Boston College

School of Social Work

Dissertation Examination Committee:

Dr. Shanta Pandey, Co-chair

Dr. Vincent Fusaro, Co-chair

Dr. Scott D. Easton, Member

Dr. Eve Spangler, Member

Precarious Employment among Millennials in the United States: Psychological Distress and the Role of Social Policy in the Post-Great Recession Era

A Dissertation

By

LEILA DAL SANTO

Submitted to Boston College in partial fulfillment

of the requirements for a degree of

Doctor of Philosophy

JULY 2024

PRECARIOUS EMPLOYMENT AMONG MILLENNIALS IN THE UNITED STATES: PSYCHOLOGICAL DISTRESS AND THE ROLE OF SOCIAL POLICY IN THE POST-GREAT RECESSION ERA

A dissertation

by

LEILA DAL SANTO

Doctor of Philosophy in Social Work

Dissertation Co-Chairs: Drs. Vincent Fusaro and Shanta Pandey

Abstract

It is well established that employment conditions are a key determinant of health, including mental health. Research conducted in the wake of deindustrialization and the onset of neoliberal reforms—reforms that significantly weakened the collective bargaining power of workers—has consistently shown that job loss, perceived job insecurity, and temporary employment increase the risk of depression, anxiety, and psychological distress. The secular erosion of standard employment relationships compounded by specific exigencies introduced by the Great Recession (2007-2009) has resulted in a concerning rise in *precarious employment:* employment forms characterized by stagnant wages, irregular working hours, and lack of fringe benefits are now the norm rather than the exception. This dramatic change in the conditions of employment has been especially challenging for Millennials, many of whom were entering the workforce at the time of the Great Recession and experienced high levels of unemployment.

As the converging challenges of the COVID-19 pandemic, technological advances, and inequality threaten to further destabilize Millennials' participation in the labor market, research is needed to better understand the interplay between precarious employment and mental health as well as risk and protective factors for mental wellbeing. To date, few studies examining the health implications of precarious employment have focused on young adults. Moreover, research on the relationship between job precarity and mental health has relied primarily on cross-sectional studies. This dissertation contributes to this literature, leveraging nationally representative panel data from the Panel Study on Income Dynamics to 1) identify subgroups of precarious employment (PE) trajectories among Millennials residing in the United States following the Great Recession (2009-2019); 2) examine associations between PE trajectory subgroups and mental distress; and 3) explore the moderating role of social welfare benefits on the relationship between PE and mental distress.

A total of 1303 Millennial respondents were included in the study. Growth mixture models identified three subgroups of PE trajectories across the study period: nearly three-quarters of respondents belonged a subgroup experiencing stagnant employment quality, a second subgroup (16% of the sample) faced declining employment quality, while a third subgroup (12% of respondents) enjoyed steadily rising employment quality. Millennials in the negative EQ growth class compared to the low- and high-growth

subgroups were more likely to have lower levels of educational attainment; to be divorced, separated, or widowed; to be low-skill, white- or low-skill, blue-collar workers; and to have mothers with less than a high school level of education. With respect to the relationship between precarious employment and psychological distress, mixed-effects logistic regression models revealed that fewer years of education and widowed/divorced/separated marital status (compared to married/cohabitating status) were associated with higher odds of severe psychological distress. Models examining moderate psychological distress outcomes, meanwhile, demonstrated that Millennials who were younger, female, experiencing declining EQ over time, and single/never married or divorced/separated/widowed had higher odds of endorsing symptoms of moderate mental distress. Contrary to expectations, none of the three social welfare policies—minimum wage, state EITC rate, and state unemployment insurance replacement rate—conferred a moderating effect on the relationship between EQ and psychological distress.

These findings have important implications for social work research, policy, and practice. Beyond filling an important gap in our understanding of the ways in which the shifting landscape of work contributes to young adults' mental health, the study's attention to the moderating role of social welfare policies on the association between PE and mental wellbeing should serve as a stepping stone for future research aimed at elucidating policies that can best protect the mental health of workers in a political and economic climate marked by accelerating technological change and rising labor contentiousness.

ACKNOWLEDGEMENTS

Completion of this project would not have been possible without the invaluable support of my mentors, colleagues, and family. First, I am indebted to my co-chairs who provided the methodological—and emotional—support necessary to undertake such an ambitious study. To Dr. Pandey, I am so grateful for your mentorship throughout my journey in the doctoral program. It is no wonder so many students gravitate toward you as an advisor—your kindness and deep commitment to the principles of social justice paired with analytical prowess ensures we reach our full potential as scholars. To Dr. Fusaro, my interest in social policy (and how we might go about evaluating the successes and pitfalls of various social protection programs) stems from the social welfare class you taught my first year in the doctoral program. Thank you for modeling and encouraging the importance of asking big questions—ones that by nature are interdisciplinary and require thinking outside the proverbial box. And of course, your methodological support throughout this project has ensured that this is a sound a study as possible.

To Dr. Easton, I have so enjoyed working with you over the last several years. Your incisiveness and attention to detail are qualities I have honed in the course of our collaboration and ones that have made me a better researcher. This study is much richer following your thorough and thoughtful feedback. I would also like to thank Dr. Spangler, who instilled a love of theory in an otherwise methods-driven student and cultivated an understanding of the wide-ranging contributions of social theory to contemporary issues—I appreciate your guidance in these last years of the doctoral program. To Debbie Hogan, thank you for always being in our corner. I'm grateful for always being able to pop over to your office to say hello and for your words of encouragement as we made our way through the doctoral program.

Other professors during my time at Boston College have indelibly shaped my research trajectory. In keeping with the spirit of social work practice, Professors Kerry Mitchell, Carolyn Romano, Susan Tohn, and Paul Kline were constant reminders of the importance of adopting a person-in-environment framework when working with clients. To Dr. Theresa Betancourt, whose longitudinal research on war-affected youth in Sierra Leone kindled my interest in understanding the mental health implications of precarious work, thank you for the opportunity to work with you and the rest of the RPCA team—your guidance, advice, and constant check-ins throughout the PhD program were a huge source of support.

Finally, to my husband Colin, who took many hours out of his work day to get me over the finish line (and took on the lion's share of household duties as well) and has always been a pillar of support, thank you for all your patience, reassurance, and pep-talks along the way.

Table of Contents

Chapter 1. Introduction

1.1. Statement of the Problem

Mental health problems are on the rise among Millennials (those born between 1981 and 1996 (Dimock, 2019)) in the United States, with nearly one in three individuals of that generation currently experiencing a behavioral health condition (Blue Cross Blue Shield [BCBS], 2019). Between 2014 and 2018, the prevalence rate of depression among Millennials increased by a staggering 43%, while prevalence rates for substance use disorders increased by 17% (BCBS, 2019). These trends are not isolated to the United States, however. Mental health disorders constitute one of the most significant public health challenges facing the European Union as well, with depression and anxiety affecting roughly one-fourth of the European population annually (World Health Organization, 2021). The adverse effects of poor mental health are profound and far-reaching (Prince et al., 2007), impairing functioning in social, educational, and professional domains. Indeed, today mental disorders such as depression, anxiety, and substance use are a leading cause of long-term disability and important contributors to mortality (Global 2019 Disease and Injuries Collaborators, 2020).

It is well established that employment conditions are a key determinant of health, including mental health (Bartley et al., 2011, Paul & Moser, 2009; Popham et al., 2012). Research conducted in the wake of deindustrialization and the onset of neoliberal reforms—reforms that significantly weakened the collective bargaining power of workers—has consistently shown that job loss, perceived job insecurity, and temporary employment increase the risk of depression, anxiety, and psychological distress (Ferrie et al., 1999; Sverke et al., 2002; Artazcoz et al., 2004; Virtanen et al., 2008). The secular erosion of standard employment relationships compounded by specific exigencies introduced by the Great Recession (2007-2009) has resulted in a concerning rise in *precarious employment:* employment forms characterized by stagnant wages, irregular working hours, and lack of fringe benefits are the norm rather than the exception (Benach et al., 2014). This dramatic change in the conditions of employment has been especially challenging for Millennials, many of whom were just entering the workforce at the time of the Great Recession and, consequently, experienced high levels of unemployment, reduced wages, and limited upward career mobility (Bialik & Fry, 2019). Indeed, a recent study of 26 European countries by the Organization for Economic Co-operation and Development (OECD) found that 60% of jobs created between 2007 and 2013 were non-standard jobs. In the United States, meanwhile, there was no net increase in full-time jobs in the decade following the Great Recession, with virtually all job growth in "alternative" work arrangements (Katz & Krueger, 2016).

Unsurprisingly then, the collapse of the global economy wrought by the Covid-19 pandemic has resulted in an alarming rise in mental health issues among young adults worldwide, the majority of whom were already suffering through financial uncertainty and tough labor market conditions prior to the outbreak of the virus (International Labour Organization [ILO], 2020). Emerging evidence suggests that young adults who lost their jobs due to the pandemic were twice as likely as their still-employed counterparts to be at risk of anxiety or depression (23% versus 14%, respectively) (ILO, 2020). Among employed Millennials, nearly half (44%) reported feeling anxious or stressed most of the time, and just one in four workers expressed believing that their generation would be happier than that of their parents (Deloitte Global, 2020) according to a 2020 global survey[1] on mental health in the workplace.

[1] The survey was conducted in 42 countries, including both Global South (e.g., Colombia, Nigeria) and Global North (e.g., France, the United States, Sweden) country contexts (Deloitte, 2019).

While the macrostructural forces of globalization, financialization, and digitalization that accompanied[2] neoliberal reforms have left no advanced capitalist countries untouched, the adverse effects of these forces on the employment conditions and wellbeing of workers in post-industrial nations *are not predetermined*. Rather, the *incidence* and *consequences* of precarious work are contingent upon a country's configuration of social protection and labor market policies (Kalleberg, 2018). Such policies are themselves a function of a nation's political dynamics, social and cultural values, and the degree of state involvement in the economy.

1.2. Study gaps

As the converging challenges of COVID-19 pandemic, technological advances, and inequality threaten to further destabilize Millennials' participation in the labor market, research is needed to understand the interplay between precarious employment and mental health as well as risk and protective factors for mental wellbeing. To date, few studies examining the health implications of precarious employment have focused on young adults (Allmang, 2019; Asahina, 2019; Gilek, 2020; Gray et al., 2021). Moreover, research on the relationship between job precarity and mental health has relied primarily on cross-sectional studies (Brown et al., 2017; Jonsson et al., 2021a; Julia et al., 2019; Moscone et al., 2016; Seong et al., 2021; Vives et al., 2011). Finally, studies do not typically focus on intra-country variations in social policies, employment conditions, and mental health outcomes. Such intra-country comparative approaches that explore differences in precarious employment and mental health outcomes as well as the macro structures in place that influence these outcomes are sorely needed to inform state- and federal-level social policies.

1.3. Purpose of the Study

[2] Or "prompted" or "resulted from" depending on one's vantage point.

The following research aims to contribute to this literature, leveraging nationally representative panel data to better understand the mental health trajectories of precariously employed Millennials residing in the United States.

A1: To identify subgroups of precarious employment trajectories among Millennials residing in the United States in the years following the Great Recession (2009-2019).

The Great Recession has defined a new epoch of employment in the low-end service sector (characterized most notably by the explosion of the "gig economy"). This research aim uses data from the Panel Study of Income Dynamics (PSID), the world's longest-running longitudinal household survey, to first generate employment quality (EQ) scores and then examine trajectories of employment quality among Millennials in the period between 2009 and 2019. Specifically, a composite employment quality score (EQ is a proxy for precarious employment widely used in the occupational health literature) is created based on five key dimensions of employment conditions: job stability, material rewards, working time arrangements, workers' rights and protections, and collective bargaining arrangements. Growth mixture modeling models are then fitted to illuminate contemporary patterns in Millennial employment conditions and sociodemographic variation in "subgroups" of these patterns.

A2: To examine associations between precarious employment trajectory subgroups and mental distress in the post-Great Recession period.

The aforementioned dataset is used to explore the burden of psychological distress across the study period (2009-2019). The association between each employment trajectory "subgroup" identified in Research Aim 1 and later-life prevalence of mental distress (i.e., mental distress symptoms present at future survey waves) is examined. Individual-level risk factors that are considered in this analysis include age, education level, gender, race/ethnicity, immigrant status, and rural/urban residence. Family-level factors that are assessed include parents' education and marital status. Mixed-effects logistic regression is used to assess the longitudinal relationship between employment quality subgroup and the risk of psychological distress.

A3: To explore cross-state variances in labor market and social protection benefits and the moderating role of social welfare benefits on the relationship between precarious employment and mental distress.

This aim explores the moderating role of social welfare provision and labor regulations on the relationship between precarious employment and mental wellbeing. Among those identified as consistently precariously employed, the effect of the availability and generosity of specific social protection programs—minimum wage, unemployment insurance, and earned income tax credit (EITC)—is explored in moderation analyses. The effect of each state's program benefit on individual mental health outcomes is explored in separate models (with each program as a moderator).

Chapter 2. Background

Employment conditions have long been recognized as an important determinant of mental wellbeing. Indeed, a rich research literature spanning the disciplines of economics, occupational health, social work, and sociology has emerged over the last three decades that documents how aspects of employment quality—from role-related stress and perceived job insecurity to temporary employment and union membership status—contribute to mental health outcomes. More recently, with the accelerated degradation of standard employment contracts and the ascendancy of the "gig economy," scholarly interest has turned to understanding the relationship between *precarious employment* and mental health. The following pages will trace the emergence of precarious employment as a social determinant of health in the research literature, first highlighting some critical historical junctures in the deterioration of workers' rights, then detailing how contemporary studies have conceptualized and operationalized the construct of precarious employment, and finally, providing an overview of the literature to date on the mental health of those with insecure attachments to the labor market.

2.1. The Erosion of Worker Rights and the Rise of "Flexible" Work Arrangements

Heightened scholarly interest in the prevalence and consequences of precarious employment is a function of key trends in work arrangements over the last half century, namely the transition away from standard employment contracts and toward more "flexible" and exceedingly precarious work conditions. While the era of Keynesian and welfarist policy in the years immediately following the Second World War was one in which labor relations were marked by stable employment, strong collective bargaining, and robust worker protections, the global economic recession in the 1970s and the subsequent ascendance of neoliberal reforms permanently reshaped employer-worker relations. A complete account of the confluence of cultural, economic, and political factors that have shaped the trajectory of the neoliberal project (and its effects on labor) over the last half century is beyond the scope of this chapter. Nevertheless, it is worth highlighting some of the critical junctures in neoliberalism's progression within the American and European context, particularly as concerns the reshaping of employer-worker relations.

2.1.1. The Rise and Triumph of Neoliberalism in the United States

Though neoliberalism has been rendered a fuzzy concept in recent times (Springer, 2016) due to the variance with which it has been defined and applied, as relates to this particular subject matter, the project I refer to derived from a moral-political supposition that individual freedoms and collective prosperity were best advanced through free markets, free trade, and strong private property rights (Harvey, 2007). Corollary to this, neoliberalism limited the state's ideal role to securing an institutional framework conducive to the making, working, and expansion of markets. This being the case, the ideological project in question never constituted a return to the libertarian, laissez-faire government philosophy of the 19th century. Rather, it dictated that the state use the powers of the sovereign—legal, legislative, or coercive—to both create the space for markets and to protect the property holdings of private persons and corporations (Harvey, 2007). Translated to practice, this entailed the commodification and privatization of public assets, the expansion of the financial sector (and the ensuing suite of predatory and speculative practices), and the redistribution (through state policy) of wealth toward the upper echelons of society.

While the neoliberal movement was largely peripheral in academic and policy making circles throughout the 1950s and 1960s,[3] the financial crisis of the 1970s (a crisis of capital

---

[3]The neoliberal project can be traced to the discontent experienced by a coterie of intellectuals and a fraction of the capitalist class, both of whom were disturbed by the post-WWII Keynesian and welfarist policy era. The charge

accumulation, which manifested in stagflation) provided it with an opportunity to enter the fray. Specifically, austerity measures imposed across beleaguered American cities decimated public housing, crushed labor movements, and allowed for a corporate welfare-oriented ethos to take root (Harvey, 2007; Wacquant, 2009). The New York City fiscal crisis, in particular, served as the blueprint for how to restore capitalist class power: After the banking class refused to roll over the city's debt, thereby forcing it into bankruptcy (a move encouraged by Gerald Ford's Secretary of the Treasury William Simon and young White House staff member Donald Rumsfeld), the restructuring process that ensued favored corporate tax breaks and subsidies at the expense of public investment and the economic wellbeing of working-class families (Phillips-Fein, 2017).

Taking note of these shifts toward corporate welfare at the municipal level, corporate elites quickly mobilized at a national level to secure their pro-business agenda. The number of firms represented by the U.S. Chamber of Commerce, now the largest lobbying group in the United States, exploded from 60,000 in 1972 to over 250,000 within a decade (Harvey, 2007), and corporations began pouring millions into congressional lobbying efforts. Meanwhile, the proliferation—with corporate backing—of neoliberal think-tanks such as the Heritage Foundation, the Hoover Institute, and the American Enterprise Institute in tandem with the circulation of neoliberal epistemologies and theories within the halls of the academy (initially out of the University of Chicago's economics department, where Milton Friedman was based), served to further discredit Keynesian ideas and elevate free market principles (Soss, et al., 2011).

---

against these types of state interventionism was led by Austrian economist and political philosopher Friederich von Hayek. Flanked by a small group of fellow travelers that included Milton Friedman, von Hayek established a vanguardist epistemic community organized through the Mont Pèlerin Society (founded in 1947). Perceiving individual freedoms as "under constant menace from the development of current tendencies of policy" (Mont Pèlerin Society, 1947), the group quickly garnered the support of wealthy individuals and business elite in the United States who were eager to shake the regulatory restraints placed upon them through Rooseveltian efforts aimed at protecting labor and promoting full employment (Phillips-Fein, 2009).

Already gaining steam, neoliberalism's momentum was further accelerated by the Reagan administration. Bemoaning the overreach of "big government," the Reagan administration famously and systematically rolled back government oversight in the financial, health, and environmental sectors (Ehrman, 2005). It also ruthlessly attacked organized labor, eroding the bargaining power of employees and ushering in a four-decade run of wage stagnation and inequality. Under a Democratic-controlled House, Reagan et al. oversaw the passage of corporate and personal income tax breaks that functioned to shepherd a greater share of the national income toward the top 1% (Pierson, 1994; Collins & Mayer, 2011)—a springboard toward today's staggering levels of income and wealth inequality.

In seeking to contest Reagan's immense popular appeal, a new group within the Democratic Party began working to move their institution away from its New Deal roots and toward a politics more closely resembling those of their opposition. As their faction—which included future president Bill Clinton—consolidated power, neoliberalism became bipartisan orthodoxy (Béland et al., 2002; Lewis & Surender, 2004). One need look no further than the push in the early 1990s to link welfare to work to find evidence of this reorganization of the welfare state around market principles: Third Way Democrats and Republicans alike were ardent in their beliefs that existing welfare programs precluded recipients' from realizing their full potential as productive members of the American workforce—welfare was a *disservice* to people with low incomes according to this logic (Carcasson, 2006). Factions of domestic capital, meanwhile, recognized the opportunity workfare presented to restructure the labor market, effectively "mobilizing and socializing workers for jobs at the bottom of the new economy" (Peck, 2003, p. 80)—an economy marked by increasing underemployment, wage stagnation, and contract work. The resulting legislation, the Personal Responsibility and Work Opportunity

Reconciliation Act (PRWORA) of 1996, effectively dismantled the entitlement-based federal welfare program Aid to Families with Dependent Children (AFDC), transferring authority over welfare programs to the states in the form of block grants (Temporary Assistance for Needy Families (TANF) program).

Neoliberalism has even infused logics and praxes into domains once insulated from the demands of the market, such as the social work profession. The "marketization" of social welfare services, for example, has resulted in the prioritization of efficiency and performance-based outcomes over the mission and quality of services (Abramovitz & Zelnick, 2015). Today's social work graduates must contend with a professional landscape marked by the contraction of state-funded social services and increasing competition among non-profit agencies over dwindling resources (Hasenfield & Garrow, 2012). Sustained state and federal budget cuts have constricted community-based mental health agencies—agencies which have historically served the most vulnerable members of society—resulting in reduced staff and elimination of programming (Larrison et al., 2015). Meanwhile, the expanded role of the private sector in the provision of social services has resulted in lower employee wages and benefits (e.g. hiring more fee-for-service employees), fewer training and staff development opportunities, and a focus on service provision to more affluent clients (Reisch, 2013).

2.1.2. The Liberalization of Europe and the United States: Three Broad Approaches

While the United States represents one of the more extreme case studies with respect to the transformative effects of neoliberal reforms on the bargaining power of labor, Europe experienced its own reckoning with global pressures to liberalize national economies. Many of the economic, social, and political rights[4] enjoyed by workers in Europe today are rooted in the "historical compromise" between labor and capital in the post-war era (Toivanen et al., 2020). These rights are linked—directly or indirectly—to long-term employment contracts. In the context of global competition, however, such contracts became appealing targets for those looking to boost profit rates through controlling labor costs.

The consequent rise of precarious employment (e.g., short-term contracts, part-time work, and on-demand gigs through online platforms like Uber) across the European Union that coincides with the ascendance of neoliberal ideology threatens to undermine these states' traditional social contracts (Neufeind et al., 2018).[5] That said, the degree to which the pursuit of greater labor market flexibility has eroded worker power has been dictated by country-specific political, social, and economic dynamics. Three distinct approaches to liberalization have been identified in the literature (Thelen, 2014; Kalleberg, 2018), each of which corresponds with the welfare regime typology proposed by Danish sociologist Esping-Andersen in *Three Worlds of Welfare Capitalism* (1990).

Social-Democratic welfare regimes,[6] as exemplified by the Scandinavian countries of Denmark and Sweden, opted for what has been dubbed an *embedded flexibilization* approach to liberalization (Thelen, 2014). Here, greater labor market flexibility was achieved through strong state involvement in public policy and the investment of resources in ensuring that the most vulnerable workers in society could get and maintain "good jobs" (i.e., the risks of work in this shifting labor market landscape were collectivized). This approach has been characterized as

[4] Economic rights incudes job and income security, and bargaining rights over income and employment terms. Social rights vis-à-vis the workplace include occupational health and safety (Standing, 2014).
[5] By "social contract," I am referring to the set of agreements (implicit and explicit) between the sovereign state and individual members of society regarding the rights and obligations of each party to the other (Loewe et al., 2021).
[6] According to Esping-Andersen's welfare state typology, social-democratic regimes are characterized by high levels of decommodification (i.e., the belief that the ability to meet one's basic needs should not be contingent market participation), cross-class solidarity, and universal welfare benefits (Esping-Andersen, 1990).

being highly inclusive, in large part due to high levels of cross-class (and cross-industry) solidarity and union membership.

The path forged by Germany reflects a *dualization* approach to liberalization, whereby only certain groups of workers were protected from the vicissitudes of market forces (Kalleberg, 2018). Specifically, workers in "core" industries that had historically benefited from strong government intervention in the economy continued to enjoy robust employment protections and centralized collective bargaining arrangements.[7] Meanwhile, "outsiders," primarily workers in the burgeoning service sector and "peripheral" manufacturing sectors, were forced to reckon with growing work insecurity and instability. Kalleberg (2018) notes that this sharp divide between "core" and "peripheral" sectors can be attributed to two interrelated factors, namely deindustrialization and the inability of unions to organize members in the private service sector. Germany's dualization approach is consistent with Esping-Andersen's "continental model" of welfare capitalism, in which solidarity has traditionally been stratified by occupational status, the provision of welfare benefits is predicated on earnings, and social welfare policies underscore the nation's emphasis on the preservation of traditional family values (Esping-Andersen, 1990).

Finally, the approach of *deregulatory liberalization* was pursued by "liberal" welfare regimes[8] (Esping-Andersen, 1990), such as the United States and its European counterpart, the United Kingdom. In brief—and as detailed in the previous section—, this approach has entailed the "direct frontal assault on institutions supporting the collective regulation of labor regulations" (Thelen, 2014, p. 13) and the offloading of risk away from employers and onto individuals.

---

[7] The condition of these protections was the acceptance of a smaller labor share of income. For example, German autoworkers accepted compensation well below productivity (which allowed firms to provide big returns for owners and grow export income through ensuring the price of cars stayed relatively low) in exchange for steady jobs.

[8] "Liberal" welfare states are marked by meager, means-tested benefits; the supremacy of free-market principles, and low levels of decommodification (Esping-Andersen, 1990).

2.1.3. The Great Recession and the Rise of the "Gig Economy"

Arriving at a juncture when global conditions were already pressuring employers to cut the costs of inputs and encouraging deregulation policies that could facilitate the mobility of capital (Standing, 2009), the Great Recession unsurprisingly served to erode standard employment relationships even further. Quality jobs that were lost during the recession were replaced with precarious work opportunities, ones that typically involved lower wages, temporary contracts, and no benefits (Kessler, 2018). In Europe, 60% of the jobs created between 2007 and 2013 were "non-standard" jobs, whereas virtually all of the nine million jobs created in the decade following the Great Recession in the U.S. were in "alternative" work arrangements. Moreover, the expansion of the "gig economy,"[9] accelerated by advances in digital technology (e.g., digital apps), meant companies could route jobs directly to workers and conveniently circumvent minimum wage laws by classifying these workers as "independent contractors.[10]" The poor quality of these work opportunities is reflected in recent labor market statistics: Contingent workers (e.g., temporary, sub-contracted, and freelance workers) earn 10.6% less per hour, are two-thirds less likely to report having a work-provided retirement plan, and are three times more likely to report having been laid off in the previous year compared with standard full-time workers (Government Accountability Office, 2015). Moreover, a 2016 study by Freelances Union and Upwork found that 20% of full-time freelancers reported not having health insurance, compared with 10.3% in the general population (Upwork, 2016).

2.1.4. Precarious Employment among Millennials in the United States

Millennials were especially vulnerable to the expansion of flexible work arrangements in

[9] Used here to mean a large workforce of part-time or temporary workers, or independent contractors.
[10] Independent workers are not protected by U.S. minimum wage laws.

the years immediately following the Great Recession. This generation of workers was just entering the workforce or in the early stages of their careers when the Recession hit and faced an exceptionally challenging job market, resulting in disproportionately high unemployment rates and lasting impacts on future earnings and wealth. For example, the percentage of American young adults ages 18 to 24 who were employed in 2011 (54% compared to 67% and 62% in 2000 and 2007, respectively) was the lowest on record since the US government began collecting data in 1948 (Pew Research Center, 2012). Moreover, American young adults employed in full-time roles experienced a greater reduction in weekly earnings (a 6% drop) between 2007 and 2011 compared with any other age group. Concerningly, research on the long-term consequences of labor market entry in the midst of a recession suggests that entrants can experience reduced wages for up to 10 years (Kalleberg & von Wachter, 2017).[11] Indeed, while college-educated Millennials earn incomes roughly equal to those of Generation Xers in 2001, Millennials with less than a college degree earn less than previous generations did at the same age: Millennial workers with some college education reported annual earnings of $36,000 in 2018, $2900 less than Baby Boomer workers made at the same age (Bialik & Fry, 2019).

