER ^a -like non-union	SER ^a -like union	Stably high-wage	Wealthy self- employed	Poor self- employed	Precariously employed	Exiting the labor force
Transport	31 (8)	35 (19)	29 (10)	3 (3)	6 (9)	4 (4)	2 (3)
Trade	64 (17)	16 (9)	44 (15)	15 (15)	11 (16)	18 (18)	15 (22)
NILF	11 (3)	3 (2)	12 (4)	3 (3)	4 (6)	3 (3)	8 (12)
Unemployed	21 (6)	3 (2)	2 (1)	2 (2)	1 (1)	9 (9)	14 (21)
Disability ^g	35 (10)	5 (3)	7 (2)	7 (7)	8 (12)	7 (7)	11 (16)

Cells for categorical variables show counts and percentages. Cells for continuous variables show medians and quartiles 1 and 3.

^aStandard employment relationship.

^bTotal family income in tens of thousands of 2017 dollars at baseline (1) and at the end of follow up (2).

^cMarried or cohabiting with a partner.

^dFamily's wealth when respondent was growing up.

^eOperators is operators, fabricators, and laborers. Production is precision production, craft, and repair. Sales is technical, sales, and administrative support. NILF is not-in-the-labor force. 0 respondents had a military occupation.

^fFIRE is finance, insurance, and real estate. Transport is transportation, communications, and other public utilities. Trade is wholesale and retail trade. NILF is not-in-the-labor-force. Excludes 11 respondents in mining industry. 0 respondents were in military industry.

^gRespondent had disability that limited the type or amount of work they could do.