Today precarious employment is common among all young adults, regardless of education level (Toivanen et al., 2020). Current estimates posit that between 60% of young adults in the US do some type of independent work. Contrary to the ideological tropes through which "being your own boss" has been glamorized and legitimated, many of these persons have

[11] These financial markers of wellbeing have not appreciably improved in recent years. In the United States, earnings for young workers have flatlined over the past 50 years. Despite American Millennials with a college degree earning roughly equal amounts compared to college-educated Generation X workers in 2001 (Bialik & Fry, 2019), Millennials with some college education or less fare worse in terms of annual earnings compared to their counterparts in prior generations. Specifically, a Millennial worker with some college education today makes approximately $36,000 compared to what early Baby Boomer workers aged 25-37 would have made in 1982 ($38,900). Similar patterns have been observed with respect to wealth and homeownership (Bialik & Fry, 2019; Choi et al., 2018).

forgone traditional full-time jobs out of necessity rather than by choice (Keller, 2018).

2.1.5. Unmet Expectations: How Key Milestones Remain Out of Reach for Millennials

Defined by the Pew Research Center as those born between 1981 and 1996 (ages 28 to 43), Millennials now constitute the largest adult generation in the United States—72.1 million compared with 71.6 million Boomers (ages 60 to 78) and 65.2 million Generation Xers (ages 44 to 59) (Fry, 2020). Compared with their older generational counterparts, Millennials are the most racially and ethnically diverse generation of adults in US history. They are also more educated than the generations of their parents and grandparents, with women especially having made impressive gains in educational attainment over the last five decades—the percentage of Millennial women with a college degree is higher than that of men (Bialik & Fry, 2019). Due to their respective positions in the life cycle (i.e., "life cycle effects") as well as the historical context in which members of this generation have come of age (i.e., "cohort effects"), there are several noteworthy characteristics that distinguish this generation from previous ones (Pew Research Center, 2015).

With respect to ideological and political preferences, marked differences exist between Millennials and older generations. The majority of Millennials (57%) hold consistently or mostly liberal positions, compared to 33% of Boomers and 43% of Gen Xers (Pew Research Center, 2018). In contrast with their older generational counterparts, Millennials are far more supportive of same-sex marriage and "bigger government," are more likely to identify as religiously unaffiliated, and are more likely to endorse the belief that good diplomacy rather than military strength is the best way to ensure peace (77% among Millennials compared with 52% of Boomers). This latter ideological divide is likely explained by Millennials having grown up in the backdrop of the post-9/11 long wars in Afghanistan and Iraq.

Perhaps the most distinguishing feature of this generation—or at least, the most germane to the study at hand—is the inability of Millennials to reach the milestones typically associated with adulthood. Homeownership, marriage, having children, working in a full-time, permanent job, saving for retirement—all remain elusive targets for many of this generation. For example, Millennials have accumulated far less wealth than Boomers had at the same age (median net worth of $12,500 among Millennial-headed households in 2016 compared to $20,700 among Boomer-headed households in 1983), attributed in part to having taken on significantly more student debt than previous generations (Bialik & Fry, 2019). Moreover, despite being the most populous generation, less than half of Millennials (48%) are homeowners, in stark contrast with 77.8% and 69% homeownership among Baby Boomers and Gen Xers, respectively (Wilson, 2021). Among the suite of reasons contributing to this disconnect between homeownership aspirations and reality include the rising cost of living (particularly in metropolitan areas where Millennials tend to live) and outstanding student and medical debt (Wilson, 2021). Finally, beyond the general trend of delayed marriage/partnership among Millennials compared to previous generations, the ballooning cost of raising a child to the age of 18 (a whopping $267,233 according to 2021 estimates from the Bureau of Labor Statistics (LaPonsie, 2021) has resulted in nearly three in five Millennials citing unaffordability as a reason for not wanting children (Williams, 2020).

Having been socialized to believe hard work would pay off and that higher education would be the key to secure, middle-class jobs, it is unsurprising that many Millennials cite feelings of despair and frustration at missing out on traditional life milestones (Wilson, 2021). A rich literature rooted in the social psychology and sociology disciplines suggests the potential for mental health problems in the face of unrealized expectations (Reynolds & Baird, 2010).

Experimental studies, for example, how revealed that the gap between how people currently see themselves and how they hoped to be (their ideal selves) is a risk factor for mental health conditions such as anxiety and depression (Scott & O'Hara, 1993; Strauman, 1989). A more contemporary study by Culatta et al. (2021) similarly found a positive association between young adults (18-29 years of age) falling behind perceived expectations of their peers regarding markers of adulthood and anxiety symptoms. This study also revealed significant associations between falling behind perceived expectations of parents and society regarding markers of adulthood and depressive symptoms. To date, however, studies have not explored how this construct of "unmet expectations" *might underlie the relationship between poor job quality and mental health outcomes,* a gap that might be explained by the reliance on large datasets and quantitative methods to examine the association between employment indicators and wellbeing.

2.2. Precarious Employment as a Social Determinant of Health: An Overview

Research on precarious employment as a determinant of worker health and wellbeing has evolved over the years in response to the shifting nature of work. Early studies on employment precarity and mental health focused on *unidimensional* aspects of employment conditions, such as unemployment, job insecurity, and temporary employment. It is only within the last decade, with the expansion of "flexible" employment relationships, that researchers have begun to leverage multidimensional approaches to investigate the mental health implications of work precarity.

2.2.1. Unidimensional approaches to study employment conditions

Throughout the 1970s and into the 1990s, in the wake of deindustrialization and workplace closures, social epidemiology and occupational health research largely attended to the mental and physical health effects of organizational *restructuring* and *downsizing* (Benach et al., 2014). A review of 15 longitudinal workplace closure studies conducted between 1968 and 1995 found that nearly all workers experienced adverse physical and/or psychological outcomes due to job loss (Ferrie, 1999); such outcomes were reported by respondents both at the time of workplace closure and during the first year of unemployment. Negative physical health outcomes included an increased risk of cardiovascular risk factors (e.g., blood pressure, cholesterol) and events (e.g., cardiovascular mortality) as well as a decline in self-reported health status. Among the most prominent of workplace studies during this period was a prospective study of 100 blue-collar workers from two plants (one urban and one rural) who were followed prior to and two years after job termination due to a plant shutdown (Cobb & Kasl, 1977). Physical and psychological symptoms among these plant workers were compared to 74 controls from four plants that did not face closure. Physiological changes documented upon the experience of job loss included changes in blood sugar and uric acid (suggestive of increased risk of diabetes), peptic ulcer, and gout. An uptick in arthritis and hypertension were also noted. In terms of mental health consequences, respondents reported changes in self-identity and non-significant changes in affective state—regarding the latter, the authors emphasize that the "numbers don't seem commensurate with the very real suffering that we observed" (Cobb & Kasl, 1977, p. 180).

Amidst this backdrop of deindustrialization and workplace closures, researchers began to probe the health and mental health implications of *anticipated* job loss. Beale and Nethercott (1985), for example, followed 129 British workers (80 men and 49 women) in the Calne area of England who learned two years prior to job loss that production operations might cease. In the years following this news, the authors found significant increases in healthcare consultations as well as referrals to and admittances to hospital outpatient departments, results which led the researchers to conclude that the period marked by threat of job loss induced stress equal to if not greater than the actual event of losing one's job. Research on "survivors" of these downsizing waves, meanwhile, underscored how the effects of greater workload, reduced job control, and uncertainty about the continuity of employment contributed to increased physical morbidity and poor mental health outcomes—mental health outcomes such as anxiety, burnout, distress, and suicide (Brockner, 1988; McHugh, 1998; Vahtera, Kivimäki, & Pentti, 1997). The Rasio study, conducted among local government employees of Rasio, south-western Finland, was one of the first studies to explore the physical health ramifications of downsizing on survivors (Vahtera, Kivimäki, & Pentti, 1997). Musculoskeletal problems and poor self-rated health were two times greater among survivors of downsizing in the town, outcomes the authors attributed in large part to increased work stress following the downsizing. The psychological wellbeing of Swedish social insurance organization employees was the subject of a 1995 case study by McHugh (1998), who found that the government's pivot toward rationalization of the workforce—resulting in reductions in staff and limited resources—was a source of heightened anxiety and burnout among survivors of the financial cutbacks.

The threat of job loss experienced by "survivors" of restructuring and downsizing efforts prompted a pivot in the 1990s toward research that assessed the association between *perceived job insecurity* and physical and mental health (Benach et al., 2014). Studies conducted in the last two decades have underscored the *chronic* rather than acute nature of perceived job insecurity and have suggested the existence of a dose-response relationship between anticipated job loss and poor mental health. Domenighetti, D'Avanzo, and Bisig (2000) estimated the odds of 10 indicators of health and well-being according to levels of perceived job insecurity (low, middle, and high) among a random sample of the Swiss general population (N=1150). Their findings point to deteriorating health with increasing levels of perceived insecurity: Adjusting for sociodemographic characteristics, high levels of job insecurity were significantly associated with low self-esteem, daily or weekly consumption of tranquilizers, regular lower back pain, poor health, and regularly smoking. Similarly, Ferrie and colleagues (2002) surveyed 3360 white collar office workers in the British Civil Service on two occasions (1995/96 and 1997/99) to better understand the role of chronic job insecurity on self-reported health and minor psychiatric morbidity. The authors measured job insecurity using a four-category item—"How secure do you feel in your present job?"—and compared participants whose job was insecure or very insecure to those whose jobs were secure or very secure. Chronic job insecurity (insecure or very insecure at both timepoints) among both male and female respondents was significantly associated with poor self-rated health and higher General Health Questionnaire and depression subscale scores (Ferrie et al., 2002).

In keeping with the principles of the life course perspective, Burgard and Seelye (2017) argue that charting the long-term history of perceived insecurity is critical, as the *timing* of such insecurity matters. Perceived insecurity midlife or closer to retirement, for example, might induce more stress than early in one's career when younger adults have fewer caregiving responsibilities and health problems. Using data from the Americans' Changing Lives (ACL) study, a five-wave longitudinal study spanning 25 years, the authors examined the link between four trajectories of job insecurity—never insecure, early insecure, recently insecure, and persistently insecure—and psychological distress. Distress scores were significantly higher among those who were persistently insecure compared to those who were recently insecure and never insecure (predicted value of 1.43 compared to 1.26 and 1.19, respectively).

Though the extant literature on the consequences of perceived job insecurity on population health showcases how perceived job security operates separately and distinctly from more objective measures of job insecurity, there are important limitations to this construct. Specifically, while an individual's cognitive appraisal of the continuity of work depends in part on macro contextual factors (e.g., labor market dynamics, social protection coverage, etc.), it is also heavily influenced by individual-level factors: the interpretation of external threats to job security is likely to vary between individuals. This subjective component of the job security construct has precluded a thorough accounting of the particular aspects of the employment relationship that are most salient to worker wellbeing.

Temporary employment status is another unidimensional measure widely used in the social epidemiology to capture *objective* states of job insecurity (Benach et al., 2014). In contrast with unemployment/job loss and perceived job insecurity, the evidence base on the physical and mental health consequences of temporary employment is more mixed (Bardasi & Francesconi, 2004; Dawson et al., 2015; Pirani & Salvini, 2015). An analysis of 10 waves of panel data from the British Household Panel Study (1991-2000) found that temporary work arrangements (seasonal work/casual work and fixed-term work) were not associated with poor self-reported health after controlling for sociodemographic characteristics; however, male and female respondents in seasonal work arrangements (compared to their permanent contract counterparts) had 1.5 and 1.2 times the odds, respectively, of ill mental health (Bardasi & Francesconi, 2004). Dawson et al. (2015) leveraged data from the same panel study to explore the causal pathway between temporary employment arrangements and mental health. Leveraging approximately 50,000 observations from 8000 individuals followed between 1991 and 2008, the authors find that respondents who were in permanent employment and subsequently become temporarily employed reported significantly higher levels of psychological distress than those who never became temporarily employed. The authors surmise from these findings that individuals with poor mental health self-select into temporary work arrangements and that cross-sectional analyses may overestimate the effects of temporary contracts on mental health outcomes.

In contrast, a longitudinal study of nearly 2000 Italian workers that aimed to estimate the causal effect of temporary work on worker health found a negative association between temporary work arrangements and self-reported health. The authors used a propensity-score-based approach (inverse-probability-of-treatment weights) to estimate the causal effect of temporary contracts on self-rated health, controlling for selection effects, thereby allowing the authors to conclude the causal relationship is in the work-to-health direction (Pirani & Salvini, 2015). Similarly, Quesnel-Vallée et al. (2010) employ propensity scoring to account for mental health selection into non-standard employment arrangements in their analysis of the effect of temporary work on depressive symptoms among respondents in the U.S. National Longitudinal Survey of Youth (1991-2002). Workers who had experienced temporary work in the two preceding years had significant increases in depression symptom severity (1.8 additional depressive symptoms than if they had not been exposed). This heterogeneity of findings across these studies on temporary employment arrangements likely reflects the wide range of temporary working conditions (e.g., fixed-term, project-specific, on-call, etc.) and the potential implications of each for worker wellbeing. These mixed findings might also be explicated by the variance in social protection schemes and labor laws in the countries were these studies were conducted (i.e., Italy, United Kingdom, and the United States).

Whether temporary work arrangements are *voluntary* or *involuntary* is another critical consideration when assessing the health consequences of flexible forms of employment. For example, a study by Guest et al. (2006) on contractual arrangements among 1532 UK pharmacy workers found that when more flexible forms of employment are a voluntary choice, they enhance self-reported job satisfaction and quality of life. An innovative and recent study by Albæk & Andrade (2023) examined differences in mental health outcomes among full-time employees involuntarily on a temporary contract and those employed full-time on a permanent contract. Linking Danish panel data from the European Labour Force Survey with administrative data on prescription drug use for mental health problems, the authors found a 12.8% increase in medications use among female workers who faced six quarters of involuntary temporary work. No statistically significant effects of involuntary temporary employment on mental health were observed among male participants in this study.

Involuntary work arrangements—both full-time and part-time—were the subject of a study by De Moortel et al. (2020), who pulled four waves of data from the German Socio-Economic Panel survey (2004-2010) to investigate whether these involuntary work arrangements were associated with a deterioration in mental health. The authors found important differences in outcomes across gender lines: among female participants, involuntary part-time work and involuntary full-time work were not associated with worse mental health scores. In contrast, involuntary full-time work was significantly associated with reduced mental health scores for men—this relationship was stronger among men who were partnered. Moreover, a significant relationship was observed between involuntary part-time work status and mental health deterioration among men with a high household workload. The authors posit that considerable household duties among men who are unsatisfied with their part-time work arrangements (and are seeking full-time opportunities) might threaten their "breadwinner" identity.

Finally, with the accelerated shift toward non-standard work contracts in the years following the Great Recession, researchers have sought to unpack the relationship between various forms of employment contracts and mental wellbeing. For example, using nationally representative data from South Korea to explore depressive symptoms and suicidal ideation among 6266 adult wage workers, Han et al. (2017) defined precarious employment based on whether respondents fell into one of the six following worker categories: temporary workers, daily employed workers, part-time workers, dispatched workers, subcontracted workers, and workers with other atypical employment (full-time and permanent wage workers were classified as non-precarious workers). Logistic regression analyses revealed significant differences in the odds of self-reporting depressive mood between the precarious and non-precarious worker groups (OR=1.312, CI=1.02-1.71), adjusting for covariates such as gender, age, education, and marital status.

Similarly, Ruiz et al. (2017) examined population health effects of informal employment in Chile by classifying survey participants into four employment profiles, including dependent formal workers (i.e., employees, homeworkers, and domestic workers with a contract), non-dependent formal workers (i.e., self-employed professionals and employers with five or more workers), dependent informal workers (i.e., employees and homeworkers with fee contract or without contract), and non-dependent informal workers (i.e., employers with fewer than five workers and non-professional self-employed). Consistent with the research literature, men and women in dependent informal employment had a higher prevalence of poor mental health compared to those in dependent formal employment; however, this relationship was only significant among male workers (prevalence ratio of 2.43, CI=1.59-3.70), a finding the authors attribute to the higher likelihood of exposure to hazards and accidents among male informal workers.

2.2.2. Multidimensional measures of precarious employment

Recognizing the limitations of unidimensional constructs in elucidating the growing phenomenon of work precarity, there has been a movement within the last decade to conceptualize, operationalize, and validate *multidimensional* measures of precarious employment. Scholars at the forefront of such research efforts have advanced a conceptualization of precarious employment that emphasizes the following three dimensions: 1) work that is insecure and uncertain; 2) work that provides meager (if any) economic and social benefits, such as a living wage, health insurance, and pensions; and 3) work that offers limited labor rights (i.e. not protected by labor laws or regulations) (Allan et al., 2021; Kalleberg & Vallas, 2018). Such work is *insecure* in the sense that one is constantly concerned about job loss and *uncertain* in the sense that work hours and schedules are unpredictable/irregular.

Despite a broad consensus on the need for studies that account for these multiple dimensions of precarious employment, however, there remain deep divisions within academic and policy-making circles regarding the operationalization of these dimensions. In brief, contemporary operationalizations of precarious employment tend to fall in one of two camps: those that employ both subjective and objective indicators of employment conditions and those that rely exclusively on objective items.

Among those who endorse the inclusion of subjective items (citing the subjective experience of unequal power relations), the Employment Precarious Scale (EPRES)[12] has gained traction as a reliable and valid measure of precarious employment, particularly for use among waged and salaried workers in Europe. The scale consists of the following six dimensions: 1) temporariness (i.e., employment instability); 2) powerlessness/disempowerment (e.g.,

---

[12] The PSID dataset I am proposing to use for my dissertation does not include the subjective items necessary to construct the EPRES scale, thereby necessitating use of the more objective Employment Quality (EQ) measure. Nevertheless, I believed it was important to provide a brief overview here of the two schools of thought on employment precarity measurement (i.e., those who advocate for subjective measures versus those who employ objective markers of job precarity).

individualized versus collective bargaining); 3) vulnerability (degree to which worker is defenseless to unacceptable work conditions); 4) low/insufficient wages; 5) limited rights (limited entitlement to worker rights and social security benefits); and 6) incapacity to exercise rights (powerlessness, in practice, to exercise worker rights). Subscale scores are calculated as a simple average (ranging from 0 to 4) and then averaged into a global EPRES score ranging from 0 (not precarious) to 4 (most precarious). To date, research using data from salaried workers in Catalonia, Chile, Italy, Spain, and Sweden has revealed higher distributions of precarious employment among women, immigrants, younger adults, and those with a high school degree as highest education. These same studies have also found significant associations between EPRES scores and poor general and mental health (Benach et al., 2014; Jonsson et al., 2021a; Vives et al., 2013; Vives et al., 2020).

Alternatively, those advocating for a more objective, multidimensional construct of precarious employment have developed and validated an *Employment Quality* (EQ) measure, which includes both contractual and relational aspects of the worker-employer relationship. Researchers have identified the following seven dimensions of EQ: 1) employment stability (the continuity of employment); 2) material rewards (inclusive of wages and non-wage benefits of the work arrangement); 3) workers' rights (denotes employees' rights in the workplace, such as protection from discrimination); 4) working-time arrangements (the regularity and number of work hours); 5) training and employment opportunities (e.g., opportunities for skills development and worker advancement); 6) collective organization (the presence of worker organizations, such as unions, where workers can advance their interests); and 7) interpersonal power relations (the distribution of decision-making between workers and management) (Andrea et al., 2021; Eisenberg-Guyot et al., 2020; Van Aerden et al., 2016). In contrast with EPRES, the

EQ construct is typically measured using typological (e.g., cluster analyses) rather than linear approaches—the rationale being that general and mental health outcomes might depend on certain configurations of employment dimensions rather than the sheer number of dimensions to which one is exposed.

Consistent with studies using the EPRES construct, US- and Europe-based studies examining the distribution of EQ with working populations have found that women, migrants, lower-skilled and lower-education workers, and younger adults are most affected by poor employment quality (Andrea et al., 2021; Eisenberg-Guyot et al., 2020; Puig-Barrachina et al., 2013). Eisenberg-Guyot et al. (2020), for example, leveraged data from the 1985 to 2017 survey waves of the Panel Study of Income Dynamics to examine EQ clusters and mental health among mid-career workers in the United States. Using multichannel sequence analysis, a technique that allows for the clustering together of individuals with similar life-course trajectories of "states" (e.g., full-time work status), the authors found that people of color and less-educated participants were more likely to be located within poor employment quality subgroups and were also more likely to self-report poor health. Specifically, female workers with minimal attachment to the workforce had greater prevalence of mental distress at follow-up compared with standard employment relationship (SER)-like-non-union workers. With respect to men's mental health outcomes, stably-high-wage workers, the wealthy self-employed, and SER-like union workers had lower mental distress prevalence compared to their SER-like-non-union counterparts. Interestingly, the poor self-employed and precariously-employed workers were shown to have a *similar* prevalence of mental distress compared to SER-like-non-union workers (Eisenberg-Guyot et al., 2020).

Studies by De Moortel et al. (2014) and Gevaert et al. (2021) have used this same seven-dimension typology of employment quality to explore the association between contemporary employment arrangements and mental wellbeing among salaried workers in the European Union. Using data from the 2010 European Social Survey (n=11,940), a biannual cross-national survey conducted in 27 European countries, De Moortel and colleagues (2014) underscored gender differences in both employment quality and mental health outcomes. Specifically, female respondents were less likely to report having a sufficient income and more likely to endorse higher rates of involuntary part-time employment than their male counterparts. With respect to mental health outcomes, the authors found that regardless of welfare state typology (e.g., traditional family, Southern European, market-oriented, etc.), several sub-dimensions of employment quality were associated with poor mental health. Specifically, having an insufficient household income, having irregular/unsocial worker hours, and lacking representation and participation in the workplace were employment quality indicators associated with poor mental wellbeing among both male and female respondents.

A 2021 study by Gevaert et al. expanded upon this evidence base, using latent class analysis to explore associations between different arrangements of employment quality and mental and physical health outcomes among waged and self-employed participants in the 2015 European Working Conditions Survey (n=31,929). The researchers found clear evidence of a health gradient among the different configurations of employment quality, a gradient that did not distinguish between wage and self-employment. Compared with those with standard employment relationship (SER)-type jobs, especially poor mental wellbeing situations were found for those with insecure self-employment (OR=2.73), jobs in small trades and farming (OR=1.88), precarious intensive jobs (OR=1.78), and dependent self-employment (OR=1.79).

An impressive longitudinal study based in Sweden linked health and employment data from multiple registers to explore how low and high-employment quality typologies influenced risk of common mental health disorders, substance use disorders, and suicide attempt (Jonsson et al., 2021b). Using multiple national registers, the authors first pulled participants' employment information for the years 2005 to 2009 (n=2,743,764) to trace employment trajectories. They then determined future risk of mental health problems based on whether participants had documentation of inpatient or specialized outpatient care in their health records (2010-2017). Compared with individuals in a constant standard employment relationship, men and women in all low-quality employment trajectories except solo self-employment were at increased risk of being diagnosed with a common mental disorder or substance use disorder. A follow-up study by Pollack et al. (2022) used the same low- versus high-quality employment trajectories variable and linked population registries to differences in mental health outcomes according to Swedish and foreign background. Adjusted hazard ratios revealed that those in low quality employment trajectories—regardless of sex or foreign background—were at increased risk of common mental disorders (i.e., anxiety, depression, and stress-related disorders), though male and female migrants in low-quality employment trajectories were at higher risk of CMD than their Swedish-born counterparts.

Other study-specific multidimensional measures of precarious employment have been proffered in the research literature. Though the indicators for these alternative PE constructs differ from those of the EQ and EPRES measures, they nevertheless underscore the nature of work that is unstable and insecure. For example, in longitudinal study examining mental health outcomes following spells of precarious employment, Canivet and colleagues (2017) operationalized precarious employment based on a combination of categorical variables including present unemployment (yes/no), involuntary unemployment in the past three years (yes/no), temporary versus permanent employment (yes/no), and perceived job insecurity (high, moderate, low, none). The authors found that 42.2% of survey respondents ages 18-34 years in Sweden were precariously employed (compared with 36.3 and 29.8% among 35-to 44-year-olds and 45-to 54-year-olds, respectively). Moreover, controlling for baseline mental health, the incident rate of poor mental health (defined as a score of 2 or higher on the General Health Questionnaire) was 1.7 times higher among those ages 35 to 44 years who were precariously employed at either the first or second survey wave (1999/2000 or 2005). Interestingly, the association between precarious employment and mental health was not significant among the study's youngest and oldest age groups. The authors speculate that precarious employment among mid-career workers might be more detrimental psychologically than for workers at the beginning or end of their career trajectories (e.g., younger workers might be more willing forgo employment stability to establish themselves in the labor market).

Pfortner et al. (2019) constructed a four-variable measure of employment precarity using data from the German Socio-Economic Panel. Intent on deciphering the effects of different periods of labor reforms and economic downturns (e.g., 1995-1997 deregulation, 1998-2001 re-regulation, 2008-009 Great Recession from 2008 to 2009) on precarious employment, the authors focused their analyses on the period between 1915 and 2015. Precarious employment was measured using four indicators, including working poverty (income less than 60% of the median), low wages (gross hourly wages less than two-thirds of the median wage of employees), working time arrangements (non-standard arrangements including part-time, temporary, fixed-term, and marginal work), and perceived job insecurity (the degree to which respondents were concerned about their own job security). Results of the multivariate analysis exploring differences in self-reported health (SRH) by precarious employment indicators revealed significant relative and absolute risk reductions in SRH across time by perceived job insecurity among men but not for women. Furthermore, working poverty (for both men and women) and low wages (for men) were associated with differences in poor SRH in the Great Recession and post-Great Recession periods, a consequence the authors speculate could be attributable to the growth of flexible, low-wage jobs in the post-Great Recession period.

Demiral et al. (2022) examined the mental health implications of precarious employment on a representative sample of German workers. Drawing on data from the German Study on Mental Health at Work (n=2009), a nationwide cohort study with baseline measurements in 2012 and follow-up in 2017, the authors operationalized precarious work through five indicators related to job insecurity and instability, contractual arrangements, and wages. The authors found that men who experienced job insecurity and low wages at baseline (2012) were significantly more likely to have depressive symptoms (as measured by scores on the Patient Health Questionnaire) at the five-year follow-up (odds ratios of 2.47 and 3.79 for job insecurity and low wages, respectively). Moreover, male participants experiencing two or more indicators of precarious work at baseline had more than five times the odds of meeting the cut-off for depressive symptoms at follow-up compared to those who did not endorse any indicators of precarious work. this association did not hold for female workers. While female participants were significantly more likely to be engaged in marginal part-time and low-wage work than their male counterparts, this study did not find any association between the cumulative exposure index of precarious work and depressive symptoms among women.

Finally, Guidici and Morselli (2019) analyzed 20 years of longitudinal data from the Swiss Household Panel to understand how prolonged exposure to nonstandard occupational trajectories affects mental health over the life course. The authors traced occupational trajectories by first gathering variables related to respondents' main and secondary occupations for each survey wave—indicators included hours worked per week, periods of work inactivity, temporary work, unemployment, and social assistance. Next, the authors used a data mining approach to identify trajectory types based on the twelve possible combinations of job states (e.g., "full-time occupation and temporary job," "double- part-time job," etc.). While the most common type of 20-year occupational trajectory was characterized by "full-time" employment (46% of the sample), 13% of the sample experienced an interruption in the first few years of their careers and remained mostly "inactive" for the remaining period, 11% were working part-time jobs (many of whom began in full-time employment and transitioned to part-time work), and 5% of trajectories were dubbed "discontinuous," characterized as having several job statuses over the course of the study period. Unsurprisingly, discontinuous employment trajectories were most likely to be associated with having mental health problems across the life course compared with full-time and inactive trajectories, even after controlling for demographic variables such as age and sex. Current depressive symptoms were also more likely to be observed among discontinuous trajectory workers compared with full-time workers when adjusting for covariates.

2.2.3. Qualitative Research on Precarious Employment and Mental Health

Extensive qualitative work has also been conducted to contextualize the relationship between job precarity and mental health. Indeed, a scoping review of qualitative evidence on the effect of precarious employment and mental health yielded a total of 35 relevant studies (32 unique studies) (Irvine & Rose, 2022). While the review takes objectively insecure forms of employment (e.g., temporary agency, fixed-term, casual, gig work) as its point of departure to identify eligible studies, a synthesis of the qualitative evidence revealed four interconnected, core experiences of precarious work that cut across all studies. These dimensions included financial instability, temporal uncertainty, marginal status, and employment insecurity. Brief summaries of each of the qualitative studies identified in this scoping review can be found in that study's appendix, though it is worth elaborating upon findings from key qualitative studies here.

Bosmans et al. (2016) explored pathways between precarious employment and mental wellbeing among a sample of temporary work agency workers in Belgium. They found that while some workers appreciated the "freedom" afforded them by temporary work (e.g., the possibility of learning new skills while on-the-job as well as the ability to "take a break" after stretches of work), these feelings were typically endorsed by workers with high qualifications. Most participants expressed feeling powerless to exercise their rights or claim worker benefits for fear of jeopardizing a future permanent contract (Bosmans et al., 2016). Many of these sentiments around freedom (or lack thereof) to choose temporary assignments were echoed in a second qualitative study by Bosmans and colleagues (2017), which relied on in-depth interview data (n=41) from temporary agency workers in Canada. Those with sought-after skills and creative talent, such as graphic design, appreciated having the freedom to choose which jobs they accepted or refused. Similarly, those for whom temporary work was an ideal fit given their lifestyle choices (e.g., frequently traveling abroad, studying), cited feeling much more in control over their lives than those for whom temporary work was involuntary. These exceptions aside, many temporary workers cited the stress associated with income insecurity, describing how the uncertainty around personal finances precluded them from making medium- and long-term plans or taking on big expenses. These workers often resorted to taking on credit card debt or borrowing money from family and friends to make ends meet. Participants also detailed the mental health toll of engaging in high uncertainty and high effort work. Specifically, the strain of constantly putting in effort to search for and/or keep work combined with the protracted uncertainty of finding the next work opportunity led to feelings of frustration and low self-esteem. Emotional and financial support from family and friends was identified as an important protective factor for mental health, though such support was not available to all participants.

Interviews with precariously employed young workers in Sweden similarly revealed a number of troubling themes regarding the effects of precarious employment on the wellbeing of participants, including the inability for participants to plan their day (e.g., arrange for child care, go out with friends, tec.) given the possibility of needing to work, the constant worry about making ends meet, and alterations in sleeping and eating behaviors due to relentless stress (Toivanen et al., 2020). Interestingly, the authors observed that adults who were able to shift blame away from themselves (and onto external, macro-level factors such as labor market dynamics), the less likely their employment situations were to negatively influence their physical and mental health.

The degree to which the health effects of PE depend on one's life stage was the subject of a qualitative study by Clarke et al. (2007). Drawing from a larger population-based survey sample (n=3244), the authors interviewed 82 workers between the ages of 25 and 50 who had been engaged in precarious employment for at least two years. A key query during the interviews was whether participants wanted to remain in precarious employment, which allowed the researchers to identify three clusters of individuals: those in "unsustainable" employment relationships (nearly half of the interviewees), those on a path to more secure employment (34% of interviews), and those with "sustainable" precarious employment (approximately one-fifth of respondents). Those in the "unsustainable" precarious employment group wanted more secure employment but to date had been unsuccessful. These respondents were less likely to have family that could provide financial support (many had partners who were also engaged in precarious work) and overwhelmingly described work as stressful given their constant worry over finances and need to find future work. These respondents were also more likely to report deteriorating physical and mental health—physical health symptoms included headaches, stomach problems, hypertension, and muscle aches were among the mentioned health symptoms, while anxiety and depression were among the mental health conditions cited by several participants.

Finally, a timely mixed-methods study on French gig workers navigating national lockdown protocols at the height of the Covid-19 pandemic showcases the precarity of independent work arrangements, particularly during economic crises.[13] Specifically, gig workers in France could not claim unemployment benefits, nor could they tap into the "partial unemployment" payment scheme that was instituted in France and a number of other European countries. Data were collected both prior to and during the national lockdown, and respondents included those working in food delivery services, cleaning or care services as well as those engaged in freelance work. Predictably, workers' anxiety around their economic precarity, particularly the lack of government benefits available to them, emerged as a key theme in the qualitative data. In terms of changes to work hours and earnings, approximately half of respondents (52%) had stopped working after the start of the lockdown (those who were able to work remotely reported significantly higher incomes at baseline). Furthermore, when asked to report changes in income in the last 30 days, respondents, on average, reported a 28% decrease in income (two-thirds reported a decrease in income and 30% reported that their income had

[13] Literature to date on the mental health implications of gig work has found mixed results: gig workers do cite greater autonomy and flexibility as perks of the work but also report experiencing higher levels of anxiety than other workers (Apouey et al., 2020).

stayed the same). This decrease, however, was most substantial *among those who reported that gig work constituted their main source of income* (a 67% decrease in income, on average).

2.2.4. Gaps in the Literature

Despite a flurry of research activity within the last decade aimed at understanding the link between precarious employment and mental health, there remain key gaps in the extant literature. First, the vast majority of studies on the link between work precarity and mental health rely on cross-sectional studies, which limit one's ability to draw causal inferences or to determine the dose-response nature of the relationship. Studies with samples from across the European Union (Julia et al., 2019), South Korea (Seong et al., 2021), Italy (Moscone et al., 2016), Spain (Vives et al., 2011), Sweden (Jonsson et al., 2021a), and the United States (Brown et al., 2017) have all explored the deleterious impact of precarious employment on mental health; however, each of these studies relied on cross-sectional data from *one point in time.* While significant contributions to a nascent research literature, such work cannot offer causal explanations on the nature of this relationship.

The few quantitative studies that have leveraged longitudinal data to trace the mental health implications of precarious work (or economic stressors more generally) do not center around the particular experiences of Millennial workers. Instead, these studies include wide age ranges in their samples (e.g., 18 to 61 years; 29 to 50 years; 31 to 60 years) and treat age as a covariate in the analyses (Demiral et al., 2022; Eisenberg-Guyot et al., 2021; Pollack et al., 2022). For example, Eisenberg-Guyot et al.'s (2021) study on employment quality and health outcomes explored employment trajectories of 2779 PSID respondents who were observed at least once between the ages of 29-31 and once between the ages of 48 and 50 (i.e., observed over a two-decade period). Though groundbreaking in its use of a multidimensional measure of employment quality and multi-wave panel data, the authors' methodological approach precluded a more nuanced understanding of the employment trajectories *of Millennials in the decade following the Great Recession*. Research on precarious employment hailing from Germany and Sweden, home to ongoing panel studies that collect both employment- and health-related data, is similarly sparse vis-à-vis the work experiences of Millennial workers. Demiral et al.'s (2022) study examining the effects of precarious employment on depressive symptoms among German workers focused primarily on the experiences of mid- to late-career adults (only 15% of the sample was between the ages of 30 and 36 and baseline in 2012). Similarly, just a fraction of the participants in Jonsson et al.'s (2021b) and Pollack et al.'s (2022) Sweden-based studies, which linked health and employment data from multiple registers for the years 2005 to 2009, were members of the Millennials generational cohort.

The few studies that do center on the experiences of Millennials either lack causal power given their cross-sectional study designs (Gilek, 2020; Oswald et al., 2021; Seong et al., 2021) and/or do not account for post-Great Recession employment experiences (Allmang, 2019; Canivet et al., 2017). For example, Seong et al.'s (2021) study of young adult precarious workers in South Korea (ages 25-34 years), which found that the pathway between unstable employment and suicidal behavior was mediated by depression and anger, employed a cross-sectional study design. Oswald et al. (2021) similarly used a *one-time,* online survey to explore the role of employment precarity (operationalized based on type of work contract and regularity of working hours) on mental health outcomes among young Australians during the Covid-19 pandemic.

With respect to the latter point regarding lack of post-Great Recession work experiences, Allmang's dissertation used two waves of data (2001/2002 and 2008/2009) from the National Longitudinal Study of Adolescent Health to assess the relationship between a multidimensional measure of PE and depression—her study design by definition cannot elucidate the employment trajectories of Millennial workers in the last decade. In addition, a study by Canivet et al. (2017) involved two follow-ups with a cohort of Swedish young adults ages 18 to 34 years (n=1135)—a five- and 10-year follow-up in 2005 and 2010, respectively. While robust in terms of study methods and relevant with respect to the sample population, this study nevertheless reveals little regarding the long-term trajectories of Millennials in the decade following the Great Recession. In short, the research literature on the association between precarious employment and mental health among *young adults* remains underdeveloped. Moreover, studies on American Millennials' employment trajectories and mental health in the post-Great Recession period appear to be non-existent.

Finally, to date no study has used longitudinal survey data to examine intra-country variations in precarious employment trajectories and mental health problems. Moreover, no study has looked at the interaction of specific U.S. social welfare programs *on the association between precarious employment and mental health*. This dissertation project therefore makes an important contribution to the efforts of social welfare scholars and practitioners working at the intersection of labor market and occupational health policies.

Chapter 3. Theoretical Frameworks

Though a number of grand and middle-range theories spanning the disciplines of economics, occupational health, and political science would be of value to this research endeavor, four theories, in particular, anchor my study design and interpretation of findings. Psychology of Working Theory (PWT) and Stress Process Theory interrogate the ways in which systems of social stratification shape an *individual's* opportunities for decent work and exposure to and manifestations of stress, respectively. At the macro level, Segmented Labor Market Theory considers the political and economic forces that have contributed to deep divisions within the labor market—divisions often demarcated by race, gender, socioeconomic status, and immigrant status. Finally, Power Resources Theory examines the influence of political, social, and economic actors on welfare state policy and will be leveraged to contextualize study findings regarding the differential effects of social protection policies on mental health. A brief description of the history and applicability of each theory is described in the following pages, beginning with those that are focused on the individual as the unit of analysis and concluding with those that are focused on the macro-level forces shaping the labor market (and by extension, individual-level outcomes).

3.1. Psychology of Working Theory

With origins in counseling psychology, the Psychology of Working Theory (PWT) aims to explain the work-based experiences of more disenfranchised and marginalized people who have less volition in shaping their work experiences. First proposed by Blustein et al. (2006), PWT is rooted in decades of research that has attempted to explain individual-level factors that influence career decision-making and satisfaction with work. In a departure from these classic vocational and counseling psychology theories, however, PWT emphasizes the role of contextual and structural factors in shaping work-based experiences. Specifically, Blustein et al. posit that in explicating career development and work experiences, 20th century counseling psychology theories foregrounded the role of individual-level factors (e.g., self-efficacy beliefs) while not sufficiently attending to how contextual factors such as discrimination or labor market dynamics influence one's ability to engage in "decent work." In short, PWT theorists argue that prior theoretical perspectives have largely explored the work lives of people with privilege and high levels of agency, which does not accurately reflect the working conditions of the contemporary working class.

In terms of the basic tenets of PWT, Blustein et al. posit that sociocultural factors are paramount to understanding the career decision-making and work experiences of individuals, particularly those that come from more marginalized and disenfranchised backgrounds (Duffy et al., 2016).[14] Key assumptions of PWT include that 1) work is a critical component of life and an important part of mental health; 2) the study of "work" should be inclusive and take into account all individuals that want to work (not just those able to work); 3) work fulfills three fundamental needs, including basic survival needs, the need to contribute to society, and the need for social connection; and 4) efforts to understand the psychological nature of work must incorporate social, economic, and political factors that facilitate/hinder one's access to work.

"Decent work," which the authors define as consisting of five human rights-based attributes[15] (a definition consistent with that of the International Labor Organization), is the central variable in PWT. Certain psychological and contextual variables are hypothesized to

---

[14] The authors state at the outset that PWT is grounded in a North American perspective, which emphasizes the value of individual fulfillment at work.

[15] These five components include the right to a safe work environment, access to health care, sufficient earnings, hours that allow for free time and rest, and organizational values consistent with family and social values (ILO, 2008).

predict access to decent work, *moderate* the relationship between these predictors and decent work, and be *outcomes* of engaging in decent work (Blustein et al., 2020). This conceptualization of "decent work" is consistent with the proposed aims of this dissertation project: one's likelihood of being mired in cycles of precarious work can be explained by macrostructural factors (e.g., labor market dynamics) and individual-level factors such as gender and race/ethnicity.

PWT guides both the analysis and contextualization of findings regarding Millennials' employment trajectories: Differences in employment experiences are assessed by key sociodemographic characteristics (e.g., gender, race/ethnicity, immigration status), and macrostructural factors (e.g., country-specific social protection and active labor market policies), as they are critical to understanding socially-patterned membership in precarious employment trajectories. While PWT can help to illuminate the socially patterned nature of an individual's work trajectory, it does not provide a framework to understand the process through which stressors such as precarious employment impact mental wellbeing. A theory that explicates the mechanisms underlying the relationship between work-related stressors and mental health outcomes is therefore warranted.

3.2. Stress Process Theory

The stress process model, first advanced by American sociologist Leonard Pearlin in the early 1980s, is among the most influential theoretical paradigms to interrogate the effect of social sources of stress on mental wellbeing. Critical of the narrow lens through which his contemporaries examined the stress process (researchers at the time relied primarily on biomedical, *individual-level* explications for the origins of stress), Pearlin emphasized the need to consider the role of social structures in shaping one's experience of stressful events and/or conditions. Central to the stress process framework are the concepts of *sources* of stress, *mediators* of stress, and *manifestations* of stress, each of which Pearlin argued is socially patterned. In other words, systems of stratification at societal, organizational, and interpersonal levels influence an individual's exposure to stressful experiences (i.e., sources of stress), ability to navigate these stressors (i.e., mediators), and physiological or psychological outcomes of stress (i.e., manifestations). A brief overview of each component of the stress process model, including examples related to the proposed dissertation project, is outlined below.

The stress process paradigm distinguishes between two sources of stress: life events of an acute nature (e.g., job loss) and "chronic strains" (e.g., work overload). (Pearlin, 1981, p. 339). While research often focuses on the experience of either life events or chronic strains, these situations often converge (i.e., persistent stressors culminate in adverse events or a life event triggers enduring hardships), resulting in the experience of "clusters" of stressors (Pearlin, 2010). Research has shown, for example, how a stressor such as involuntary job loss can prompt financial strain (e.g., difficulty paying bills, maintaining stable housing) and family discord; these secondary stressors in turn have the potential to expose an individual to additional stressors (e.g., eviction, divorce, etc.), fueling a cycle of "stress proliferation" (Pearlin, 2009, p., 209). In keeping with the spirit of sociological inquiry, Pearlin maintained that the distribution of stressors was not uniform within a society but rather the function of an individual's position within different social structures, stratified by characteristics such as race, gender, and socioeconomic status.

Whether an individual's exposure to stress will lead to adverse outcomes is mediated by the *coping strategies* utilized by and *social support* available to that individual. Much like the distribution of stressors, the forms and quality of personal (i.e., coping) and social resources (i.e., social support) are linked to one's location within the social order. While coping skills are almost exclusively conceptualized and analyzed at the level of the individual, Pearlin noted that coping strategies are learned from the behaviors of others, particularly those in one's own membership group/reference group. Similarly, one's access to social support[16] (and the quality of support received) in times of hardship will vary based on social stratification. A recently laid-off worker of low socioeconomic status, for example, is not likely to have access to the types of social support (e.g., family financial resources, connections to future work opportunities, etc.) available to someone within a higher socioeconomic bracket.

Stress *outcomes* refer to the manifestations of stress, which can be physiological (e.g., cardiovascular disease, hypertension) or psychological (e.g., anxiety, depression). While researchers in the medical field are primarily concerned with the mechanisms underlying the relationship between stress and its biomedical indicators, those with more sociological orientations aim to illuminate the *social origins* of these health and mental health outcomes. In short, it is one's location within stratified social systems that affects the frequency and intensity of stressors and their mental and physical health manifestations.

Having leveraged the Psychology of Work Theory to understand the socially patterned work experiences of American Millennials, the Stress Process Paradigm offers the necessary framework for linking these employment trajectories to mental health outcomes. Bridging the employment and mental health components of this study, the Stress Process Theory explicates the mental health implications of the acute stress of losing a job or the chronic uncertainty surrounding one's ability to secure decent work. While the Stress Process Paradigm is arguably the "linchpin" theory for this study, it does not provide an analytical framework for interrogating

[16] Here social support refers to the which the mix of resources—formal or informal, family or friends, individuals or organizations, etc.—an individual can leverage when problems arise.

the macro-structural factors that facilitate access to quality jobs for some groups and precarious work opportunities for others. Segmented Labor Market Theory and Power Resources Theory attend to these macro-structural economic and political forces that shape Millennials' opportunities for decent work.

3.3. Segmented Labor Market Theory

Segmented Labor Market Theory, as its name would suggest, posits that there are persistent divisions within the workforce based on characteristics such as gender, race/ethnicity, education level, and industry. This "segmentation" or "compartmentalization" manifests in certain groups of workers essentially operating in separate labor markets, with different opportunity structures available in each. In keeping with *neo-institutional*[17] interpretations of labor market dynamics, Segmented Labor Market Theory argues that these divisions between workers are the product of *political and economic forces* that have—over time—facilitated the segmentation of the labor market into separate "submarkets" (Reich et al., 1973).

First introduced by Michael Reich and colleagues in 1973, Segmented Labor Market Theory proposes that the presence of "submarkets" with the labor market is the consequence of four segmentation processes that cut both horizontally and vertically: 1) segmentation into primary and secondary markets; 2) segmentation within the primary market into "subordinate" and "independent" jobs; 3) segmentation by race; and 4) segmentation by gender. With respect to the compartmentalization between primary and secondary markets, Reich et al. distinguish between "primary jobs"—jobs characterized by relatively high wages, good prospects of skills acquisition, and potential for upward career mobility—and "secondary jobs," where "…wages are low; turnover is high; and job ladders are few" (1973, p. 360). Within the primary market,

---

[17]Neo-institutional theories emphasize the role of political, social, and economic institutions in shaping social phenomena.

divisions exist between those who perform routine tasks that require discipline and dependability (i.e. "subordinate jobs") and those who play more "independent" roles that allow for and reward creativity, problem-solving skills, and initiative-taking. Finally, Reich et al. underscore how racial minorities and women often experience segmentation within "primary" and "secondary" markets (and within "subordinate" and "independent" jobs). Women, for example, have historically been encouraged to pursue jobs in the "serving" economy—one need look no further than the ratio of women to men in the social work or nursing professions to understand this phenomenon.

Segmented Labor Market Theory informs both the design and interpretation of findings for this study.[18] Gender, race/ethnicity, and immigrant status are treated as covariates in the first analysis that aims to identify employment trajectories between 2009 and 2019. It is likely that within this already segmented group of workers (Millennials), women, people of color, and immigrants are over-represented in trajectories marked by consistent work precarity. When interpreting findings, close attention is paid to the types of labor market policies (e.g., active labor market policies, employment protection legislation) that might explicate the probability of precarious employment trajectories along gender, race/ethnicity, and immigrant status lines.

Thus far we have traced the segmentation of workers into different submarkets—each with varying degrees of worker autonomy, opportunities for upward mobility, and wage structures—(Segmented Labor Market Theory), the work trajectories associated with individuals located within in each of these submarkets (Psychology of Working Theory), and the mental health implications of such employment trajectories (Stress Process Theory). Missing from this analysis is a systems approach, one which nests these processes within their larger political,

---

[18] Arguably, the entire rationale for this study is based on recent evidence that young workers are segmented into secondary markets (i.e. precarious jobs) at disproportionate rates compared to other generations of workers.

economic, and social contexts. Power Resources Theory illuminates the larger system within which these labor market processes (and their consequences for wellbeing) operate.

3.4. Power Resources Theory

Power Resources Theory offers guidance for those seeking to account for variation in the social welfare systems (i.e. social protection and labor market policies) of advanced capitalist nations. Advanced throughout the 1970s and 1980s by sociologists like John Stephens, Walter Korpi, and Gøsta Esping-Andersen, Power Resources Theory holds that differences in welfare state policy can be explained by the distribution of power between different social, political, and economic interest groups within a country (Kalleberg, 2018). Specifically, the generosity of welfare benefits and of protections for workers depends upon the strength of labor movements *and* their political allies. Though perhaps not an obvious fit for this study—after all, this dissertation *does not* intend to trace and explicate the distribution of power resources among worker movements and their political allies in the U.S.—Power Resources Theory nevertheless provides a helpful framework for contextualizing findings. It is important to understand how power dynamics between different political, social, and economic interest groups have shaped social protection and labor market policy (and therefore in Millennials' employment conditions and mental wellbeing) in the post-Great Recession period.

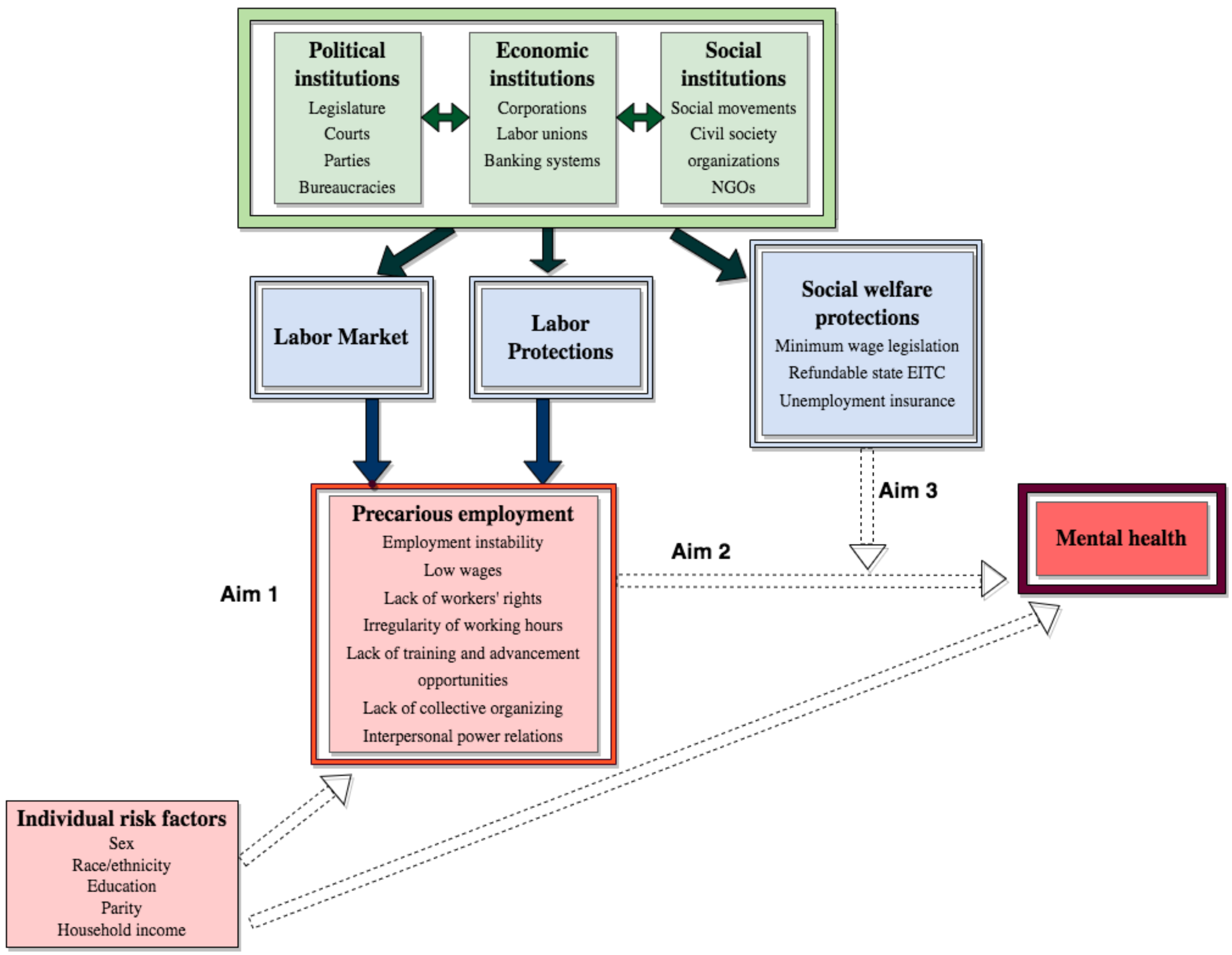
3.5. Proposed Conceptual Framework

The conceptual framework depicted below (Figure 1) reflects the tenets of each of these theories and orients both the study design and interpretation of study findings. Embedded in the light green boxes at the top of the figure are institutional factors—political, economic, and social—that influence a country's labor market dynamics as well as the protections afforded to workers. These institutions are themselves interconnected. One can imagine, for example, how legislative and executive policies or judicial decisions might influence actors operating within the economic or social spheres of society. Likewise, economic institutions, such as corporations and banking systems, might have an outsized influence on the policy-making calculus of political actors in certain countries (one need look no further than the lobbying efforts of Big Oil to omit key climate change provisions from the recent bipartisan infrastructure bill in the United States (Davenport & Friedman, 2021).

Political, economic, and social institutions play an important role in shaping labor market dynamics as well as the kinds of labor protections and social welfare programs that have to potential to buffer some of the adverse effects of a liberalized economy. Labor market dynamics and labor protections (or lack thereof), in turn, influence an individual's risk of precarious employment (as illustrated in the model, sociodemographic factors are also implicated in one's risk of precarious employment).

While all three research aims will be elaborated in more detail in Chapter 4, a brief introduction to this study's conceptual model is in order. Research **aim 1** involves identifying different subgroups of employment trajectories based on employment conditions such as employment and working hours instability, material rewards (the economic and social benefits of one's job), and union membership. The dotted arrows illustrated in Figure 1 reflect the hypothesized relationships between precarious employment and mental health. Persistently high levels of precarious employment, which are affected by the aforementioned structural factors as well as individual-level sociodemographic factors, are proposed to directly influence individuals' mental health (Research **aim 2**). Finally, three social protection and labor market policies—minimum wage legislation, state earned income tax credits, and unemployment insurance—are predicted to moderate the relationship between precarious employment and Millennial mental health (Research **aim 3**).[19]

Figure 1. Conceptual model linking precarious employment with mental health among Millennials in the United States



Adapted from Benach et al. (2014). Precarious employment: Understanding an emerging social determinant of health. Annu. Rev. Public Health 2014. 35:229–53

[19]There are arguably other social welfare policies that might buffer the effects of low quality, unstable employment on mental health. For example, it could be worth interrogating the health outcomes among residents of states that have chosen to expand Medicaid or enact paid family leave compared to their counterparts in "less generous" welfare states. That said, I have chosen to exclude these policies from my moderation analyses primarily for **methodological reasons.** States have adopted each of these policies at different points throughout the study period (2009-2019). This temporal limitation makes a clear-cut binary coding of welfare generosity (e.g., coding a state 1 if they adopted Medicaid expansion at any point in the study period and 0 if not) quite difficult. In other words, the potentially moderating effect of Medicaid expansion for a state that expanded in 2019 would not manifest until much later compared to a state that did so in 2013.

Chapter 4. Study Purpose, Research Questions, and Hypotheses

Guided by a diverse set of theories that elucidate how systems of social stratification shape an *individual's* opportunities for decent work and manifestations of stress, this dissertation aims to close some of the key gaps in the research literature identified in Chapter 2. Specifically, this comparative study explores cross-state variation in precarious employment and mental health trajectories among Millennials residing in the United States, allowing not only for a better understanding of the post-Great Recession employment and mental health trajectories of young adults but also of the types and configurations of social protection programs that may buffer the adverse effects of job precarity on mental health. The study's research aims, research questions, and hypotheses are detailed in the following pages.

Research aim 1: To identify subgroups of precarious employment trajectories among Millennials residing in the United States in the years following the Great Recession (2009-2019).

Given the continued deterioration of standard employment relations and the explosion of the "gig economy" in the wake of the Great Recession, this research aim serves to illuminate contemporary patterns in Millennial employment conditions and sociodemographic variation within each identified subgroup. Data from a longitudinal*, panel study* in the United States (the Panel Study of Income Dynamics) are used to examine these trajectories between 2009 and 2019. Specific research questions that are addressed under this study aim include the following:

1) What are the characteristics of precarious employment trajectories among Millennials in the years between 2009 and 2019? How many clusters (classes) of precarious employment trajectories can be identified?

2) How do socioeconomic and demographic factors (i.e., age, gender, immigration status, parents' education[20], race/ethnicity, urban/rural residence, education, region) vary across these precarious employment trajectories?
3) Are race/ethnicity and/or gender *predictive* of one's location with a particular subgroup?

Hypothesis 1a. A greater proportion of respondents with low education levels will be found in trajectory clusters marked by persistently precarious employment, whereas participants with post-secondary education levels will cluster in more stable employment trajectories.

Hypothesis 1b. Race/ethnicity will be predictive of employment trajectory membership, such that Black and Hispanic respondents will be more likely to be in poor employment quality trajectories compared to their White counterparts.

Research aim 2: **To examine associations between precarious employment trajectory subgroups and mental distress in the post-Great Recession period.**

The aforementioned dataset is used to explore the burden of poor mental health across the study period (2009-2019) for *each employment trajectory subgroup* identified in Research Aim 1. Individual-level risk factors that are examined for this analysis include education level (time-varying), gender, race/ethnicity, immigrant status, and rural/urban residence. Family-level factors that are assessed include marital status (time-varying) and parental education. Specific research questions that are addressed under this study aim include the following:

1) Does the risk of mental distress at the final study timepoint (2019) differ by employment trajectory subgroup?

[20] While childhood SES would be the preferred variable these research aims, it is not available in this main PSID individual datasets. As such, I use parental education as a proxy for childhood SES, which has often been used to measure SES (Erola et al., 2016; Korupp et al., 2002; Jalovaara & Andersson, 2018). There is also evidence that parental education is associated with children's occupation in adulthood (Erola et al., 2016).

2) What individual- and family-level factors contribute to/protect against mental distress among Millennials in consistently precariously employed subgroups?

Hypothesis 2. Millennials in subgroups marked by consistent precarious employment will be at higher risk for onset of mental distress compared with Millennials in subgroups with lower intensity precarious employment trajectories.

Research aim 3: To explore cross-state variances in the labor market and social protection benefits and the moderating role of social welfare benefits on the relationship between precarious employment and mental distress.

The analysis for this research aim involves a quantitative assessment of whether the level of social welfare protection *available* in respondents' respective states moderates the association between each employment quality cluster and mental distress. Building off the models fitted for Research Aim 2, unemployment insurance, minimum wage, and state earned income tax credit (EITC) rates are explored for moderation effects. The specific research question addressed under this study aim is whether the availability of certain social protection policies moderates the relationship between precarious employment and mental wellbeing among Millennials.

Hypothesis 3. The availability of more generous social welfare programs will moderate the relationship between precarious employment and psychological distress, reducing the effect of PE on psychological distress.

Chapter 5. Methodology

5.1. Research Design

This study involved the use of *longitudinal* data from an ongoing panel study in the United States, the Panel Study of Income Dynamics (PSID). Based out of the University of Michigan's Institute for Social Research, PSID is the longest running longitudinal study in the world (first wave of data collection occurred in 1968). To explore Millennial employment trajectories and their mental health consequences in the wake of the Great Recession, this study leveraged individual data for the years 2009 through 2019. Importantly, by following the same individuals across time, this secondary dataset allows for a more precise measurement of employment trajectories compared to studies leveraging independent samples. All three research aims entailed quantitative analyses using these PSID data.

5.2. Sampling

To understand Millennial employment trajectories in the years following the Great Recession, data for this study were limited to the survey waves that capture Millennials' work experiences in the years between 2009 and 2019. Specifically, given the biennial frequency of data collection, PSID data came from the following survey waves: 2009, 2011, 2013, 2015, 2017, 2019. With respect to the sample, all reference subjects and their spouses born between 1981 and 1996 (28-43 years of age at the time of the interview) were included in the analysis, with the exception of Millennials who repeatedly indicate being unable to work at all, retired, or keeping house.[21] Although it was possible that Millennials move in and out of school and/or training categorizations throughout the study period, individuals in school or in training *were not*

[21] PSID asks respondents about their current work status at each survey wave. I will exclude those who endorse the "permanently disabled; temporarily disabled, " "housewife; keeping house," or "retired" response options *across all six timepoints* included in this analysis (arguably those who indicate this status across six waves of data collection (i.e., ~12 years).

excluded from the analysis—the time-varying nature of these characteristics was instead be accounted for in the analysis.

As such, this was not a comparative study where the employment trajectories and mental health outcomes of Millennials were compared to their counterparts in the Generation X and Boomer generations. Rather, this analysis was restricted to those born between 1981 and 1996 (and who met the aforementioned criteria regarding desire and ability to work). This age range is consistent with the Pew Research Center's definition of the Millennial generation, though strict adherence to this age range is not without limitations: It is likely, for example, that an individual aged 43 would be more similar (culturally, professionally, etc.) to someone aged 44 compared to a 28-year-old.

The following sub-section describes the process for identifying eligible Millennial participants from the "main" PSID data files, including the specific steps undertaken to 1) create unique identifiers for each household member and to 2) link household heads and their spouses to their respective employment and mental health data across time.

5.2.1. Data Structure and Sample Extraction

The initial 1968 study sample consisted of 4802 families across 40 states, including an oversample of 1872 low-income households and a nationally representative sample of 2930 households. Over the past 50 years, the panel survey has evolved to reflect demographic changes within the original study sample (i.e., children of original-sample members establishing their own family units) as well as trends in immigration. Regarding the latter changes, PSID undertook multiple rounds of refresher sampling, including the addition of a new immigrant sample in 1997/1999 and 2017. In 2019, a total of 9,569 households participated in the PSID survey, providing data on 26,084 household members.

Two types of "main" PSID data files are available for researchers to download: single-year family files (41 single-year family files in total, from 1968 through 2019) and a single cross-year individual file. As the name suggests, the single-year family files contain *family-level* variables related to household income dynamics, household wealth, household expenditures, household debt, etc. It is important to note that employment-related data in the family-level data file pertain only to the *reference person* (formerly known as the "head of household") and *partner/spouse.* For example, in the 2009 family-level data file, the two "salary amount" variables, ER42182 and ER42434, correspond to the salaries of the reference person and partner/spouse, respectively. Furthermore, only the *household member responding to the family survey* (i.e., the person providing all information regarding the characteristics of household members, household wealth, and household income dynamics to the surveyor) completes the 6-item Kessler psychological distress scale (K-6)[22]—in the overwhelming majority of cases, the family survey respondent is either the reference person or spouse. In other words, while the family-level file for a given survey wave contains employment data on two household members (the head of household and partner/spouse), mental health data for that survey wave are available for only a *subset* of these individuals with employment data.

The second type of data file available to researchers is the cross-year individual file. This file contains records for every individual who has ever lived in a PSID study household.[23] In addition to sociodemographic information (e.g., age, sex) and several health insurance variables, this file contains important information regarding the individual's relationship to the head of household/reference person in a given survey year (i.e., an individual is either a reference person, spouse, child, brother/sister, or parent.). Because employment data in the family-level data file

[22] PSID introduced the K-6 as a measure of emotional distress beginning in 2001.
[23] Each row in the cross-year individual file corresponds to a particular household member in a given survey year.

pertain only to reference persons and spouses, it is imperative that the cross-year individual file be used to identify which household members are the reference person and spouse/partner in a given survey year. In short, assembling a dataset that allows for analysis of employment- and mental health-outcomes at the individual-level requires the use of both single year *family files* (files which contain all the employment and mental health-related data) as well as the cross-year individual file (which allows the researcher to identify how each household member in a given survey wave is related to the household reference person).[24]

Identifying PSID Household Members across Time

As the individual serves as the unit of analysis for all study analyses, the first step in preparing the data files for analysis involved creating an individual identifier variable. Per PSID data management guidance, this unique individual identifier variable was generated using a combination of two pre-existing variables: the 1968 Family Interview Number variable (ER30001) and the household person number variable (ER30002). Specifically, the following equation was used to create the unique ID variable: (1968 Family Interview Number * 1000) + Person Number.[25]

Linking Individuals to their Respective Employment Data

Because employment data are available only for the reference person and spouse/partner, the next step after creating a unique ID variable involved identifying which household members in the individual-level file were reference persons or spouses/partners between 2009 and 2019.

---

[24] Data were downloaded from the PSID data center (https://simba.isr.umich.edu/default.aspx) in November 2022 using the Variable List data download option. This method allows for researchers to copy and paste an exhaustive list of all desired variables for their analyses (including variables from both the single-year family files and cross-year individual file) into the search engine. The resulting data file is a long format file where each row represents an individual household member in a given year (e.g., respondent 4180 in 2009).

[25] The following Stata command was used to generate this unique identifier: gen unique_id=(ER30001 * 1000) + ER30002

Per PSID guidance,[26] individuals who, in a given survey year, had a value of 1 for the "Sequence Number" variable *and* a value of 10 for "Relationship to Reference Person" were flagged as reference persons. Spouses/partners, meanwhile, had values of 2 for "Sequence Number" and either 20 or 22 for "Relationship to Reference Person." All household members who were not the reference person or spouse/partner in 2009, 2011, 2013, 2015, 2017, and 2019 were dropped from the dataset. Once all reference persons and spouses/partners for the study period (2009-2019) had been identified, eligibility criteria related to respondent age and labor force status (e.g., disability, keeping house, and retired status) were applied.

A total of 9991 individuals in the family-level datasets were identified as Millennials, 1320 of whom were classified as household heads or spouses (i.e., individuals with corresponding employment-related data). Of these 1320 Millennial heads and spouses, 17 individuals reported being disabled, retired, or keeping house across all six timepoints, rendering them ineligible for study inclusion. Thus, the final sample for Research Aim 1, which aims to identify employment quality trajectories among Millennial respondents, was 1303. While there is no steadfast rule regarding the requisite sample size for the proposed statistical approach to identify employment trajectories—growth mixture modeling (GMM)— this study's sample size far exceeds the minimum threshold required to identify at least four latent classes assuming low proportions of missing data (Kim, 2012; Muthén, 2004). Indeed, researchers have leveraged GMM techniques with samples as small as 300 subjects, with acceptable maximum likelihood estimation (Kim, 2012).

Linking Individuals to their Respective Mental Health Data

---

[26] Detailed information regarding how to assemble a Reference Person/Spouse file from an individual file is available on the PSID FAQ page: https://psidonline.isr.umich.edu/Guide/FAQ.aspx (#7--"How do I assemble a Reference Person/Spouse file from an individual file?)

As noted above, only the household survey respondent in a given survey wave completes the psychological distress screener.[27] As such, a critical step in linking survey respondents to their respective mental health data involved aligning the value of the "survey respondent" variable with that of the "Relationship to Reference Person" variable. For example, if the survey respondent for the 2009 survey wave was the household reference person, then the value for the "survey respondent" variable would be 1 and the value for the "Relationship to Reference Person" variable would be 10. As only Millennial reference persons and spouses/partners were relevant to the study at hand (employment quality data are only available for reference persons and spouses/partners), a variable was created for each timepoint to denote whether the household member was the survey respondent *and* the household reference person or spouse.[28]

Once survey respondents for each survey wave were confirmed to be either reference persons or spouses/partners, then it was necessary to determine the number of times across the study period (2009-2019) these individuals completed the psychological distress screener. For example, a household's reference person may have been the survey respondent in 2009, 2013, and 2015 while the spouse/partner may have been the survey respondent for waves 2011, 2017, and 2019 (in this case, each individual has a total of 3 mental health timepoints). Respondents were dropped if they had mental health data for fewer than three timepoints (i.e., if they were the respondent for fewer than three survey waves). As will be detailed in the "data analysis plan"

---

[27] In the long data file that was downloaded from the PSID data center (based on the variable list input), each household member in a given survey year would have *the same* values for the mental health screener. In other words, the mental health responses provided by the survey respondent were assigned to every household member.
[28] For example, the Stata code for ensuring the survey respondent is either the reference person or spouse in 2009 would be as follows:

```
gen resp_match_2009=0
replace resp_match_2009=1 if (ER46697==1 & ER34003==10) | ((ER46697==2 &
ER34003==20)|(ER46697==2 & ER34003==22))
```

where ER46697 denotes the survey respondent and ER34003 denotes the relation to household reference person—values of 10 and 20/22 correspond to reference person and spouse/partner, respectively.

subsection (p. 64), models for the mental health analyses were fitted for those with 3, 4, 5, and 6 mental health data points (i.e., the effect of employment quality class membership on psychological distress outcomes was assessed separately for those with 3, 4, 5, and 6 mental health data points).

5.3. Measures

5.3.1. Dependent Variable—Mental Health

The Panel Study on Income Dynamics uses the Kessler Psychological Distress Scale (K-6), which contains six items designed to identify adults with significant psychological distress based on questions related to anxiety and depression. Respondents are asked to indicate how often in the past 30 days they experienced each feeling (e.g., being nervous, hopeless, restless or fidgety, worthless) on a 5-point Likert scale, where 0=all of the time and 4=all of the time (range 0-24). The scores of the six items are summed, with a score of 13 or higher indicating serious mental illness (SMI) (Kessler et al., 1996). Because this 13 or higher cut-off score on the K-6 scale might overlook individuals who are below the threshold for a SMI but who are nevertheless experiencing depressive and anxiety symptoms, two binary variables were created for the purposes of this dissertation study, one for severe distress and a second for moderate distress.

Respondents received a score of 1 for severe psychological distress if they endorsed a total score of 13 or higher on the screener. For moderate distress, respondents received a score of 1 if they endorsed a total score of 5 or higher on the screener (this would also include all those who met the threshold for severe distress) and a score of 0 if they did not meet this “moderate distress” threshold—this cutoff value for moderate distress has been found to be valid and consistent across diverse ethnic/racial groups (Prochaska et al., 2012) and has since been applied in occupational health studies (Eisenberg-Guyot et al., 2020). An overview of the mental health items included in the PSID survey is provided in Table A1 in Appendix A (p. 178). As noted in Table 1, the six K-6 items were reverse-coded to ensure higher scores reflected greater levels of psychological distress.

The rationale for this study's use of the K-6 to capture mental health outcomes is rather straightforward. It is the only mental health measure available in the PSID dataset. This limitation of secondary data analysis aside, psychological distress is the ideal mental health measure for a study such as this one, which aims to explore the psychological ramifications of insecure work. Study after study in behavioral economics has demonstrated that when it comes to economic choices, the overwhelming majority of Americans do not view losses and gains equally. Rather, losses (e.g., drops in income, downward mobility) are much more psychologically difficult than gains (Hacker, 2019). Much like the age-old adage "one in the hand is worth two in the bush," research shows that most people would rather maintain the economic security they have than risk losing it for the *possibility* of financial gain (Hacker, 2019; Kahneman & Tversky, 1979; Pew Charitable Trusts, 2015). Given this "aversion to loss," possible psychological responses to the negative experience of economic insecurity would include non-specific symptoms of stress, anxiety, and depression (i.e., psychological distress).

With respect to the psychometric properties of the K-6, previous research has shown the scale to have excellent reliability and validity. Originally developed for use in the U.S. National Health Interview Survey (NHIS), the six-item scale had an alpha of 0.92 in the NHIS pilot study and yielded consistent levels of severity across sociodemographic subgroups (Kessler et al., 2002). Importantly, the scale was found to be extremely sensitive in distinguishing cases versus non-cases of serious mental illness. The K-6 has since been validated for use with other populations (e.g., adolescents, youth, and the elderly) as well as with non-English speaking populations (Easton et al., 2017; Mewton et al., 2016; Min et al., 2015).

5.3.2. Independent Variable—Employment Quality

As noted in the background section, there are two multidimensional measures of precarious employment that are widely used in contemporary studies on employment conditions and their social consequences: multidimensional precarious employment (PE) measures (e.g., the Employment Precariousness Scale (EPRES)) and the employment quality (EQ) construct. This study opts for the latter, more *objective measure* of employment conditions, building on the work of scholars in Europe and the United States (e.g., Andrea et al., 2021; Eisenberg-Guyot et al., 2020; Van Aerden et al., 2016) who have operationalized employment quality based on the following seven dimensions: 1) *employment stability* (the continuity of employment); 2) *material rewards* (the wage and non-wage benefits of the job); 3) *worker's rights and protection* (upholding labor rights, such as the right to protection from workplace discrimination or overtime pay); (4) *working-time arrangements* (the predictability and duration of working hours); 5) *training and employment opportunities* (the opportunities available to advance one's skills/position in workplace); 6) *collective organization* (the presence of worker representation organizations—e.g., union membership); and 7) *interpersonal power relations* (the degree of decision-making power held by worker).

The rationale for using a more objective measure of precarious employment is twofold: First, as Eisenberg-Guyot and colleagues (2020) have noted, it is possible that participant responses to subjective measures of precarious employment included in the Employment Precariousness Scale (e.g., "afraid to demand better working conditions," "made to feel easily replaceable") are affected by family- or community-level factors outside the employment relationship. Second, given that this proposed project involves secondary data analysis, I am limited to the items available in the PSID questionnaires, all of which are objective items pertaining to the respondent's employment relationship.

A total of six proxy-indicators for employment quality, which map onto the five dimensions described above, were used to examine employment quality in the post-Great Recession period. Because PSID does not collect information pertaining to promotions[29] and interpersonal relations[30] in the workplace, this study was unable to operationalize these two dimensions of employment quality. An exhaustive description of and coding scheme for each of the items is presented in Table B1 in Appendix B (p. 179)). In brief, each dimension of employment quality was worth 1 point for a total score ranging from 0 to 5 (each sub-dimension of the second dimension, material rewards), was worth half a point. The five dimensions of employment quality were operationalized as follows:

- *Employment stability:* The variable "unemployed in the past year" was used to assess employment stability. Respondents who endorsed being unemployed in the past year received a score of 0; those who were not received a score of 1.

---

[29] While there is no clear-cut variable within the questionnaire to examine employment opportunities, I had originally planned to use a proxy indicator to assess employment opportunities. This indicator was to be based on **whether respondents had received a raise greater than the standard 3% increase/year since the last survey period.** However, upon closer inspection of the downloaded data files, I learned that there is no variable in the 2009-2015 datasets among *hourly workers* that corresponds to annual wages/salary amount for current main job. Rather, hourly worker respondents are asked to report annual income for *all jobs.* Given that I would only be able to gauge changes in annual salary for salaried workers, who constitute a minority of the Millennial sample (less than one-quarter of Millennial heads/spouses are salaried workers), I decided not to include this employment opportunities dimension when constructing the employment quality composite variable.

[30] Eisenberg-Guyot et al. (2020) leveraged PSID's item on self-employment status as a proxy for interpersonal power relations, arguing that those who are self-employed would have a greater degree of autonomy than those who are not. While this may be true, a binary self-employed/not self-employed categorization of interpersonal power relations does not account for those who are not self-employed but hold managerial positions within an organization. Moreover, there are inherently *no interpersonal relations* in a self-employment situation, which makes this choice of proxy for interpersonal relationships in the workplace even more dubious.

- *Material rewards:* Two indicators were used to measure the wage and non-wage benefits dimensions of material rewards. Guided by the approach adopted by Eisenberg-Guyot et al. (2020) in their study on the health effects of employment quality, respondents' **annual income from all jobs** (in 2019 dollars—i.e., adjusted for inflation) was used to capture the wage-related component of material rewards, while the provision of **employer-based health insurance** (yes/no) corresponded to the non-wage subdimension of material rewards. Each sub-dimension was worth 0.5 points.
    - *Annual income from all jobs*: PSID asks respondents at each survey wave to provide the total wages/salary earned by reference persons and spouses/partners from all jobs in the previous year. To account for the positive skew of income data, a variable was first created to represent the natural log of each participant's income (ranging from 0 to 13.305). Next, to convert this variable to a scale from 0 to 1, the natural log value for each participant was divided by the highest natural log odds value for income across all timepoints (13.305) (as such, the individual with the highest natural log income value across the six survey waves would have a value of 1).
    - *Employer-based health insurance:* At each survey wave, PSID asks respondents to report the source of health insurance/health care coverage for each household member. Millennial heads and spouses/partners who indicate receiving employer provided health insurance (current or former employer) were assigned a score of 1; all others were assigned a score of 0.

- *Workers' rights and protections:* Whether respondents "**would get paid for extra hours of work**" (yes/no) was used to operationalize this dimension of EQ.[31] Those who indicated receiving overtime pay received a score of 1; all others received a score of 0.
- *Working-time arrangements*: **Average hours a week worked on all jobs in the previous year**, was used to assess long working hours. Consistent with the method employed for annual income, the average work hours variable was converted to a 0 to 1 scale by dividing each respondent's "average hours" value by the highest value reported across the six survey waves.[32] The individuals with the highest value for average hours worked per week (112 hours) received the maximum score of 1 on the 0-to-1 scale.
- *Collective organization:* Whether respondents **belong to a union *or* hold jobs covered by a union contract** was used to assess collective organization. At each survey wave, participants who endorsed either of these criteria were awarded a score of 1; those who did not were assigned a score of 0.

Other researchers who have leveraged this seven-dimensional construct of EQ in their analyses have faced similar limitations regarding availability of employment quality indicators in their respective datasets, necessitating a project-specific approach to generating and scoring the EQ measure. Eisenberg-Guyot et al. (2020) and Andrea et al. (2021) were able to map indicators

[31] There is no item within the PSID questionnaires that assesses experienced workplace discrimination or policies in place to prevent/address discrimination.
[32] I had initially considered grouping average weekly hours into quartiles and then assigning those in quartiles 2 and 3 a score of 1 and those in quartiles 1 and 4 (i.e. very low and very high weekly hours) a score of 0. However, after careful consideration, this seemed like a subjective tactic, as I have no way of knowing the respondents' preferences with respect to work hours. For example, it could be the case that someone working 60 hours a week is quite content with his/her work schedule and the income earned based on these higher weekly hours.

from their respective datasets onto six of the seven dimensions of EQ—it is worth noting that each of these authors used a different number of items for their EQ measure (the former used six items while the latter used 10 items to operationalize EQ). Oddo et al. (2020) were able to operationalize all seven dimensions of precarious employment using data from the National Longitudinal Survey of Youth; however, unlike Andrea et al.'s (2021) approach of assigning greater weight to certain items based on the findings from a principal components analysis, Oddo et al. assigned each dimension one point for a total EQ score of seven.

Related to this issue of data availability hindering standardization of a multidimensional EQ measure is the question of the psychometric properties of the EQ measure. While mental health screeners such as the PHQ-9, the K-6, and the GAD-7 have been subject to rigorous psychometric testing over the years, to date there have been no efforts to test the reliability and validity of the EQ. Rather, the construct of EQ is a theory-driven construct that researchers have operationalized based on the data available to them. Because no two datasets are the same (i.e., a researcher in Sweden might have access to a different set of employment indicators than a researcher working off data collected in England), it is not yet possible to standardize EQ in the same manner that mental health practitioners have managed to standardize measures to assess the mental health status of a patient. Indeed, as Kreshpaj and colleagues (2020) note in a systematic review of definitions and operationalizations of precarious employment, there is no shortage of theory-driven definitions of precarious employment. Rather, the problem is that current operationalizations of precarious employment in quantitative research studies are an "accommodation" to available data. These limitations aside, it is important to emphasize that the multidimensional EQ construct is theoretically sound and rooted in the seven dimensions of employment precarity that have been identified as salient by both occupational health researchers and the labor movement.

5.3.3. Moderating Variables—Social Welfare Policies

Moderating effects of social welfare and labor market policies—state EITCs, unemployment insurance, and state minimum wage laws—on mental health outcomes of millennials were explored *in separate moderation models.* This helps us understand how, if at all, these policies influence the strength of the relationship between employment quality and mental health.[33] *For each state*, state EITC rates, unemployment insurance, and minimum wage levels were calculated for each PSID data collection wave (i.e., 2009, 2011, 2013, 2015, 2017, and 2019). Each year-specific policy variable (e.g., minimum wage level for the state of New York in 2009) was then be mapped to respondents living in that respective state at each survey wave.[34]

Like the federal EITC, **state EITCs** provide a credit to taxpayers based on their income and family situation (i.e., number of dependents and marital status). In the majority of states, these credits—like the federal EITC—are refundable, meaning that if the refundable credit is greater than the state income tax owed, then the taxpayer would receive the excess amount of the credit as payment from the state. For the purposes of this analysis, a **state EITC rate variable** was created that denotes a state's EITC rate as a percentage of federal credit. For example, in 2017 the EITC offered by the state of California was 85% of the federal credit amount, which was reflected as "85.0" in the dataset. States that do not offer refundable EITCs (or do not offer

[33] For a discussion of the rationale for including these specific policies in the analyses, please refer to the footnote on page 36.
[34] In terms of how this worked from a data management perspective, I first created separate PSID files based on year (six files, one for each survey wave) and then merged in state-level moderating variables, using "current state" as the merging ID. Once I had six merged PSID-state datasets (one for each timepoint), I appended the six datasets.

EITCs at all) have values of 0 for this variable. All state-specific EITC rates over the study period (2009-2019) were pulled from the University of Kentucky Center for Poverty Research Welfare Dataset (https://ukcpr.org/resources/national-welfare-data).

Unemployment insurance (UI) values were based on state replacement rates, which refers to the proportion of worker wages replaced by unemployment insurance. Data for these variables were pulled from the U.S. Department of Labor's online "Unemployment Insurance Chartbook" (https://oui.doleta.gov/unemploy/chartbook.asp). State-level data were downloaded for the years corresponding with PSID survey waves (2009, 2011, 2013, 2015, 2017, and 2019).

State-specific **minimum wage** information (adjusted for constant dollars) was pulled from the US Department of Labor's historical tables recording changes in basic minimum wages in non-farm employment (Department of Labor, 2022). For the purposes of this study, year-specific minimum wage levels were generated for each state, such that each state has a value for the years 2009, 2011, 2013, 2015, 2017, and 2019 (300 variables in total will be created in this process). Next—and consistent with the procedure for EITC and UI variables—state- and year-specific values were assigned to individuals based on the state in which they resided at each survey wave. Note that here were a handful of states (e.g., Kansas) who had state minimum wage values that were *lower* than the federal minimum wage value. In such cases, the federal minimum wage ($7.25) was used in lieu of the state value given that employees covered by the Fair Labor Standards Act (FLSA) are entitled to the federal minimum wage—the vast majority of workers in the United States fall under the protection of the FLSA An example of the categories of workers exempt from minimum wage provisions of the Fair Labor Standards Act include farm workers employed at small farms, tipped workers (so long as these workers receive at least $5.12 an hour in tips), full-time students, and youth under the age of 20 in their first 90 consecutive days of employment, and workers in the fishing industry—the state minimum wage value applied to only a handful of participants in this study sample.

In sum, state-specific EITC, minimum wage, and unemployment insurance variables were generated for each PSID data collection (2009, 2011, etc.). These state-and year-specific values were then assigned to each study participant based on his/her state of residence at the relevant timepoint. For example, a PSID respondent who indicated living in New York state in 2009 has corresponding variables for NY minimum wage levels, state EITC rate, and unemployment insurance coverage for 2009. Should that individual have moved to a different state in 2011, then the values for minimum wage, EITC, and UI variables would correspond with the 2011 values for that state.

5.3.4. Covariates

A series of time-varying and time invariant covariates were included in the analyses to identify employment trajectories and to assess each trajectory group's risk of mental distress onset. Key sociodemographic variables that were explored in these analyses include *sex* (time-invariant—as reported at baseline[35]), *race/ethnicity* (time-invariant—as reported at baseline), *immigrant status* (time-invariant—as reported at baseline), *education level* (time-varying), *parents' education level* (time-invariant—as reported at baseline), *marital status* (time-varying), *region* (time-varying), and *rural/urban residence* (time-varying). For the Research Aim 1 analyses exploring the sociodemographic characteristics of individuals in each identified subgroup of employment quality, the blue collar-white collar status of participants was also examined. Specifically, participants were classified into four groups: blue-collar, high skill; blue-

[35] In this context baseline refers to the first of six survey waves included in this analysis (i.e., 2011 survey).

collar-low skill; white collar-high skill; and white-collar-low skill. Table C1 in Appendix C (p. 182) presents a comprehensive summary and coding scheme for each of these covariates.

5.4. Data Analysis Plan

Research aim 1: To identify subgroups of precarious employment trajectories among Millennials residing in the United States in the years following the Great Recession (2009-2019).

The goal of this aim was to identify employment trajectory classes. Growth mixture modeling (GMM), an extension of growth curve modeling, was used to identify multiple subgroups within employment quality data and to describe subgroup differences in longitudinal change between and within these unobserved groups.[36] Specifically, GMM identifies *unobserved* subgroups (i.e., class membership is a latent variable) based on responses provided/observations measured on multiple occasions—in this case, the employment quality composite score observed across six waves of data collection (2009-2019). Growth mixture models provide information about the mean change in employment quality between the unobserved groups, the extent of interindividual differences in change in employment quality, and the probability that each individual belongs to each group (Ram & Grimm, 2009).

Following the step-by-step procedures for GMM outlined by Ram and Grimm (2009), four steps were implemented to conduct the GMM analysis: 1) problem definition, 2) model specification, 3) model estimation, and 4) model selection and interpretation.

---

[36] A number of trajectory modeling techniques for longitudinal data could be leveraged for this research aim (e.g., repeated measures latent class analysis (RMLCA), group-based trajectory modeling, latent transition analysis. While RMLCA is arguably preferable given that it does not require distilling employment quality into a composite linear score (which might obscure the pernicious effects of certain combinations of employment conditions on mental health outcomes), ultimately this method was rejected given the large number of indicators and corresponding response categories comprising my employment quality measure (RMLCA models would have failed to converge given that the models would have included 36 indicators (6 items at each timepoint), with at least 4 response option indicators per item.

Characterized as the processing linking theory to method, **problem definition** entails formulating initial GMM hypotheses based on theory, existing research evidence, and preliminary examinations of the data. Relevant questions to consider during this step include the following: How many unobserved groups might be expected based on longitudinal, individual plots of the raw data How do these anticipated unobserved groups differ with respect to mean change and interindividual differences in change? Next, a series of baseline single-group curve models (linear, quadratic, etc.) were fitted in order to "find the best single-group representation of change" (Ram & Grimm, 2009, p.5).

Model specification involves specifying a series of multiple group models, with attention to if and how groups differ with respect to mean change in EQ (a *Means* only model) and the extent of interindividual differences in change (a *Means+Covs* model). Ram and Grimm (2009) suggest fitting sets of models that allow for the possibility of at least one more group than the number of groups anticipated. As three unobserved groups of employment quality trajectory were expected (one stagnant, one with positive growth, and one with negative growth), I fitted models to accommodate the possibility of four EQ subgroups. Accordingly, I began with 2-class models, initially fitting a 2-class linear as well as a 2-class quadratic model, assuming no variation in intercepts among members of the same unobserved subgroup. I then ran two additional sets of 2-class linear and quadratic models, allowing for random intercepts for class 1 only and then both classes. Finally, I ran a series of 2-class linear and quadratic models allowing for the possibility of random slope variation for class 1 and then for classes 1 and 2. These same steps were repeated for 3- and 4-class models: fully-constrained models were fitted, followed by models allowing for random intercepts for class (random intercepts allowed for one class at a time—i.e., class 1, then classes 1 and 2, then classes 1, 2, and 3, etc.), and finally, allowing for random slopes (again, random slopes allowed for one class at a time).

With respect to **model estimation**, GMM models can be estimated using either maximum likelihood or Bayesian methods. Mplus 8.9, the statistical program used to estimate GMM for this study, uses the expectation-maximization (EM) procedure, where parameter estimates (means, variances, covariances) and posterior probabilities[37] of individual class membership are obtained through iterative procedures to maximize the likelihood of the observations given the model parameters. Mplus uses full information maximum likelihood to accommodate missing data on the outcome variable (i.e., employment quality).

Model selection involves determining which of the fitted models provides the "best" fit of the observed data. As there are no "deterministic" set of rules to follow to select the best-fitting model (Ram & Grimm, 2009), model selection incorporates theory, prior research findings, and a number of fit statistics. Following the model selection steps for GMM outlined by Ram & Grimm, I first examined the estimation output for each fitted model, paying close attention to any problems in estimation or out-of-bound estimates (e.g., the analysis output or error messages suggesting negative variances). Beyond verifying that the models make sense mathematically, I also examined the conceptual soundness of each model. For example, a four-class model where two classes have nearly identical employment quality intercept and slope is less compelling conceptually than a three-class model with distinct change patterns for each subgroup.

Next, I compared the relative fit *information criteria* of the models, specifically the Bayesian Information Criteria (BIC) and Akaike Information Criteria (AIC). Lower values for

[37] Posterior probabilities refers to the probability of assigning observations to groups given the data.

these information criteria indicate better fit. Random intercept and slope models that did not fit better than the baseline (fully constrained) models were not retained. The best fitting models for each two-class, three-class, and four-class series were retained and further examined.

Finally, I assessed for each fitted model the confidence with which study participants were classified as belonging to a particular subgroup. Two statistics in particular from the model outputs were examined: the *entropy* values and the *average latent class probabilities for most likely class membership***.** Entropy is a statistic of classification probability quality ranging from 0 to 1, with higher values indicative of clearer delineation of classes (Celeux & Soromenho, 1996). Entropy values above 0.8 indicate that individuals have been placed into subgroups with high confidence. Mplus output also provides information on the average latent class probabilities for the most likely latent class membership. This table indicates the percentage certainty that individuals were assigned to each class (e.g., individuals assigned to class 1 were, on average, assigned with 86% certainty, individuals assigned to class 2 had a probability of 94.8% of belonging to class 2, etc.—classification accuracy on average would be considered high for both these classes).

Research aim 2: To examine associations between precarious employment trajectory subgroups and mental distress in the post-Great Recession period

Once trajectory classes had been identified, mixed-effects logistic regression models were fitted to examine the contribution of each employment quality trajectory to psychological distress. Mixed-effects logistic regression is typically used for modeling binary outcome variables when data are clustered (e.g., time nested within persons in the case of longitudinal data and/or persons nested within group such as schools, families, etc.) or there are both fixed and random effects (University of California, Los Angeles, n.d.). This technique is therefore appropriate given the *binary mental health variable* (i.e., meets the threshold for moderate/severe psychological distress or not), the *clustered nature of the data* (repeated measures nested within individuals), and the time-varying and time-invariant nature of the covariates.

For the purposes of this research aim, mixed-effects logistic regression was used to assess the longitudinal relationship between employment quality group membership and risk of psychological distress. In these models, sociodemographic variables with more than three categories were dichotomized when it was possible and meaningful to do so. Specifically, parental education level was recoded into a binary variable to reflect whether the parents (either mother or father) of each respondent had completed college. While other researchers have dichotomized race/ethnicity for the purposes of regression analyses (e.g., Eisenberg-Guyot et al., 2020), the three-category race/ethnicity variable was maintained for the regression models.

Three fully adjusted models were run, the first of which accounted for the influence of all covariates found to be marginally significant in bivariate analyses with severe or moderate psychological distress (respondent's age was included in all regression models regardless of significance in bivariate analyses). Following backward variable selection procedures, the least significant variable was removed in each additional model until only significant variables ($p<0.05$) remained in the final (third) model.

The log odds of the event (meeting the threshold for moderate psychological distress) can be expressed mathematically in the following models:

Model 1: Unadjusted: $\eta_{ti} = (\beta_{0i} + u_{0i}) + \beta_1(\text{EQ trajectory class}_{ti}) + e_{ti}$……………………………..*(Eq 1)*

Model 2: Adjusted (Model 1): $\eta_{ti} = (\beta_{0i} + u_{0i}) + \beta_1(\text{EQ trajectory class}_{ti}) + (\beta_2 + u_{2i})(\text{age}_{ti}) + \beta_3(\text{sex}_{ti}) + (\beta_4 + u_{4i})(\text{marital status}_{ti}) + (\beta_5 + u_{5i})(\text{education}_{ti}) + (\beta_6 + u_{6i})(\text{residence}_{ti}) + \beta_7(\text{race}_{ti}) + \beta_8(\text{immigrant}_{ti}) + e_{ti}$------------*(Eq.2)*

where,

- η_{ti} (eta) represents the log-transformed predicted value (i.e., $\ln\left(\frac{\hat{P}}{1-\hat{P}}\right)$) of moderate psychological distress repeatedly measured at time t for individual i ;
- β_{0i}: represents the global intercept for individual i;
- β_1(EQ trajectory class$_{ti}$): indicates the slope of a precariously employed EQ trajectory class compared to reference group (more stable employment)
- β_2(age$_{ti}$): indicates the coefficient for each additional year of age
- β_3(sex$_{ti}$): indicates the coefficient for women (compared to men)
- β_4(marital status$_{ti}$): indicates the coefficient for non-married/cohabitating (a)
- β_5(education$_{ti}$): indicates the coefficient for education (reference group will be high school)
- β_6(residence$_{ti}$): indicates the coefficient for rural residence (compared to urban residence)
- β_7(race$_{ti}$): indicates the coefficient for race (white as reference group)
- β_8(immigrant$_{ti}$): indicates the coefficient for immigrant respondents (compared to non-immmigrant respondents)
- u: indicates the random intercepts
- e_{ti} represents the subject's residuals or error terms

Research aim 3: To explore cross-state variances in labor market and social protection benefits and the moderating role of social welfare benefits on the relationship between precarious employment and mental distress

This component of the study involved a moderation analysis to explore whether receipt and availability of certain social protection and labor market policies influence the strength of the relationship between precarious employment and mental health. An extension of the longitudinal models fitted for the second research aim, each social welfare policy (i.e., state EITC, minimum wage legislation, and unemployment insurance), was assessed separately in moderation analyses—three moderation models in total. As an example, the unadjusted and adjusted models for **minimum wage legislation** would be as follows:

Model 3: Unadjusted minimum wage model (inclusion of minimum wage as covariate in Eq.2):

$\eta_{ti} = (\beta_{0i} + u_{0i}) + \beta_1(\text{EQ trajectory class}_{ti}) + (\beta_2 + u_{2i})(\text{age}_{ti}) + \beta_3(\text{sex}_{ti}) + (\beta_4 + u_{4i})(\text{marital status}_{ti}) + (\beta_5 + u_{5i})(\text{education}_{ti}) + (\beta_6 + u_{6i})(\text{residence}_{ti}) + \beta_7(\text{race}_{ti}) + \beta_8(\text{immigrant}_{ti}) + \beta_9(\text{minimum wage benefit}_{ti}) + e_{ti}$ ------------*(Eq.3)* *where*

β_9(minimum wage benefit$_{ti}$): indicates the minimum wage coefficient for individual *i at* time *t*

Model 4: Adjusted minimum wage model (Eq.3 plus multiplicative term)
$\eta_{ti} = = (\beta_{0i} + u_{0i}) + \beta_1$(EQ trajectory class$_{ti}$) + $(\beta_2 + u_{2i})$(age$_{ti}$) + β_3(sex$_{ti}$) + $(\beta_4 + u_{4i})$(marital status$_{ti}$) + $(\beta_5 + u_{5i})$(education$_{ti}$) + $(\beta_6 + u_{6i})$(residence$_{ti}$) + β_7(race$_{ti}$) + β_8(immigrant$_{ti}$) + β_9(minimum wage benefit$_{ti}$) + β_{10}(EQ trajectory class$_{ti}$)*(minimum wage benefit$_{ti}$) +e_{ti}------------ *(Eq.4)*

where

β_9(EQ trajectory class$_{ti}$)*(minimum wage benefit$_{ti}$): indicates the coefficient for the minimum wage by EQ trajectory class interaction for individual *i at* time *t*

The same unadjusted and adjusted models were fitted for the remaining two moderating variables—the state EITC and state unemployment insurance.

5.5. Missing Data

Without appropriate protocols in place, missing data in a study as quantitative-heavy as the one proposed here can lead to decreased statistical power, biased estimates of parameters, and reduced generalizability of findings. As such, prior to fitting regression models, analyses were performed to determine whether missing data for the outcome variable (psychological distress) were systematically or randomly missing. Little's test for missing completely at random (MCAR) and the dummy variable approach for MCAR were used to distinguish between MCAR and missing at random (MAR)—the latter approach involved creating a dummy variable for whether psychological distress variable was missing and then running t-tests and chi-square tests between this dummy variable and other variables (e.g., sex, race/ethnicity, education) to see if the missingness was related to values of these other variables (Janz, n.d.).

5.6. Research Ethics

The Institute for Social Research at the University of Michigan, where PSID is housed, requires applicants to complete registration forms describing the nature of their project prior to transferring de-identified, publicly-available data.[38] As part of this registration process, applicants agree to conditions such as not attempting to identify study participants and reporting any identification of study participants or data errors immediately to PSID. IRB approval was also obtained from Boston College *prior* to use of these secondary datasets (approval received on September 15, 2022).

[38] The majority of PSID data and documentation are de-identified, free, and publicly-available. Individuals who wish to obtain restricted data such as geospatial identifiers must provide a data security plan that meets PSID data safeguarding requirements and must have approval from their institution's human subjects review and/or privacy board. This project used de-identified PSID data.

Chapter 6. Results

6.1. Descriptive Analyses

6.1.1. Sociodemographic Characteristics

Sociodemographic characteristics of Millennial reference persons and spouses (n=1303) at timepoint 1 and timepoint 6 are presented in Table 1 on the following page.[39] The mean age of participants in 2009 (timepoint 1) was 25.1 years and the majority of Millennial reference persons/spouses were female (56.4%). With respect to highest level of education achieved, just over half (56.3%) of participants had completed high school and some college education and one third of (33.3%) had completed at least a college level of education. By 2019 (final timepoint), the percentage of college graduates had risen slightly to 37.2%. Over three-quarters (76.9%) of study participants self-identified as White and 13.8% as Black,[40] and most respondents (64.6%) lived in urban areas. In 2009, a plurality of respondents resided in the South (35.6%), followed by the West (25.5%) and North Central (24.3%) regions of the United States. The majority of respondents were married in 2009 (52.8%)—this figure increased 10 percentage points (to 62.7%) by 2019. Approximately 10% of participants were from families selected for the immigrant sample; these immigrant families were first interviewed in 1997 or 1999. Finally, as pertains to the educational attainment of respondents' parents (this study's proxy indicator for childhood socioeconomic status), the plurality of parents had completed high school, though nearly one-third of respondents' fathers and mothers had received a college degree (32.6% and 32.3% for fathers and mothers, respectively).

---

[39] Cross-sectional survey weights have been used for all descriptive analyses (i.e., the 2009 cross-sectional survey weights were used for descriptive analyses involving timepoint 1 data, 2011 cross-sectionals survey weights were used for descriptive analyses involving timepoint 2 data, etc.).

[40] An unweighted frequency distribution of race/ethnicity shows a higher percentage of Black participants: 37.0% Black participants (n=478) compared with 54.8% White participants (n=707).

Table 1. Sociodemographic characteristics of Millennial reference persons and spouses, Panel Study on Income Dynamics, 2009 (timepoint 1) & 2019 (timepoint 6) (n=1303)

	2009		**2019**	
Characteristic	% or mean (SE)	95% CI	% or mean (SE)	95% CI
Mean age	25.15 (0.09)	24.96-25.34	35.13 (0.10)	34.93-35.32
Sex				
Male	43.60	40.79-46.46	40.53	37.33-43.82
Female	56.40	53.54-59.21	59.47	56.18-62.67
Years of completed education	13.80 (0.10)	13.59-14.01	13.86 (0.14)	13.57-14.15
Education				
Less than high	10.37	8.28-12.90	10.78	8.64-13.37
High school	25.66	22.10-29.57	21.38	18.36-24.74
Some college	30.70	27.45-34.15	28.98	25.42-32.82
College	33.28	28.99-37.86	38.86	34.19-43.75
Race				
White	76.89	71.12-81.80	71.71	65.65-77.07
Black	13.79	9.93-18.84	15.35	11.08-20.88
Non-white	9.32	6.89-12.5	12.94	9.84-16.84
Residence				
Rural	34.98	60.01-68.97	18.64	14.78-23.22
Urban	64.62	30.55-39.68	80.48	76.00-84.30
Foreign country	0.40	0.11-1.42	0.88	0.44-1.740
Region				
Northeast	14.13	10.8-18.28	12.59	9.39-16.67
North Central	24.26	20.63-28.3	24.29	20.42-28.62
South	35.64	30.63-40.99	36.60	31.65-41.85
West	25.46	19.60-32.38	25.56	19.67-32.5
Alaska, Hawaii	0.10	0.01-0.76	0.08	0.001-0.61
Foreign country	0.40	0.11-1.42	0.88	0.44-1.74
Marital status				
Married/ cohabitating	52.76	48.58	62.91	57.73-67.82
Single, never married	44.13	40.03	26.78	22.44-31.62
Widowed,	3.10	2.09	10.31	7.98-13.21
Household part of immigrant sample	10.56	7.26-15.12	11.50	7.73-16.78
Highest education of father				
Less than high	9.01	7.27-11.10	9.24	7.47-11.37
High school	35.26	31.76-38.93	36.27	32.75-39.95
Some college	13.9	11.55-16.64	13.99	11.33-17.15

College	32.65	27.67-38.06	31.66	26.82-36.93
Don't know/refused	9.18	6.82-12.24	8.84	6.61-11.72
Highest education of mother				
Less than high	8.63	6.39-11.56	9.71	7.40-12.65
High school	33.67	29.56-38.05	35.32	30.77-40.16
Some college	19.69	16.91-22.80	18.51	15.43-22.04
College	32.26	27.62-37.28	31.17	26.39-36.38
Don't	5.75	3.81-8.59	5.30	3.41-8.15

6.1.2. Psychological Distress Characteristics

The frequency distribution of Kessler-6 Psychological Distress Scores across survey waves for participants with complete mental health data for all six timepoints is presented in Table 2. While there is no discernable pattern across time, it is noteworthy that characteristics of anxiety are more frequently endorsed by respondents than characteristics of depression. The overwhelming majority of respondents (more than three-quarters of respondents across all survey waves), for example, indicated experiencing sadness, hopelessness, and worthlessness *none of the time* in the past 30 days. Moreover, less than 10% of respondents across survey waves reported feeling hopeless or worthless *some of the time.* Meanwhile, the percentage of respondents who never experienced symptoms consistent with anxiety (nervous and restless in past 30 days, for example) was much higher across survey waves, ranging from 37.6% to 54.8%. Experiencing symptoms of nervousness and restlessness *some of the time* in the past 30 days was endorsed by close to one-third of participants across the study period. These discrepancies between this experience of anxiety versus depressive symptoms aside, it is worth underscoring that, overall, low percentages of participants indicated experiencing K-6 symptoms (whether anxiety or depressive symptoms) *most* or *all of the time.* “Feeling that everything was an effort” was the K-6 item with the highest percentage of participants endorsing an "all of the time" response—this percentage ranged from 3.24% (2017) to 5.7% (2015).

Table 2. Frequency Distribution of Kessler-6 Psychological Distress Scores by Survey Wave (2009-2019), among a Subset of Millennial Reference Persons and Spouses (n=572)

	2009 % /mean (SE)	**2011** % /mean (SE)	**2013** % /mean (SE)	**2015** % /mean (SE)	**2017** % /mean (SE)	**2019** % /mean (SE)
Sadness in past 30 days						
None of the time	72.47	74.85	77.94	74.60	71.87	77.98
A little of the time	13.41	13.38	10.96	12.52	14.36	10.28
Some of the time	10.99	9.14	10.27	10.52	12.56	10.20
Most of the time	1.88	2.02	0.57	2.17	0.62	0.77
All of the time	1.26	0.60	0.27	0.20	0.06	0.78
Nervous in past 30 days						
None of the time	39.71	39.02	41.95	43.05	39.12	41.83
A little of the time	25.70	19.28	22.85	22.61	24.70	17.18
Some of the time	29.51	39.17	32.61	29.53	32.01	36.20
Most of the time	2.75	2.14	1.41	3.80	3.03	2.61
All of the time	2.32	0.38	1.18	1.01	1.14	2.17
Restless in past 30 days						
None of the time	39.91	44.43	40.32	37.57	40.13	41.07
A little of the time	24.43	14.71	22.92	21.55	19.79	16.44
Some of the time	27.26	33.42	30.68	33.49	31.85	35.14
Most of the time	4.08	4.50	2.35	4.91	4.83	4.48
All of the time	4.32	2.93	3.73	2.48	3.40	2.87
Hopeless in past 30 days						
None of the time	82.69	85.36	80.83	82.88	79.05	79.13
A little of the time	8.87	7.47	9.16	8.60	11.08	11.44
Some of the time	6.72	5.26	9.02	7.50	8.65	7.83
Most of the time	0.95	1.66	0.78	0.50	0.79	0.96
All of the time	0.77	0.24	0.21	0.52	0.43	0.63
Everything effort in past 30 days						
None of the time	49.43	48.34	51.41	54.79	52.60	51.74
A little of the time	18.52	17.67	17.66	15.26	16.79	17.30
Some of the time	22.36	23.69	22.53	19.74	20.91	23.21
Most of the time	4.27	4.34	4.38	4.47	6.47	2.89
All of the time	5.43	4.95	4.02	5.73	3.24	4.86
Worthless in past 30 days						

None of the time	83.05	86.03	87.32	87.31	86.54	83.37
A little of the time	9.21	7.20	5.61	6.45	5.22	10.27
Some of the time	5.62	5.27	6.59	4.63	7.63	5.35
Most of the time	1.37	0.87	0.27	1.10	0.23	0.98
All of the time	0.74	0.63	0.20	0.51	0.38	0.03
Average total score	4.08 (0.23)	3.97 (0.19)	3.80 (0.19)	3.90 (0.20)	4.02 (0.20)	4.00 (0.18)

The average total score for participants is presented at the bottom of the table (total scores ranged from 0 to 24). Despite slight dips in average psychological distress in the years immediately following the Great Recession, there nevertheless appears to be little variation across time—the average score hovers around 4.0 between 2009 and 2019, suggesting, on average, low levels of psychological distress among the sample.

Tables for respondents with three mental health data points are provided in Appendix E (Table E1, page 187). T-tests were conducted to examine whether average psychological distress scores were significantly different between the three-timepoint and six-timepoint samples. Significant differences in average K-6 score were observed among these two samples at timepoints 2, 3, 4, and 6—in each instance, the six-survey wave sample had statistically higher average K-6 scores than the three-survey wave sample. For example, at timepoint 2, the mean K-6 score among participants with corresponding mental health data for three survey waves was 3.62 (SE=0.17) compared to 4.14 (SE=0.16) among participants with six timepoints worth of mental health data.

The percentages of study participants who meet the thresholds for severe and moderate psychological distress are provided in Table 3. Few participants meet the threshold for severe mental distress (a K-6 score of 13 or higher out of 24) across the six timepoints. The percentage of participants with K-6 scores consistent with severe psychological distress ranges from 1.89%

in 2011 to 3.47% in 2015. In contrast, a far greater percentage—approximately one-third of participants across the study period—of the study sample endorses psychological distress scores consistent with moderate mental distress (a K-6 score of 5 or higher, inclusive of those with scores consistent with severe psychological distress). The percentage of participants with moderate mental distress per this threshold ranges from 32.6% in 2015 to 37.3% in 2019.

Table 3. Kessler-6 Psychological Distress Thresholds by Survey Wave (2009-2019), among a Subset of Millennial Reference Persons and Spouses (n=572)

	2009 %	**2011** %	**2013** %	**2015** %	**2017** %	**2019** %
Severe psychological distress (K-6 score ≥13)						
Yes	2.91	1.89	2.83	3.47	2.89	2.42
No	97.09	98.11	97.16	96.53	97.11	97.58
Moderate psychological distress (K-6 score ≥5)*						
Yes	36.02	33.89	32.57	33.10	35.60	37.34
No	63.80	66.11	67.43	66.90	64.40	62.66

*Note that those with total distress scores consistent with severe distress are included in the moderate distress cutoff of 5 or higher

The percentage of severe and moderate psychological distress outcomes among participants with corresponding K-6 data for *three survey waves* is presented in Table E2 of Appendix E (p. 188). Chi-squared tests did not reveal significant differences between the six- versus three-wave samples with respect to the prevalence of severe or moderate mental distress at any study timepoint.

6.1.3. Employment Quality Characteristics

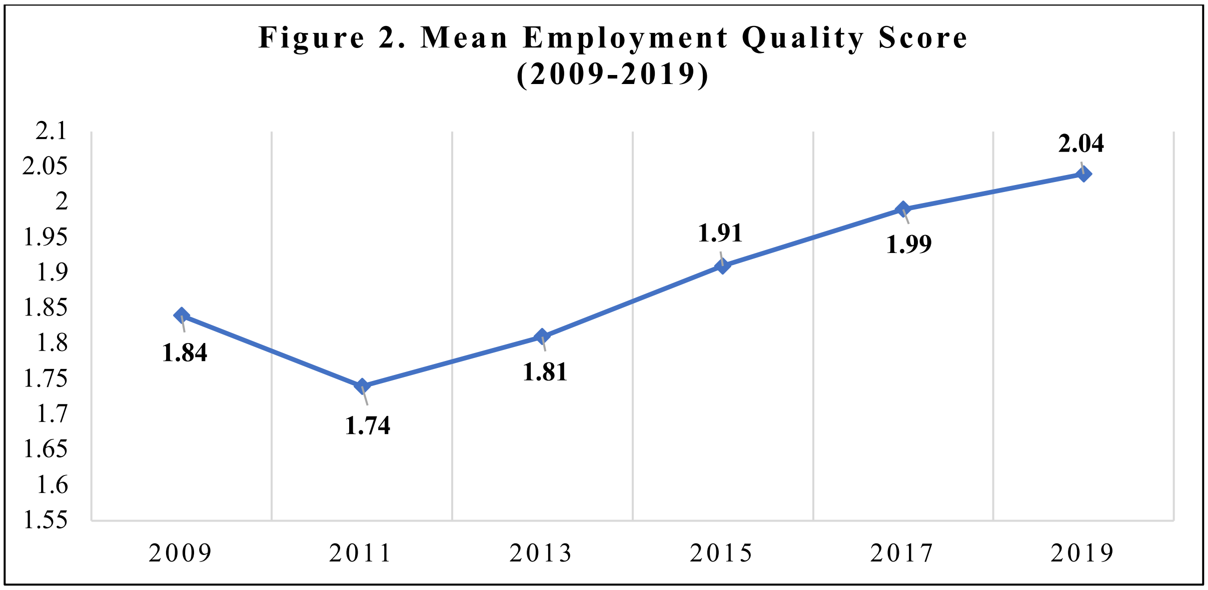
The frequency distribution of the six employment quality indicators is presented in Table 4. Consistent with the Great Recession timeline, a sizeable percentage (approximately 17%) of respondents in 2009 indicated experiencing unemployment in the previous year—this figure increased to a peak of 21% by the 2011 survey wave. As reflected in the table, unemployment in the previous year did not drop below 10% until the 2017 survey wave. With respect to the material rewards dimension of employment quality, mean income (adjusted for 2019 dollars), consistently rose across the study period: While average income only increased about $1000 between 2009 (mean income of $30,835) and 2011 (mean income of $31,871), more than a $6000 increase was observed between 2015 and 2017, and nearly a $5000 increase was seen between 2017 and 2019. Though median income levels among participants are appreciably lower than mean income levels, similar trends were observed with respect to the degree of boosts to income across the study period. Dips in the percentage of participants benefiting from employer-provided health insurance were observed in the years immediately following the Great Recession (e.g., a 7% decrease between 2009 and 2011). By 2017, a greater share of participants was covered by employer-provided healthcare than had been in 2009, and in 2019, nearly two-thirds of participants (63.4%) received healthcare through their employer.

In terms of the "workers' rights and protections" dimension of employment quality, a strikingly small percentage (5% or less across all study timepoints) of respondents indicated that they would get paid for extra hours of work should they work more hours than usual during some week. Average work hours per week hovered around 36 hours per week across the study period, with a slight increase to 37 hours per week in 2017 and 2019. The median number of hours worked per week was stable at 40 between 2009 and 2019. Finally, as concerns collective organization, the percentage of participants with current jobs covered by a union contract or who belong to a union was less than 10% across the study period (ranging from a low of 7.2% in 2009 to 9.4% in 2019), suggesting low levels of collective bargaining power among Millennial workers in this study sample.

Table 4. Frequency Distribution of Employment Quality Indicators by Survey Wave (2009-2019), among Millennial Reference Persons and Spouses (n=1303)

Dimension	**2009** Mean (SE) or %	**2011** Mean (SE) or %	**2013** Mean (SE) or %	**2015** Mean (SE) or %	**2017** Mean (SE) or %	**2019** Mean (SE) or %
Stability						
Unemployed in previous year	16.80	20.81	17.53	11.55	9.17	8.37
Material Rewards						
Annual Income						
Mean income	30835.15 (1075.59)	31871.60 (1357.56)	35547.75 (1514.33)	39019.04 (1693.78)	45316.34 (1952.06)	50061.13 (2211.40)
Median income	26824.80	28025.79	29529.90	31821.14	36618.70	40000.00
Employer Health	58.57	51.27	53.30	55.30	60.90	63.38
Workers' Rights and Protections						
Overtime	4.76	3.61	4.42	4.58	5.29	4.83
Working-Time Arrangements						
Mean work hours/week	36.58 (0.69)	35.69 (0.67)	35.75 (0.74)	36.15 (0.64)	36.85 (0.66)	37.01 (0.87)
Median work hours/week	40.00	40.00	40.00	40.00	40.00	40.00
Collective Organization						
Collective Bargaining	7.20	9.24	8.09	8.17	8.82	9.38

The mean total employment quality (EQ) score among Millennial heads of household/spouses across the study period is depicted in Figure 2, below. As detailed in the methods section, the total EQ score was derived by assigning each dimension of employment quality a one-point value (income and employer-covered health care were each worth 0.5 points, as they both fall under the "material rewards" dimension).[41] As illustrated in Figure 2, mean employment quality scores have risen slightly since 2011, when the average EQ score dipped to a low of 1.74 (out of a possible score of 5). It is worth noting here that while the general trend in average employment quality is one of positive growth, the average EQ score at the final study timepoint (2019) is only 2.04 out of a possible score of 5.



Trends in average employment quality scores by education level are reflected in Figure 3. There was a marked gap in employment quality between those with and without a college education, and this discrepancy persisted across the study period (though non-college educated Millennials managed to narrow the gap between 2015 and 2019). Moreover, college-educated Millennials did not experience the same decline in employment quality as their non-college educated counterparts: employment quality scores for college-educated Millennials consistently

[41] To convert the "annual income" variable to a score ranging from 0 to 1, first, the natural log of respondents' annual income values was derived. Then, these natural log values were divided by the highest natural log income value across the six study waves. For example, the highest natural log value for income between 2009 and 2019 was 13.30, meaning that all natural log income values were divided by 13.30—the result was an annual income score ranging from 0 to 1. A similar procedure was followed for average hours worked per week, whereby a respondent's value for working hours was divided by the highest value for hours worked per week across the study period (average working hours per week was not converted to a natural log value as a first step in this process).

remained around 2.13 between 2009 and 2013, and then increased to a high of 2.25 in 2019. Meanwhile, non-college educated Millennials experienced a decline in employment quality in the years immediately following the Great Recession—employment quality scores did not recover to their 2009 levels until 2015.

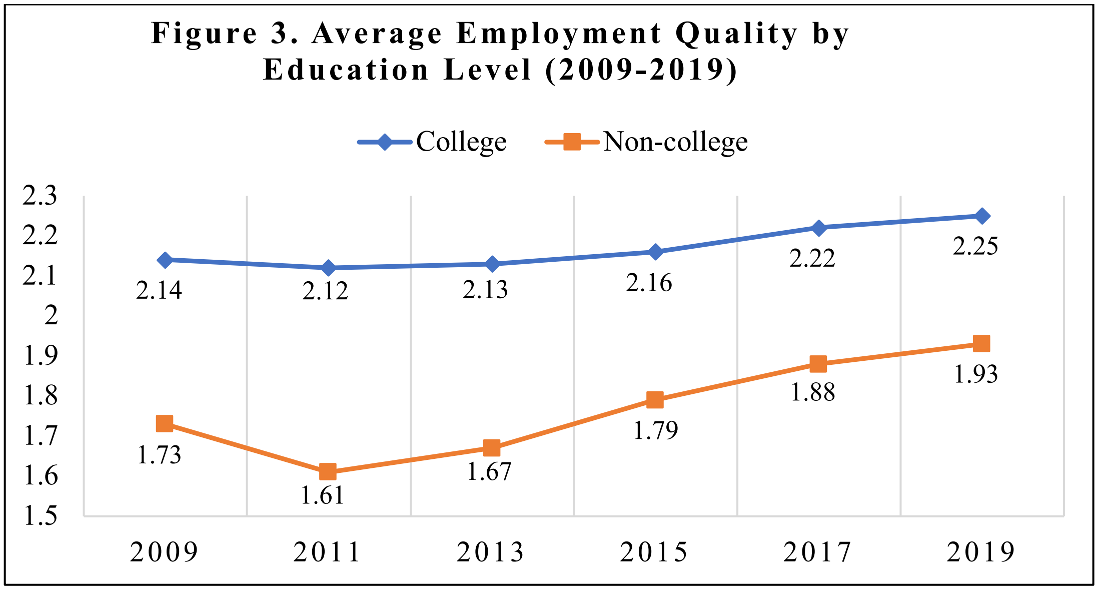


Figure 4 on the following page depicts differences in average employment quality between male and female respondents. While men and women had nearly equal average employment quality scores in 2009 (1.86 among male respondents compared with 1.82 among female respondents), the gap widens in the years following the Great Recession. Specifically, between 2009 and 2011 women experience a slightly steeper drop in EQ than their male counterparts; when average EQ scores begin to trend upward between 2011 and 2013, male respondents experience slightly higher gains in average EQ than their female counterparts. Overall, these differences in average EQ scores at each timepoint were small—only in 2019 did the difference between the average EQ score of men versus women exceed 0.20.

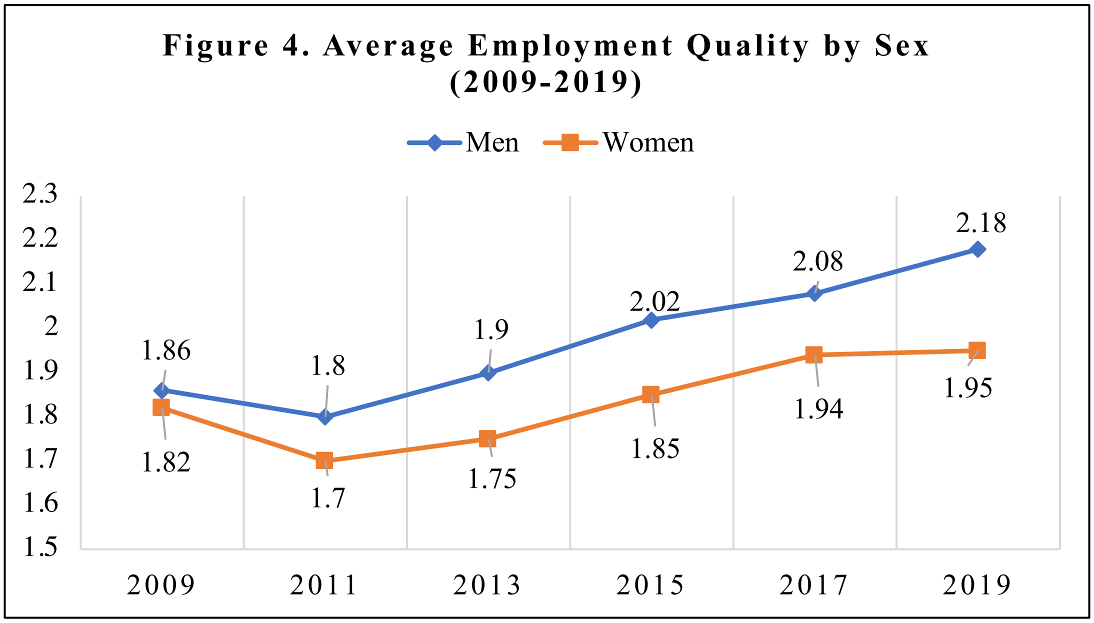


Figure 4. Average Employment Quality by Sex (2009-2019)

6.1.4. Missing Data

Missingness was explored on both the independent (employment quality) and dependent (psychological distress) variables. The frequency distribution of study participants with one or more missing EQ indicators is presented in Table 5, below. With the exception of 2009, when 11.3% of participants had at least one missing EQ indicator, fewer than 6% of participants had missing values for EQ indicators across the study period.

Table 5. Frequency distribution of missing values among Millennial heads of household and spouses, by survey wave (n=1303)

Number of missing EQ indicators	**Timepoint**					
	2009 % (n)	**2011 % (n)**	**2013 % (n)**	**2015 % (n)**	**2017 % (n)**	**2019 % (n)**
0	88.72 (1156)	93.86 (1223)	95.78 (1248)	94.55 (1232)	94.09 (1226)	94.63 (1233)
1	10.28 (134)	5.60 (73)	3.84 (50)	5.22 (68)	5.60 (73)	5.22 (68)

2	0.92 (12)	0.54 (7)	0.38 (5)	0.12 (3)	0.31 (4)	0.08 (1)
3	0.08 (1)	0.0 (0)	0.0 (0)	0.0 (0)	0.0 (0)	0.0 (0)

A dichotomous "missingness" variable was then created based on whether a study participant had missing data for any EQ indicator (i.e., if any of the six indicators of employment quality had missing values). Bivariate analyses (t-tests and chi-square tests) were performed to assess whether there were significant associations between the EQ missingness variable and a range of sociodemographic characteristics.

Table 6, on the following page, presents sociodemographic characteristics of Millennial head of households and spouses, by missingness of EQ data across the study period. These bivariate analyses revealed a missing at random (MAR) pattern, whereby greater proportions of Millennials with missing values than those without were younger, had lower levels of education, identified as persons of color, lived in the South, and were single or never married.

Table 6. Sociodemographic characteristics of Millennial head of households and spouses, by missingness of employment quality data

	2009		2011		2013		2015		2017		2019	
Characteristic	Missing ≥ 1 EQ indicator		Missing ≥ 1 EQ indicator		Missing ≥ 1 EQ indicator		Missing ≥ 1 EQ indicator		Missing ≥ 1 EQ indicator		Missing ≥ 1 EQ indicator	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Mean age	24.44 (0.22)	25.06** (0.07)	26.39 (0.31)	27.03* (0.07)	28.09 (0.39)	29.03** (0.07)	30.27 (0.35)	31.04** (0.07)	32.29 (0.32)	33.04** (0.07)	34.79 (0.31)	35.01 (0.07)
Sex												
Male	35.37	37.98	48.75	36.96*	41.82	37.50	36.62	37.74	37.93	33.77	38.57	37.63
Female	64.63	62.02	51.25	63.04*	58.18	62.50	63.38	62.26	62.07	66.23	61.43	62.37
Education												
Less than high school	29.79	12.63***	17.72	13.99	34.55	11.89***	21.13	11.96**	16.88	11.93*	30.00	13.51***
High school	31.91	27.35***	37.97	26.90	27.27	24.27***	28.17	23.10**	32.47	21.89*	27.14	21.48***
Some college	25.53	33.19***	27.85	32.86	29.09	33.09***	38.03	32.10**	31.17	32.18*	27.14	31.00***
College	12.77	26.83***	16.46	26.24	9.09	30.74***	12.68	32.84**	19.48	33.99*	15.71	34.01***
Race												
White	36.36	57.11***	37.18	55.50**	25.00	55.22***	34.29	54.68**	32.47	54.58***	31.43	54.53***
Non-white	63.64	42.89***	62.82	44.50**	75.00	44.78***	65.71	45.32**	67.53	45.42***	68.57	45.47***
Residence												
Rural	28.57	33.71	26.58	32.18	23.64	33.28	15.71	17.20	13.16	18.05	14.29	17.66
Urban	71.43	66.29	73.42	67.82	76.36	66.72	84.29	82.80	86.84	81.95	85.71	82.34
Region												
Northeast	4.76	10.52**	6.25	10.35*	1.82	9.81	4.29	9.62	10.53	9.20	8.57	9.41*
North Central	23.13	28.61**	16.25	28.10*	27.27	27.19	22.86	27.00	21.05	27.36	21.43	27.50*
South	57.82	41.04**	57.50	42.56*	52.73	43.85	58.57	44.29	51.32	44.29	60.00	43.62*
West	14.29	19.83**	20.00	18.98*	18.18	19.15	14.29	19.09	17.11	19.15	10.00	19.48*
Marital status												
Married/cohabitating	42.26	50.52	46.25	54.01	58.18	56.25	49.30	59.66**	45.45	63.78***	44.29	64.15**
Single, never married	48.98	46.19	47.50	39.85	41.82	36.62	47.89	31.57**	49.35	27.16***	40.00	26.03**
Widowed, divorced, separated	4.76	3.29	6.25	6.14	0.00	7.13	2.82	8.77**	5.19	9.05***	15.71	9.81**

**p<0.05. **p<0.01. ***p<0.001*

Specifically, study participants with missing data were almost one year younger than their counterparts without missing data (24.4 years among Millennials with missing data in 2009 compared to 25.1 years of age among Millennials without missing data). Moreover, 29.8% of Millennials with missing data in 2009 had a high school level of education compared to 12.6% of Millennials with no missing data (chi-square=38.5, p<0.001)—with the exception of the 2011 survey wave, these patterns of missingness by education persisted across the study period. Greater proportions of Millennials with missing data were non-White: 63.64% of Millennials with missing data were non-White compared with 42.89% of Millennials without missing data (chi-square=33.07, p<0.001). In terms of regional differences in missingness of employment quality indicators, Millennials with missing data were more likely to be from the South: in 2009, 57.8% of Millennials with missing EQ data were from the South compared to 41.0% of Millennials without missing data (chi-square=16.41, p =0.01). Finally, single, never married Millennials between 2015 and 2019 had higher percentages of missing data compared to their married/cohabitating counterparts (49.3% of single, unmarried Millennials had missing data in 2017 compared with 27.2% of Millennials without missing data).

Missingness on the dependent value, psychological distress, across the study period is presented in Table 7. Less than 1% of the subset of Millennial heads/spouses with mental health data[42] had missing values for K-6 indicators between 2009 and 2019. The frequency distribution of missing K-6 indicators was also explored for Millennials who were survey respondents for only 3 of the 6 timepoints. Similar patterns of missingness were observed, whereby less than 1% of those who were survey respondents for 3 of the 6 survey waves (n=1017) had missing values for any of the psychological distress indicators (frequency distribution table can be found in

---

[42]To reiterate, the Millennial heads of households and spouses in Table 7 were survey respondents for all 6 survey waves (as such, they should have psychological distress data for all six timepoints).

Appendix F, on page 189). Given such low levels of missingness on the dependent variable (e.g., less than 5 individuals at any given survey wave), bivariate analyses were not conducted to assess whether missingness was associated with certain sociodemographic characteristics.

Table 7. Frequency distribution of missing psychological distress values among Millennial heads of household and spouses, by survey wave (n=572)

Number of missing K-6 indicators	**Timepoint**					
	2009 % (n)	**2011 % (n)**	**2013 % (n)**	**2015 % (n)**	**2017 % (n)**	**2019 % (n)**
0	99.65 (570)	99.65 (570)	99.48 (569)	99.83 (571)	99.65 (570)	99.48 (569)
1	0.17 (1)	0.00 (0)	0.35 (2)	0.17 (1)	0.00 (0)	0.17 (1)
3	0.00 (0)	0.00 (0)	0.00 (0)	0.00 (0)	0.00 (0)	0.17 (1)
6	0.17 (1)	0.35 (2)	0.17 (1)	0.00 (0)	0.35 (2)	0.17 (1)

6.1.6. Comparing Millennials with Three, Four, Five, and Six Mental Health Data Points

As noted in the PSID sampling description in the methods section, only the survey respondent answered the psychological distress questions. In other words, while indicators of employment quality were available for both the household reference person and spouse/partner, psychological distress data only pertained to one of these two individuals.[43] Given that not every eligible individual with employment quality would also have accompanying mental health data, exploratory analyses were conducted to identify any appreciable sociodemographic differences between participants with three, four, five, and six psychological distress data points.

[43] It is also the case that neither the reference person nor spouse/partner answers the psychological distress questions—other household members (child, parent, sibling) may respond to the survey on behalf of the household head.

Table 8, below, presents sociodemographic differences between Millennials who were survey respondents for all six study timepoints (n=572) compared to those who were respondents for either three, four, or five timepoints. No differences were observed in terms of age; however, chi-squared tests revealed fundamental differences between the sample with mental health data at six timepoints compared to those with these data at three, four, and five timepoints. Specifically, far greater proportions of those who were respondents for all six survey waves identified as male, persons of color, single/never married, residents in urban areas, and blue-collar workers. Moreover, six-survey-wave respondents had higher levels of education than their counterparts with mental health data from three, four, or five survey waves.

These discrepancies in sociodemographic characteristics of survey respondents—particularly the stark contrasts in gender representation — are important to note at this juncture given that extant literature and theory suggests that many of these characteristics are associated with lower levels of employment quality. For example, the gender pay gap, though narrowing, still persists—women earning 20% less per hour than men according to 2019 figures (Folbre, 2021). Moreover, rural parts of the United States took much longer to recover economically following the Great Recession than metropolitan areas: According to data from the Bureau of Labor Statistics, employment in nonmetropolitan areas grew slowly and had not yet returned to 2007 levels when the COVID-19 pandemic hit in 2020 (Economic Research Service, 2023). Given the overrepresentation of certain sociodemographic characteristics in the sample of participants with mental health data from six survey waves, it was important to explore any variation in findings on mental health outcomes between this six-wave sample and the three- and four-survey wave sample.

Table 8. Sociodemographic characteristics of study participants with six compared with three, four, and five mental health data points

Characteristic	% (n) /mean (SD)			
	6 timepoints (n=572)	≥3 & <6 timepoints (n=445)	≥4 & <6 timepoints (n=335)	≥5 & <6 timepoints (n=99)
Age	34.9 (2.4)	34.9 (2.4)	34.8 (2.5)	34.4 (2.8)
Sex				
Male	57.9 (331)	11.7 (52)***	10.4 (35)***	17.2 (17)***
Female	42.1 (241)	88.3 (393)***	89.6 (300)***	82.8 (82)***
Education (in years)	13.8 (2.2)	13.3 (3.7)*	13.2 (3.9)**	11.5 (5.3)***
Race				
White	40.7 (232)	60.2 (266)***	60.4 (201)***	45.4 (45)
Black	48.8 (278)	32.3 (143)***	32.7 (109)***	46.5 (46)
Non-white (non-Black)	10.5 (60)	7.5 (33)***	6.9 (23)***	8.1 (8)
Marital status				
Married/ cohabitating	34.4 (197)	78.9 (351)***	76.4 (256)***	45.4 (45)***
Single, never married	52.3 (299)	10.3 (46)***	11.6 (39)***	23.2 (23)***
Widowed, divorced, or separated	13.3 (76)	10.8 (48)***	11.9 (40)***	31.3 (31)***
Rural residence				
Urban	87.5 (498)	79.4 (351)***	77.7 (258)***	81.8 (81)
Rural	12.5 (71)	20.6 (91)***	22.3 (74)***	18.2 (18)
Region				
Northeast	10.4 (59)	8.4 (37)	7.2 (24)	3.0 (3)
North Central	26.2 (149)	26.9 (119)	25.9 (86)	26.3 (26)
South	45.3 (258)	46.4 (205)	47.9 (159)	48.5 (48)
West	18.1 (103)	18.3 (81)	19.0 (63)	22.2 (22)
Blue collar/white collar				
Blue collar-low skill	17.2 (97)	7.9 (35)***	8.1 (27)***	10.2 (10)**
Blue collar-high skill	14.5 (82)	6.3 (28)***	5.7 (19)***	5.10 (5)**
White collar-low skill	39.3 (222)	48.2 (213)***	49.1 (163)***	51.0 (50)**
White collar-high skill	29.0 (164)	37.6 (166)***	37.0 (123)	33.7 (33)**

**p<0.05. **p<0.01. ***p<0.001*

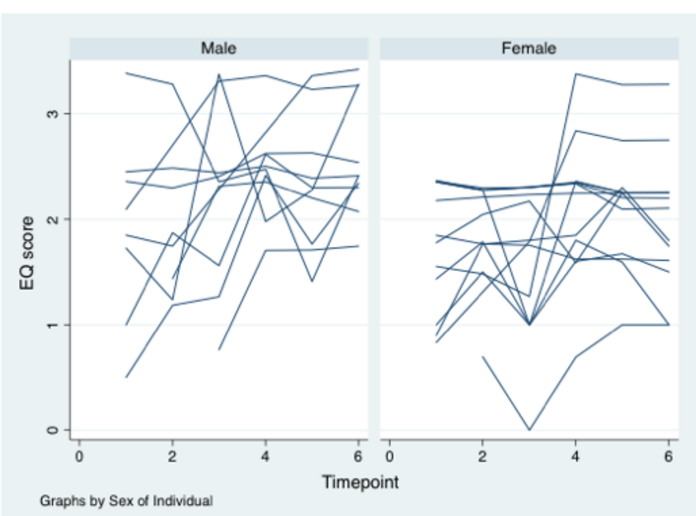
6.2. Research Aim 1: Identifying Employment Quality Trajectories

6.2.1. Justification for Identifying Classes of EQ Trajectories

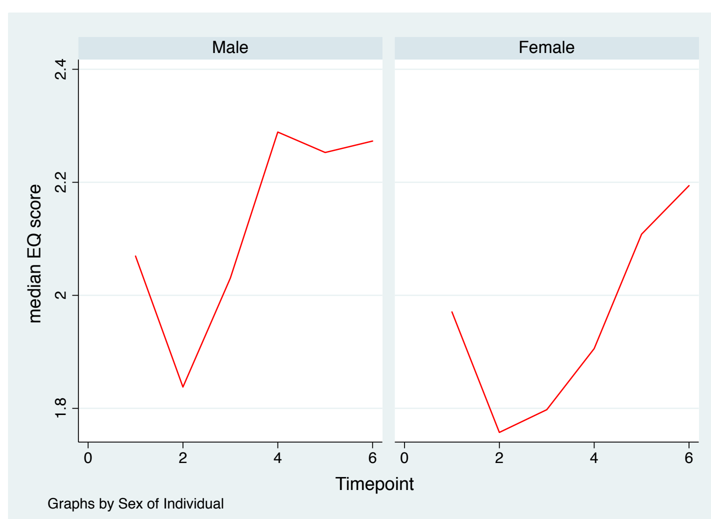
The purpose of this research aim is to identify subgroups of employment trajectories among Millennials in the years following the Great Recession (2009-2019) and to understand the sociodemographic characteristics associated with members of each identified subgroup. As detailed in the previous section ("Descriptive Statistics"), a basic plot of employment quality over time would suggest that, overall, employment quality dipped during and immediately following the Great Recession before steadily rising between 2013 and 2019. However, a closer look at individual employment quality data trajectories suggests a more nuanced approach is needed to understand how Millennials faired in terms of employment quality in the decade following the Great Recession. Indeed, plots of the individual employment quality trajectories of subsets of Millennial participants (Figure 4, below) revealed no clear pattern with respect to employment quality trends over time: Some participants experienced improved employment quality over the study period while other trajectories suggest stagnant or negative growth. In short, these data would not be characterized as having linear intraindividual changes. Such a diversity of employment quality trajectories justifies the rationale for describing possible sub-groups within the data and describing group differences in longitudinal employment quality change between these unobserved groups (i.e., estimating the growth trajectory of each of these latent classes).

Figure 4. Total EQ score for a subset of Millennial participants compared with median EQ score, by sex

Subset of respondents (by sex)



Median (by sex)



6.2.2. Growth Mixture Modeling: Step 1. Problem Definition

As GMM is an exploratory data analysis procedure, a critical first step, prior to fitting any models, was to formulate some initial hypotheses regarding the number and characteristics of underlying sub-groups (classes). Specifically, having some general hypotheses facilitates planning for how to proceed with subsequent steps in the GMM analysis. Based on the extant literature examining precarious employment in recent years as well as the examination of a series of individual EQ trajectory plots (see Figure 4, above, for example), a minimum of three and maximum of four sub-groups were expected to be identified from the PSID data. Specifically, I expected to identify one class of participants with EQ trajectories characterized by a relatively high starting EQ score and positive growth, one EQ class characterized by stagnant growth (flat growth or very minimal improvements in EQ over time), and one class with deteriorating EQ over the study period. Moreover, consistent with the literature, I anticipated that membership in the positive growth EQ class would be associated with higher levels of education (i.e., college degree), being White, and having college-educated parents, while membership in the negative EQ growth class would be more likely for those with a high school level of education, who self-identify as non-White, and whose parents were not college educated.

Having proffered some general hypotheses about what might emerge from the data, the next step in problem definition involved fitting a series of *single-group* intercept-only, linear growth, and quadratic growth curve models to determine the best baseline model prior to GMM specification. Table 9, below, presents model fit statistics for these three baseline models. The quadratic model was chosen as the one-class baseline model because the associated model had the lowest values for Bayesian information criterion (BIC) and sample-size adjusted BIC

(ABIC)—lower values indicate the quadratic model better fit the data than the intercept-only or linear models.

Table 9. Likelihood Statistics for Baseline Single-Group Employment Quality Models

Model Type	# of Parameters	Akaike (AIC)	Bayesian (BIC)	Sample-size adjusted BIC (ABIC)
Intercept-only	8	14922.61	14963.99	14938.58
Linear	11	14462.26	14519.16	14484.22
Quadratic	15	14380.52	14458.11	14410.46

6.2.3. Growth Mixture Modeling: Step 2. Model Specification

Having formulated some general hypotheses and established a baseline model, a series of multiple-group models were fitted to determine if and how subgroups differ with respect to the mean change in employment quality over the study period. First, several *two-class* models were specified, beginning with a fully-constrained two-class model where the two groups were allowed to differ with respect to mean change and culminating with a fully-free model where the intercept *and* slope of each class were allowed to vary. These series of two-class models (from constrained to fully free models) were fitted for both linear and quadratic patterns of change. This same approach of increasing the number of estimated variance parameters was then applied to three- and four-class models—here again, both linear and quadratic patterns of change were modeled. A total of 54 models were fitted in this model specification process, and comparisons among all of these models was used to infer the most likely number of unobserved groups in the data.

6.2.4. Growth Mixture Modeling: Step 3. Model Estimation

The sets of models described above were fitted using Mplus 8.0 (Muthén & Muthén, 1998-2017), which uses an iterative procedure—an expectation-maximization (EM) procedure—

to obtain parameter estimates and posterior probabilities of class membership for each individual (probabilities are obtained for each individual for *each* extracted class). Fit statistics and classification quality measures for the best fitting two-, three-, and four-class linear and quadratic growth mixture models are presented in Tables 10 and 11, below. Consistent with the types of estimation issues widely cited by those leveraging GMM methods (McNiesh & Harring, 2021; Ram & Grimm, 2009), convergence issues were common for models that allowed the variances of the intercept and slope factors to differ among classes. Specifically, negative variance values were common for the overwhelming majority of models that allowed for the variances of the intercept and slope factors to differ. Estimation output for all 54 models, including fit statistics, parameter estimates, and footnotes to denote convergence issues, are presented in Appendix G on pages 190-200.

6.2.5. Growth Mixture Modeling: Step 4. Model Selection and Interpretation

As detailed in the methods section, there are no "deterministic" set of rules to follow to select the best-fitting growth mixture model (Ram & Grimm, 2012). Rather, in addition to fit statistics (e.g., AIC, BIC) and classification quality (e.g., entropy), model selection involves examining the conceptual soundness of each model and drawing from prior research.

Fit Statistics: As reflected in Table 10, three- and four-class constrained models were better fitting than two-class constrained models, with lower AIC, BIC, and adjusted BIC values. Based on the relative fit information criteria of the models (i.e., AIC, BIC, and adjusted BIC), linear *and* quadratic four-class models were slightly better fitting than the three-class models. For example, the best-fitting linear four-class model had AIC and BIC values of 14315.02 and 14418.47, respectively, compared to 14339.90 and 14427.83, respectively, for the best-fitting three-class linear model. Similarly, the best-fitting quadratic four-class model had lower AIC, BIC, and adjusted BIC values compared with the best-fitting three class model. Specifically, the constrained quadratic four-class model had AIC and BIC values of 14103.10 and 1424.76, respectively, compared to 14184.82 and 14303.78, respectively, for the quadratic three-class model.

Classification Quality: With respect to the confidence with which study participants were classified as belonging to a particular subgroup, both *entropy* values and *average latent class probabilities for likely class membership* were examined. These classification quality measures for the best-fitting linear and quadratic growth mixture models are presented in Tables 10 (linear models) and 11 (quadratic models). Entropy values for the linear models increased slightly with each added class (from 0.80 for the two-class linear model to 0.85 for the four-class linear model). Conversely, entropy values were slightly higher for the best-fitting quadratic two-class and three-class models compared with the four-class model, though entropy values for the four-class quadratic model was still above the ideal 0.80 threshold that indicates clearer delineation of classes (Ram & Grimm, 2009).

With respect to the second measure of classification quality, the average latent class probabilities for likely class membership, the higher probabilities for the three- and four-class models suggest better classification quality compared to the two-class models. For the linear two-class model, for example, individuals assigned to the second class were, on average, assigned with only 43% certainty, whereas individuals were assigned, on average, with at least 85% certainty to each class for the three-class linear model (95% certainty for class 1, 92% certainty for class 2, and 85% certainty for class 3). With the exception of a couple of probability values under 0.80, the average probabilities for the linear and quadratic four-class models also suggest high classification accuracy.

Table 10. Fit statistics, classification quality, and counts and proportions for best-fitting two-, three-, and four-class linear growth mixture models

	Two Class			Three Class				Four Class				
Fit Statistics												
AIC	14439.608			14339.90				14315.02				
BIC	14512.022			14427.833				14418.47				
ABIC	14467.55			14373.83				14354.94				
Classification Quality												
Entropy	0.799			0.838				0.847				
Average latent		C1	C2		C1	C2	C3		C1	C2	C3	C4
class	C1	0.99	0.01	C1	0.95	0.01	0.03	C1	0.70	0.07	0.23	0.00
probabilities for	C2	0.57	0.43	C2	0.08	0.92	0.00	C2	0.00	0.95	0.01	0.04
likely class	-	-	-	C3	0.15	0.00	0.85	C3	0.07	0.12	0.81	0.00
membership	-	-		-	-	-	-	C4	0.000	0.144	0.000	0.86
(row)												
Counts and proportions	C1: 95.8% (n=1248) C2: 4.2% (n=55)			C1=70.6% (n=920) C2=10.4% (n=135) C3=19.0% (n=248)				C1=3.4% (n=44) C2=70.5% (n=919) C3=6.8% (n=89) C4=19.3% (n=251)				

Table 11. Fit statistics, classification quality, and counts and proportions for the best-fitting two-, three-, and four-class quadratic growth mixture models

	Two Class			Three Class				Four Class				
Fit Statistics												
AIC	14324.41			14184.82				14103.10				
BIC	14422.69			14303.78				14242.76				
ABIC	14362.34			14230.72				14156.99				
Classification Quality												
Entropy	0.901			0.888				0.877				
Average		C1	C2		C1	C2	C3		C1	C2	C3	C4
latent class	C1	0.99	0.01	C1	0.98	0.01	0.01	C1	0.79	0.00	0.03	0.18
probabilities	C2	0.41	0.59	C2	0.13	0.87	0.00	C2	0.00	0.94	0.00	0.06
for likely	-	-	-	C3	0.06	0.00	0.94	C3	0.19	0.00	0.78	0.03
class	-	-		-	-	-	-	C4	0.02	0.00	0.00	0.97
membership												
Counts and proportions	C1=96.8% (n=1261) C2=3.2% (n=42)			C1=72.6%, n=946 C2=15.6%, n=203 C3=11.8%, n=154				C1=14.8% (n=193) C2=12.0% (n=157) C3=3.8% (n=49) C4=69.4% (n=904)				

As indicated in the above tables, fit statistics and measures of classification quality suggest that three- and four-class models are better fitting than two-class models. The best-performing two-class model had higher AIC, BIC, and ABIC values than the best-performing three- and four-class models. Moreover, the average latent class probabilities for likely class membership were quite low for the second class in the two-class models: For example, individuals assigned to the second class in the two-class model were assigned with only 43% probability for the linear two-class model and 59% probability for the quadratic two-class model. While the entropy value for the two-class quadratic model was slightly higher than the value for the three- and four-class quadratic models, this difference was not appreciable in light of the low average latent class probabilities value.

Conceptual Soundness: Having examined the fit statistics and classification quality measures of each model, the next step of "model selection" involved assessing the conceptual soundness of each model. Indeed, given that some models had better fit statistics but not better classification quality measures (e.g., the four-class linear model has lower fit statistics values and a higher entropy value than the three-class linear model, but lower average latent class probabilities for likely class membership values), making sense of the estimation output from a non-purely mathematical standpoint can facilitate model selection. Accordingly, the estimation output for each of the best-fitting three-, and four-class models was examined, with careful attention to how groups differ with respect to the mean amount of change and the extent to which these differences are meaningful—a four class model where two or more groups exhibit nearly identical changes in employment quality, for example, might be less preferable to a three-class model with slightly higher fit statistics values but more meaningful distinctions between groups regarding mean change.

Table 12, below, presents estimation output for the best-fitting three-, and four-class linear and quadratic growth mixture models. Output for the best-fitting two-class models, as well as all other fitted three - and four-class models can be found in Appendix G (p. 190-200).

Table 12. Model Results (Means of the Intercept and Slope, Counts and Proportions) for Best-Fitting Two-, Three-, and Four-Class Quadratic GMM*

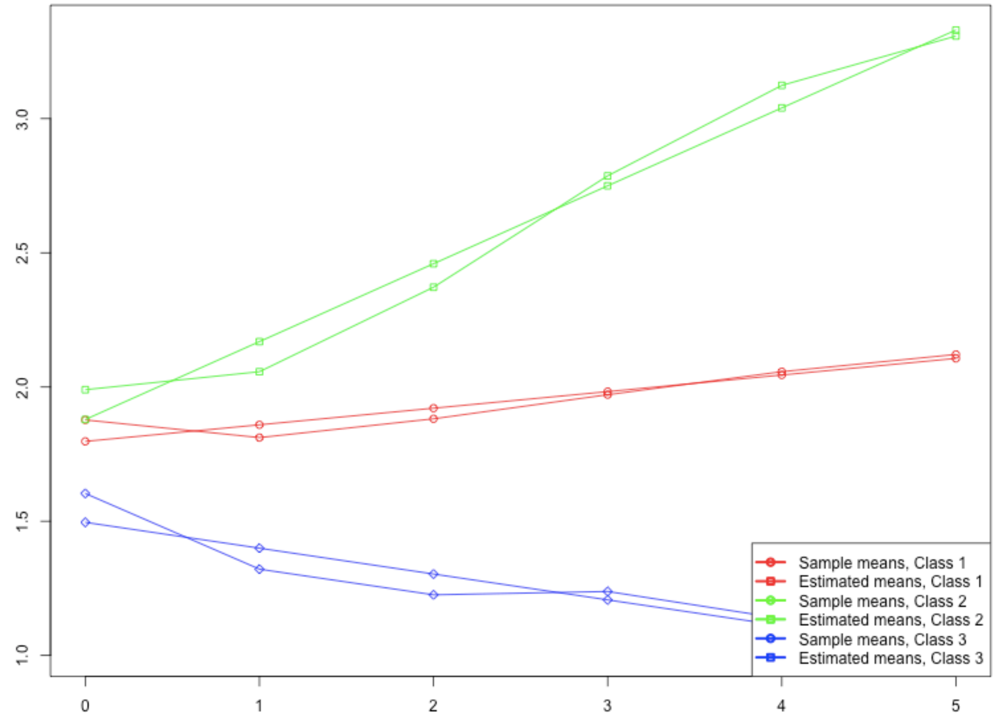
	Linear GMM		Quadratic GMM		
	3 Class (Default)	4 Class (default)	3 Class (Default)	4 Class (default)	4 Class [Random intercepts, C1 slope]
Means					
Class 1					
Intercept	1.80 (0.02) p<0.001	2.77 (0.76), p<0.001	1.87 (0.02), p<0.001	1.55 (0.09), p<0.001	1.66 (0.04), p<0.001
Slope	0.06 (0.00), p<0.001	0.12 (0.18), p=0.48	-0.04 (0.02), p=0.01	-0.09 (0.21), p=0.678	-0.04 (0.02), p=0.06
Quad	-		0.02 (0.00), p<0.001	0.001 (0.040), p=0.985	0.02 (0.005), p<0.001
Class 2					
Intercept	1.88 (0.12), p<0.001	1.80 (0.03), p<0.001	1.37 (0.07), p<0.001	1.95 (0.08), p<0.001	1.62 (0.14), p<0.001
Slope	0.29 (0.02), p<0.001	0.06 (0.01), p<0.001	0.08 (0.06), p=0.15	0.10 (0.05), p=0.03	0.04 (0.07), p=0.52
Quad	--	-	-0.04 (0.01), p=0.001	0.03 (0.01), p<0.001	-0.004 (0.01), p=0.80
Class 3					
Intercept	1.50 (0.06), p<0.001	1.35 (0.42), p=0.001	1.96 (0.08), p<0.001	1.06 (0.16), p<0.001	1.67 (0.21), p<0.001
Slope	-0.10 (0.01), p<0.001	0.38 (0.05), p<0.001	0.11 (0.05), p=0.02	0.61 (0.35), p=0.08	0.67 (0.15), p<0.001
Quad	-		0.03 (0.01), p<0.001	-0.15 (0.06), p=0.008	-0.17 (0.04), p<0.001
Class 4	-				
Intercept	-	1.48 (0.07), p<0.001	-	1.87 (0.03), p<0.001	2.11 (0.04), p<0.001
Slope	-	-0.09 (0.01), p<0.001	-	-0.04 (0.02), p=0.03	-0.02 (0.02), p=0.51
Quad	-	-	-	0.02 (0.003), p<0.001	0.01 (0.004), p=0.02
Counts and Proportions	C1=70.6% (n=920) C2=10.4% (n=135) C3=19.0% (n=248)	C1=3.4% (n=44) C2=70.5% (n=919) C3=6.8% (n=89)	C1=72.6%, n=946 C2=15.6%, n=203 C3=11.8%, n=154	C1=14.8% (n=193) C2=12.0% (n=157) C3=3.8% (n=49)	C1=56.1% (n=731) C2=8.0% (n=104) C3=4.7% (n=61) C4=31.2% (n=407)

	C4=19.3% (n=251)	C4=69.4% (n=904)

*Value in parentheses denotes standard error

When comparing the three- and four-class linear models, conceptually, the three-class linear model appeared more meaningful in terms of identifying distinct employment quality trajectories. Upon examining the three-class linear model, classes 1 and 2 had similar intercepts (1.80 for class 1 and 1.88 for class 2), though class 1, to which the majority of respondents (70%) were assigned, was characterized by very slow growth (slope=0.06) while the slope of class 2 was appreciably larger (0.29). It is worth noting that only 10% of Millennials were assigned to this high growth class. The third class in this model, to which 20% of respondents were assigned, started with a slightly—though not appreciably so—lower intercept of 1.55 and exhibited negative growth (-0.10) over time. In short, individuals in all three classes in this model started with average employment quality at timepoint 1, but diverged with respect to their growth over time: one class had stagnant growth (class 1), another moderate growth (class 2), and the third negative growth (class 3)—that respondents in each class would start with similar levels of employment quality in 2009 is plausible given that these individuals would be contending with post-Great Recession labor conditions. Plots of the sample means and estimated means of each group for the three-class model are presented below.

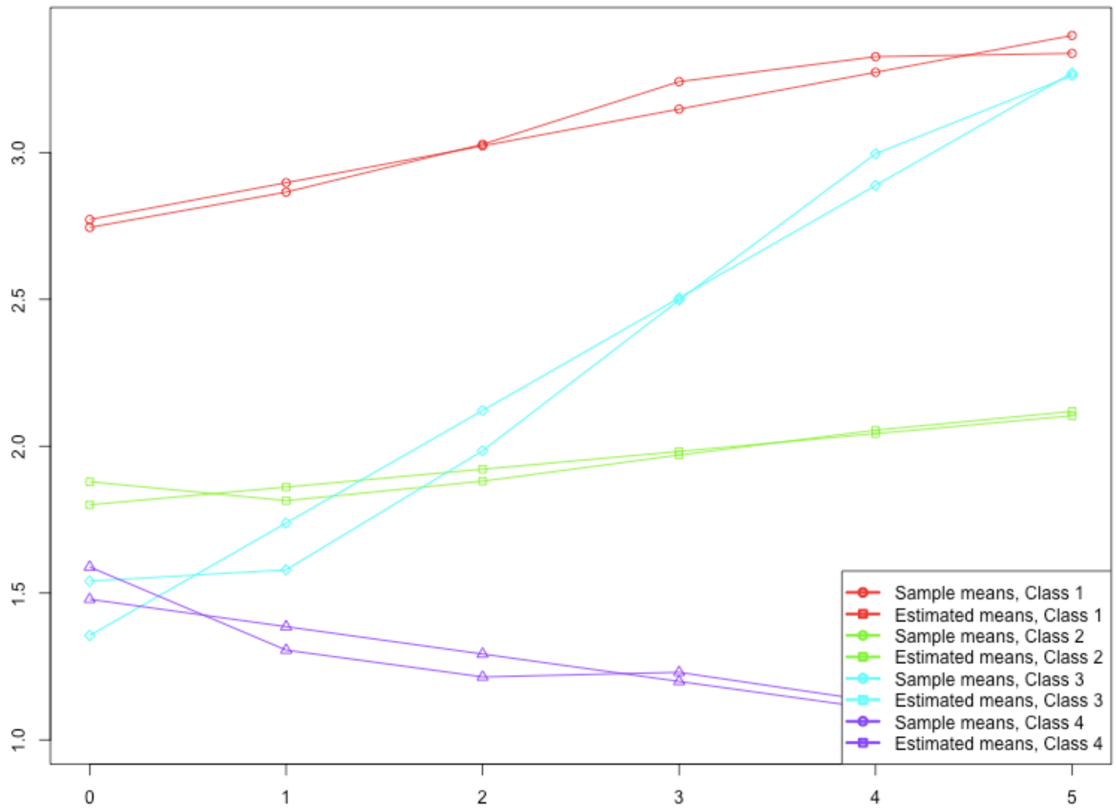
Figure 6. Sample and estimated means of subgroups for three-class linear growth mixture model



In contrast, the four-class linear model yielded more variation with respect to subgroup mean intercept and slope. Specifically, individuals in class 1 started with a very high employment quality score (2.80) and experienced gradual improvements in employment quality (slope=0.12)—less than 5% of Millennial respondents were assigned to this desirable EQ trajectory subgroup. The second EQ class, to which the overwhelming majority of Millennials (70%) were assigned, was characterized by an average level of employment quality (intercept of 1.80) and stagnant growth over time (slope=0.06). The third class of individuals was characterized by sub-average employment quality at timepoint 1 (intercept value of 1.35) but robust growth over time (slope=0.38)—only 7% of respondents belonged to this subgroup. Finally, nearly 20% of Millennials were assigned to the fourth class, which started with sub-average levels of employment quality (intercept value of 1.48) and experienced worsening employment quality over time (slope= -0.10). In short, this four-class model suggests the presence of 1) one subgroup of Millennials who enjoyed high and rising levels of employment;

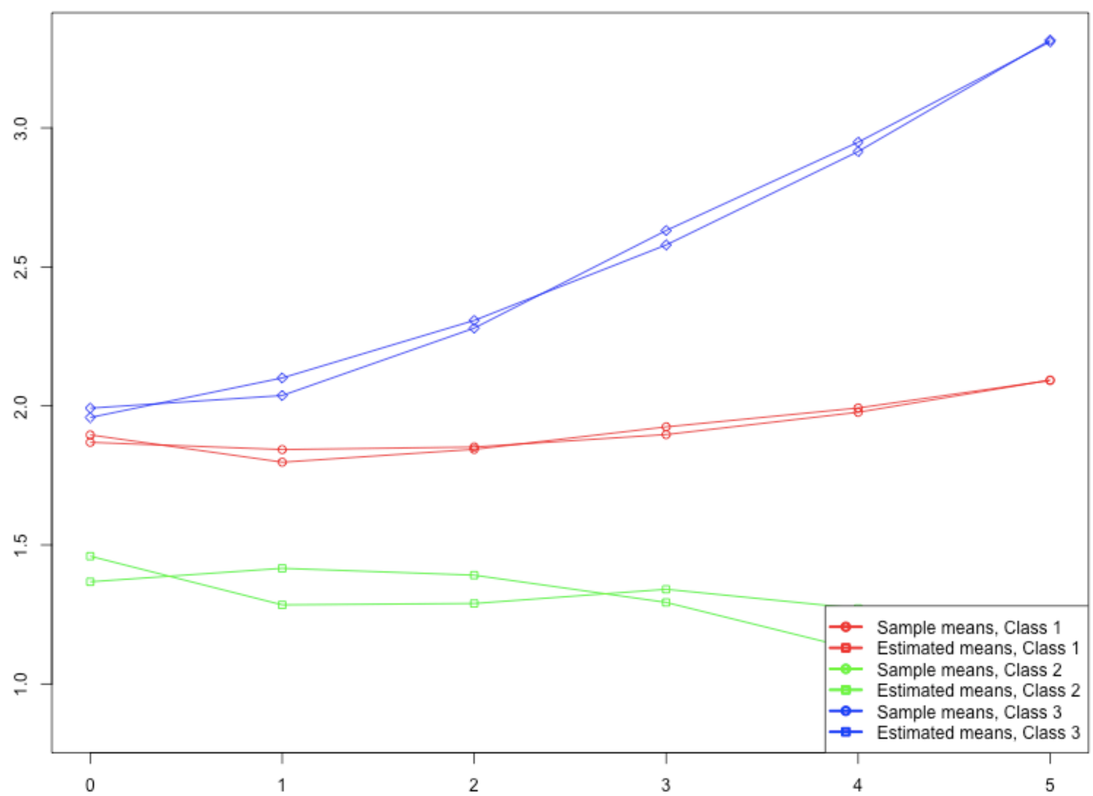
2) one subgroup with moderate but stagnant employment quality; 3) one subgroup with low but rising levels of employment quality; and 4) a final group with low and worsening employment quality over time. While the trajectories of classes 1 and 2 seem plausible (slight increases in EQ over time), the rapid growth among those in class 3 is questionable, especially given that this subgroup's estimated mean value is nearly equivalent to that of subgroup 1 at timepoint 6.

Figure 7. Sample and estimated means of subgroups for four-class linear growth mixture model



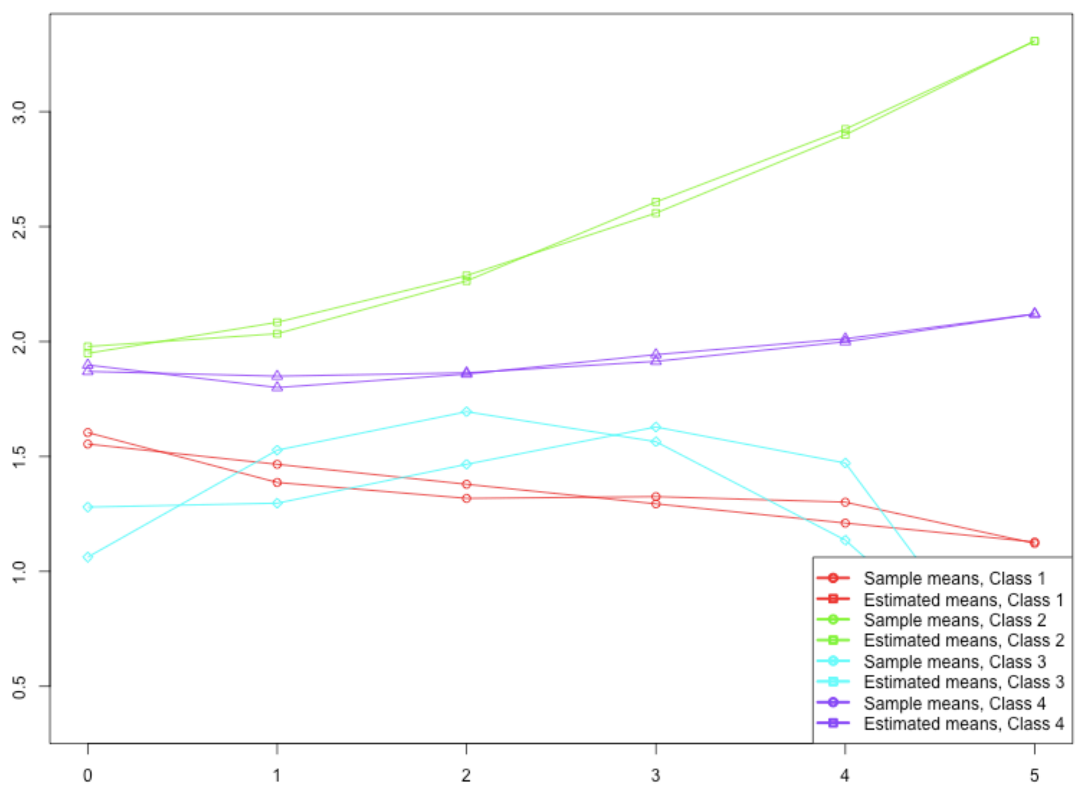
The quadratic three- and four-class models were slightly more difficult to parse out as each set of trajectories appears reasonable at face value. The first subgroup in the three-class quadratic model, to which nearly three quarters of respondents were assigned, experienced average employment quality in 2009 (intercept value of 1.87) and a negligible decline in employment quality over time (slope= -0.04)—a stagnant trajectory over time. The second class of Millennials in this three-class model is characterized by below-average employment quality at timepoint 1 (intercept value of 1.37) and modest growth over time (slope=0.08)—approximately 16% of Millennials were assigned to this subgroup. Millennials in the third class, in contrast to classes 1 and 2, enjoyed above-average employment quality in 2009 and gradual improvement in employment quality over time (slope=0.11). A little over 10% of respondents were classified as belonging to this employment quality subgroup. This set of trajectories appears plausible: one might expect to see a substantial number of Millennials with average but not improving levels of employment quality (consistent with the literature on stagnating wages among the vast majority of American workers), a smaller group of Millennials with initially low but modestly improving levels of employment quality, and a modest number of Millennials starting with above-average and improving levels of EQ.

Figure 8. Sample and estimated means for three-class quadratic growth mixture model



Four distinct trajectories were observed for the default four-class model. Specifically, the model contained one class with a sub-average EQ score (intercept value of 1.55) at timepoint 1 and declining quality over time (slope= -0.09), a second class with a high EQ intercept value (1.95) and gradually improving EQ over time (slope=0.10), a third class with a very low EQ intercept value (1.06) but high growth (slope=0.61), and a fourth class with a slightly above-average EQ value for the intercept (1.90) but gradually declining EQ (slope= -0.04)—nearly three-quarters of the sample was assigned to this final class. Like the three-class quadratic model, this four-class model had similar mean intercept values across classes (with the exception of class 3, which had an appreciably lower mean intercept value than the rest of the classes). Given the conceptual soundness of the three- and four-class quadratic models, selecting the "best-fitting" model will thus require consideration of the fit statistics and classification quality of these two models.

Figure 9. Sample and estimated means for four-class quadratic growth mixture model



Model Selection: Final Models: As detailed above, the process of selecting a "final" set of models involves weighing the fit statistics and classification quality measures of each model with its conceptual soundness. Among the set of linear models, the three-class model was arguably the best-fitting model: while the four-class model had slightly lower fit statistics and a slightly higher entropy value, the three-class model had higher average latent class probabilities for likely class membership and was more conceptually sound than the four-class model—across all classes in the three-class model, individuals were assigned to classes with at least 85% certainty. In contrast, individuals assigned to class 1 in the four-class linear model were only assigned with 70% certainty, on average. Moreover, conceptually—and as depicted in the plot of the three-class linear model—it is plausible that Millennials would start around the same level of employment quality in the wake of the Great Recession in 2009.

Among the best-fitting three- and four-class quadratic models, fit statistics would suggest the four-class model is preferential, while both measures of classification quality (entropy and average latent class probabilities) would indicate the three-class model is a better-fitting model. With respect to the conceptual soundness of each of the quadratic models, the three-class model is arguably preferential to the four-class model: While three of the four subgroups in the four-class quadratic model are nearly identical to the three-class model with respect to mean intercept and slope values, the fourth subgroup is more problematic. Specifically, individuals assigned to class 3 are assigned to this subgroup with, on average, only 78% certainty. Moreover, less than 50 individuals are assigned to this class (4% of the sample), and it is unclear why there would be a group of Millennials with such a dramatic arch (a very low initial EQ, an appreciable growth between 2009 and 2015, and a sharp decline in EQ toward the end of the study period).

Finally, with respect to whether to proceed with a linear or quadratic growth mixture model, here too the statistical and conceptual soundness of the two models was considered. As noted at the outset of this section, the quadratic one-class baseline model had lower fit statistics than the intercept-only or linear model, suggesting better fit. As additional classes were added to the linear and quadratic baseline models, it continued to be the case that the quadratic model had *lower* fit statistics and *higher* entropy and average latent class probabilities than its linear counterparts. Moreover, conceptually it is more likely to be the case that employment quality follows a quadratic rather than linear growth pattern. In short, given its superiority to the linear models with respect to fit statistics, measurement classification, and conceptual soundness, the three-class quadratic model was be used for all analyses from this point forward—specifically, to explore associations between EQ class and sociodemographic characteristics as well as between EQ class and psychological distress outcomes.

6.2.6. Exploring Associations between EQ Class and Sociodemographic Characteristics

Using the class assignments from the three-class quadratic GMM as the best-fitting model (i.e., individuals in the dataset were categorized as belonging to class 1, 2, or 3), bivariate analyses were then conducted to examine associations between key sociodemographic variables and EQ class. Table 13 presents the results of these bivariate analyses for each class, class 1 being the subgroup of modest EQ growth, class 2 the subgroup with negative EQ growth, and class 3 the subgroup with appreciable improvements in EQ over the study period. Greater proportions of individuals in class 2 were female and had lower levels of education: three-quarters (76.5%) of individuals in this negative EQ growth subgroup were female compared to 57.8% in class 1 and 47.9% in class 3, and nearly one-quarter of Millennials in class 2 had less than a high school education compared to 9.3% in class 1 and 2.2% in class 3. Moreover, while

41.7% and 44.4% of respondents in classes 1 and 3, respectively, had a college education, only one-fifth (20.5%) of respondents in class 2 were college educated. This negative EQ growth subgroup was also associated with marital status, high vs. low-skill worker status, and parental education. With respect to marital status, nearly three-quarters (72.9%) of Millennials in the ideal EQ trajectory subgroup (class 3) were married or cohabitating compared with 48.3% in the negative EQ growth subgroup (class 2) and 64.4% in the modest EQ growth subgroup (class 1). Strikingly, a significantly higher proportion of 20.5% of Millennials in class 2 were widowed, divorced, or separated (20.5%) compared to the other subgroups (9.3% among respondents in class 1 and 3.6% among those in class 3).

Bivariate associations were also explored between EQ trajectory class and occupation status. Based on a four-category coding of occupation status (low-skill, blue-collar; high-skill, blue-collar; low-skill, white-collar; and high-skill, white-collar), these analyses revealed that greater proportions of Millennials in the negative growth subgroup (class 2) were low-skill workers compared to the low growth subgroup (class 1) and the high growth subgroup (class 3). Specifically, nearly half (47.6%) of Millennials in class 2 were low-skill, white-collar workers and 20.5% were low-skill, blue-collar workers. In contrast, less than 10% of workers in both class 1 (low growth) and class 3 (high growth) were low-skill, blue-collar workers and approximately 37% in both subgroups were low-skill, white-collar workers. Indeed, the plurality of Millennials in both the low growth and high growth classes (41% of respondents in both classes) were high-skill, white-collar workers compared to almost half that amount (21.2%) among respondents in the negative growth class.

Results were mixed with respect to parental education, the proxy measure for childhood SES: significant associations were observed between EQ trajectory class and mother's level of education but not for father's level of education. Greater proportions of the Millennials in the negative EQ growth class compared to the low- and high-growth classes had mothers with a high school level of education. One-quarter of Millennials in the negative growth class reported their mother having less than a high school level of education, compared to 7.4% and 8.4% among those in the low and high EQ growth subgroups. The inverse relationship was observed with respect to college education: over one-third (36%) of respondents in the low- and high-growth classes indicated their mother had a college education, compared to 18% among Millennials in the negative growth class.

Table 13. Social and demographic characteristics of Millennials in 2019, by employment quality class (n=1303)

Characteristic	Class 1 (low, positive growth) n=946	Class 2 (negative growth) n=203	Class 3 (high, positive growth) n=154
Mean age	35.2 (0.11)	34.8 (0.28)	35.4 (0.23)
Sex			
Female	57.8**	76.5**	47.9**
Male	42.2**	23.5**	52.1**
Mean years of education	14.0 (0.16)***	12.6 (0.33)***	14.5 (0.27)***
Education (categorical)			
Less than high school	9.3***	24.2***	2.2***
High school	20.6***	25.3***	21.1***
Some college	28.3***	29.9***	32.3***
College	41.7***	20.5***	44.4***
Race			
White	74.4	61.7	67.3
Black	13.3	24.0	17.7
Non-white, non-black	12.4	14.3	14.9
Marital status			
Married/cohabitating	64.4**	48.3**	72.9**
Single, never married	26.4**	31.2**	23.5**
Widowed, divorced or separated	9.3**	20.5**	3.6**
Residence			
Urban	81.5	78.8	82.6
Rural	18.5	21.2	17.4
Region			

Northeast	11.2	11.4	24.4
North Central	24.2	22.7	29.0
South	38.0	41.5	23.3
West	26.4	24.3	23.3
Alaska, Hawaii	0.1	0.0	0.0
Immigrant sample			
Yes	87.7	91.3	89.8
No	12.3	8.7	10.2
Blue collar worker status			
Blue-collar, low skill	8.7**	20.3**	7.4**
Blue-collar, high skill	12.2**	10.9**	15.2**
White-collar, low skill	37.9**	47.6**	36.9**
White-collar, high skill	41.2**	21.2**	40.5**
Father's level of education			
Less than high school	9.8	13.8	7.3
High school	39.2	45.2	36.7
Some college	14.0	19.9	18.7
College	37.0	21.1	37.3
Mother's level of education			
Less than high school	7.4***	25.7***	8.4***
High school	37.6***	36.7***	35.9***
Some college	19.4***	19.8***	19.9***
College	35.6***	17.8***	35.8***

*$p<0.05$, **$p<0.01$, ***$p<0.001$

Notes: 1) Figures in parentheses are standard errors. 2) Bivariate analyses were also performed excluding the Alaska, Hawaii category for region with no change to the significance of the relationship between EQ class and region.

6.2.7. Summary of Research Aim 1 Findings

The objective of this first research aim was to identify patterns of employment quality among Millennial respondents in the decade following the Great Recession. Using growth mixture modeling, an extension of growth curve modeling, three subgroups of employment quality trajectories were identified from the data: One group (nearly three-quarters of respondents belonged to this subgroup) experienced stagnant employment quality over the 10-year study period; a second group (comprised of approximately 16% of respondents) experienced declining employment quality over time; and the third group (a little over 10% of respondents were assigned to this subgroup) enjoyed steadily rising employment quality over time.

Millennials in the negative EQ growth class compared to the low- and high-growth subgroups were more likely to have lower levels of educational attainment; to be divorced, separated, or widowed; to be low-skill, white- or low-skill, blue-collar workers; and to have mothers with less than a high school level of education. Having explored the sociodemographic characteristics of Millennials in each employment quality trajectory, the next section of this study explores the association between each EQ class and psychological distress outcomes.

6.3. Research Aim 2: Employment Quality Trajectories and Mental Health

6.3.1. Results from Simple Logistic and Linear Regressions (One Predictor)

The purpose of this research aim is to understand whether and how study participants' location in each of the three employment quality classes identified in research aim 1 was associated with the experience of psychological distress. Prior to fitting models inclusive of any sociodemographic variables, the relationship between employment quality class and the probability of experiencing severe and moderate psychological distress was explored among individuals with mental health data for all six survey waves. Odds ratios and 95% confidence intervals from these unadjusted models are presented in Table 14, below. As hypothesized, participants in the class with declining employment quality over time (Class 2) had 3.5 times the odds of meeting the threshold for severe psychological distress compared to those in the subgroup with stagnant employment quality over time. Moreover, participants in the "ideal" employment quality class—those whose employment quality scores increased in the decade following the Great Recession (class 3)—had significantly lower odds of reporting symptoms consistent with severe psychological distress compared to the reference group (stagnant EQ class—class 1). Specifically, the odds of meeting the threshold for severe psychological distress were approximately 80% lower for Millennials in class 3 compared to those in class 1.

Table 14. Odds ratios (and 95% confidence intervals) from logistic regression models examining Millennials' likelihood of experiencing severe and moderate psychological distress based on employment quality class, among Millennials with six psychological distress data points (n=572)

Characteristic	Severe psychological distress	Moderate psychological distress
Employment quality trajectory class		
Class 1 (stagnant EQ)	(reference)	(reference)
Class 2 (declining EQ)	3.47 (1.67-7.24)**	2.05 (1.30-3.26)**
Class 3 (increasing EQ)	0.21 (0.05-0.87)*	0.85 (0.50-1.46)

*$p<0.05$, **$p<0.01$, ***$p<0.001$

Due to the wide confidence interval, particularly for the odds ratio estimates for severe psychological distress (95% CI for class 2 ranging from 1.67 to 7.24), the distribution of mental health outcomes was explored for each identified employment quality class. As shown in Table 15, below, only four Millennials in the "ideal" EQ trajectory class endorsed psychological distress symptoms consistent with the severe-level threshold. Such a low number of respondents in this category likely explains the width of the confidence interval when estimating the odds of severe psychological distress for class 2 (compared to class 1).

Table 15. Percentage of Millennials endorsing severe and moderate levels of psychological distress, by employment class (n=572)

Characteristic	Severe psychological distress % (n)	Moderate psychological distress % (n)
Employment quality trajectory class		
Class 1 (stagnant EQ)	3.61% (90)	34.1 (850)
Class 2 (declining EQ)	8.5% (46)	45.4 (245)
Class 3 (increasing EQ)	1.01% (4)	31.6 (125)

*$p<0.05$, **$p<0.01$, ***$p<0.001$

Anticipating that additional models—models adjusted for key sociodemographic variables—would have similarly wide confidence intervals for the probability of experiencing severe psychological distress, the effect of employment quality class on *total psychological distress score* (continuous variable) was also explored prior to fitting mixed effects logistic regression models adjusted for covariates. As shown in Table 16, below, those in the worst employment quality subgroup (class 2) had statistically higher psychological distress scores compared to participants in class 1. Specifically, membership in class 2 was associated with a 1.2-point increase in psychological distress scores ($p<0.001$). No significant association was observed for membership in class 3 (compared to class 1) and total psychological distress score.

Table 16. Coefficients (and standard errors) for impact of employment quality class on total psychological distress scores, among Millennials with mental health data from 6 survey waves (n=572)

Characteristic	Total psychological distress score Coefficient (SE)
Employment quality trajectory class	
Class 1 (stagnant EQ)	(reference)
Class 2 (declining EQ)	1.17 (0.33)***
Class 3 (increasing EQ)	-0.42 (-1.15)

**p<0.05, **p<0.01, ***p<0.001*

Finally, to determine which covariates to include in the adjusted models, a series of simple logistic regressions between each covariate and moderate/severe psychological distress were conducted using the “xtreg, mle” command in Stata to account for the panel structure of the dataset. Results from these simple logistic regressions are presented in Table 17, below. Sex, race, and marital status were each significantly associated with severe psychological distress. Specifically, female Millennials, Black Millennials, and single/never married Millennials had more than double the odds of experiencing severe psychological distress compared to their male, white, and married/cohabitating counterparts, respectively. These same variables with the addition of age and parental education were found to be significant in simple regression analyses where moderate psychological distress was the outcome.

Table 17. Odds ratios (and 95% confidence intervals, p-values) from simple logistic regressions examining the relationship between Millennials' likelihood of experiencing severe and moderate psychological distress and various sociodemographic characteristics, among Millennials with six psychological distress score data points (n=572)

Characteristic	Severe psychological distress		Moderate (or greater) psychological distress	
	OR (95% CI)	p-value	OR (95% CI)	p-value
Age	0.96 (0.91-1.01)	0.14	0.95 (0.93-0.98)***	<0.001
Sex				
Male	(reference)		(reference)	
Female	2.49 (1.33-4.66)**	<0.01	2.08 (1.48-2.92)***	<0.001
Race				
White	(reference)		(reference)	
Black	2.19 (1.12-4.27)*	0.02	1.52 (1.06-2.17)*	0.02
Non-white, non-black	1.22 (0.39-3.81)	0.73	1.59 (0.91-2.77)	0.10
Marital status				
Married/cohabitating	(reference)		(reference)	
Single, never married	2.53 (1.27-5.07)**	0.01	1.96 (1.47-2.61)***	<0.001
Widowed, divorced or separated	4.28 (1.77-10.33)**	<0.01	1.66 (1.09-2.52)*	0.02
Residence				
Urban	(reference)		(reference)	
Rural	1.20 (0.90-1.60)	0.22	1.04 (0.87-1.25)	0.67
Region				
Northeast	(reference)		(reference)	
North Central	2.41 (0.62-9.34)	0.20	0.76 (0.43-1.35)	0.35
South	3.57 (0.10-12.77)	0.05	1.07 (0.63-1.82)	0.80
West	3.28 (0.82-13.15)	0.09	0.90 (0.49-1.64)	0.74
Alaska, Hawaii	(empty)		(empty)	
Immigrant sample				
No	(reference)		(reference)	
Yes	1.06 (0.31-3.71)	0.92	0.75 (0.38-1.50)	0.42
Highest level of parent's education				
Less than college	(reference)		(reference)	
College or higher	0.49 (0.23-1.04)	0.06	0.63 (0.42-0.93)*	0.02

*$p<0.05$, **$p<0.01$, ***$p<0.001$

6.3.2. Results from Adjusted Mixed-Effects Logistic Regressions

Three mixed effects logistic regression models were fitted for each psychological distress outcome (i.e., severe and moderate).[44] The first model included all covariates found to be marginally significant (p<0.10) in simple logistic regressions, including sex, employment quality class, years of education, marital status, race, and parental education.[45] Given the longitudinal nature of the analysis, age was also included in model 1 (and all subsequent models) regardless of significance in simple logistic regression models. Model 2 included age, sex, years of education, race, and marital status, as covariates (parental education was dropped from the model given its high p-value in model 1). A third model, which did not include race/ethnicity, was also fitted to determine whether this would improve model fit.

Odds ratios and 95% confidence intervals for the three models are presented in Table 18 on the following page. Neither employment quality class nor any other sociodemographic variable significantly predicted the probability of experiencing severe psychological distress in model 1. Moreover, the p-value of the Wald chi2 test for this model of 0.13 indicates that this full model does not represent a significant improvement in fit over a null or intercept only model. The Wald chi2 tests and corresponding p-values for models 2 and 3 suggest these are better fitting models: When race was included in the model (model 2), years of education and marital status were significantly associated with the odds of experiencing severe psychological distress. Specifically, holding all other variables at a fixed value, an 18% decrease in the odds of

[44] Multicollinearity was assessed by running "regress" on variables that were marginally significant in simple logistic regressions (i.e., age, sex, race, education, marital status, and parental education) and then using the "estat vif" command to get collinearity statistics. Given that multicollinearity is a property of the data, not the regression model (i.e., it's an independent variable phenomenon), there is no difference between a single and multilevel model. All VIF values were less than 2.

[45] Prior to fitting adjusted models, variables with more than three categories were dichotomized when it was possible and meaningful to do so. Specifically, parental education level was recoded into a binary variable to reflect whether the parents (either mother or father) of each respondent had completed college.

experiencing severe psychological distress was observed for a one-year increase in education. In addition, compared to participants who are married/cohabitating, those who are divorced, widowed, or separated had nearly 3 times the odds of reporting symptoms consistent with severe psychological distress. When race was dropped from the model (model 3) on account of the high p-values observed in model 2 (p=0.69 for black compared to white and p=0.79 for non-white, non-black compared to white), marital status and years of education remained significant—additional years of education maintained its protective effect while widowed/divorced/separated status increased the odds of severe psychological distress. Membership in class 2 (the declining EQ class) was also significant in this model: Compared to their counterparts with stagnant EQ over the study period, Millennials in class 2 had more than twice the odds of experiencing severe psychological distress.

As mentioned in the previous section, these odds ratios should be interpreted with caution given how few individuals, particularly in class 3, endorsed symptoms that met the threshold for severe psychological distress. Indeed, the wide confidence intervals for many of the OR estimates speaks to this potential misspecification issue. This being said, in sensitivity analyses where models 2 and 3 were fitted using a binary EQ class predictor variable rather than the three-category variable (class 1 and class 3 were combined and severe psychological distress outcomes compared with class 2), no difference was observed with respect to significant covariates: each additional year of education was associated with lower odds of severe psychological distress while divorced/separated/widowed status more than doubled the odds of this outcome. The binary EQ class variable was also statistically significant for both models: Millennials in the subgroup with declining EQ had more than twice the odds of endorsing symptoms of severe psychological distress compared to those with stagnant or improving EQ.

A different pattern emerged with respect to predictors of *moderate* psychological distress. In addition to marital status and employment quality class, sex and age also emerged as significant predictors of moderate mental psychological distress outcomes. With respect to marital status, both single, never married and divorced/separated/widowed Millennials had higher odds of moderate psychological distress compared to their married/cohabitating counterparts (odds of approximately 1.5 for each marital status category). As for EQ trajectory class, in models 2 (including race as a covariate) and 3 (without race as a covariate), membership in the declining EQ subgroup was associated with greater odds of moderate distress: Millennials in this subgroup had approximately 60% greater odds of reporting moderate psychological distress compared with participants in the stagnant EQ class. Finally increasing age and male gender were protective factors across all three models: Females compared to males had 60% greater odds of moderate distress, while each additional year was associated with approximately a 3% decrease in the odds of moderate psychological distress.

Severe and moderate psychological distress analyses were re-run to test for an interaction effect between EQ class and race (i.e., to assess whether the strength of the relationship between EQ class and psychological distress outcomes varied by race). No interaction effect was observed for either outcome. As noted above, these analyses proved especially difficult for the severe psychological distress model given that only four respondents in class 3 reported symptoms consistent with severe psychological distress. Specifically, there were no non-white, non-black respondents in EQ class 3 (positive growth class) whose psychological distress scores met the severe distress threshold.

Table 18. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining Millennials' likelihood of experiencing severe and moderate psychological distress based on EQ class and sociodemographic characteristics (n=572)^

Characteristic	Severe psychological distress			Moderate (or greater) psychological distress[b]		
	Model 1	Model 2	Model 3	Model 1	Model 2^	Model 3
Fixed effects						
Age	0.97 (0.90-1.04)	0.97 (0.92-1.03)	0.97 (0.92-1.02)	0.97 (0.94-0.99)*	0.96 (0.94-0.98)**	0.97 (0.94-0.98)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.69 (0.73-3.90)	1.45 (0.76-2.76)	1.53 (0.81-2.87)	1.71 (1.10-2.67)*	1.59 (1.11-2.28)*	1.63 (1.15-2.31)**
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	1.24 (0.46-3.30)	1.95 (0.93-4.07)	2.11 (1.02-4.37)*	1.47 (0.82-2.61)	1.61 (1.02-2.56)*	1.67 (1.06-2.64)*
Class 3	0.26 (0.05-1.27)	0.26 (0.07-1.03)	0.27 (0.07-1.04)	0.84 (0.46-1.54)	0.91 (0.54-1.54)	0.90 (0.53-1.52)
Education (in years)	0.88 (0.73-1.07)	0.82 (0.71-0.95)**	0.81 (0.71-0.94)**	1.01 (0.97-1.06)	0.99 (0.96-1.02)	0.99 (0.96-1.02)
Marital status						
Married/cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	1.47 (0.60-3.64)	1.74 (0.82-3.69)	1.77 (0.85-3.70)	1.35 (0.93-1.97)	1.56 (1.15-2.13)**	1.53 (1.13-2.08)**
Widowed, divorced or separated	1.95 (0.55-6.90)	2.93 (1.17-7.33)*	2.99 (1.21-7.40)*	1.37 (0.78-2.40)	1.53 (1.00-2.34)*	1.53 (1.00-2.34)*
Race		-				
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.11 (0.46-2.66)	1.15 (0.57-2.34)	-	1.14 (0.72-1.80)	1.10 (0.76-1.59)	-
Non-white (not Black)	0.70 (0.16-3.04)	0.85 (0.28-2.64)	-	1.64 (0.84-3.18)	1.54 (0.89-2.67)	-
Parent's education	-	-	-		-	-
Less than college	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
College or higher	0.87 (0.37-2.04)	-		0.84 (0.55-1.29)	-	-
Random Effects						
Var (_cons)	3.21 (1.72-5.98)	3.58 (2.25-5.69)	3.59 (2.27-5.70)	2.54 (1.92-3.37)	2.72 (0.31-1.93)	2.70 (2.15-3.38)
Model fit						
Wald chi2, prob>chi2[a]	15.04, p=0.13	33.64, p<0.001	35.68, p<0.001	29.63, p=0.001	48.98, p<0.001	48.1, p<0.001

**p<0.05, **p<0.01, ***p<0.001*

[a]User model compared to null model

[b]Note that those with total distress scores consistent with severe distress are included in the moderate distress cutoff of 5 or higher

6.3.3. Comparing Regression Findings among Millennials with Fewer than Six Data Points

As noted in the descriptive statistics section, several notable differences exist with respect to the sociodemographic characteristics of participants who had psychological distress data for six compared to three and four survey waves. Importantly, a greater proportion of those with corresponding mental health data for all six timepoints are white, men, urban residents, and blue-collar workers. Relying exclusively on this sample to explore associations between employment quality and mental health outcomes may mask the true of effects of race, gender, and rural residence on these outcomes. To identify any appreciable differences in terms of the effect EQ class and other sociodemographic variables on psychological distress among those with data from fewer than six survey waves, the same set of mixed effects logistic regression models were fitted for the three-, four-, and five-timepoint samples.

Findings from mixed effects logistic regression models fitted for participants with data from three, four, and five survey waves are presented in Table 19 on the following page. As was the case for the six-wave sample (model 2), participants in three, four survey, and five waves had more than twice the odds of severe psychological distress if they were members of the declining EQ subgroup compared to the stagnant EQ subgroup. Moreover, consistent with findings from the six-wave sample, additional years of education and married/cohabitating status were protective factors against severe psychological distress. Participants who were widowed, divorced, or separated had between 3.5 (5-wave sample) and 5.0 times (3-wave sample) the odds of psychological distress compared to those who were married or cohabitating. The only appreciable difference between the six-wave and three-to-five-wave models was that single/never married participants in the three- and four-wave samples had more than twice the odds of meeting the threshold for severe psychological distress compared to their married counterparts (among the six-wave sample, single/never married status was not associated with severe psychological distress). Notably—and consistent with the six-wave sample models—race was not significantly associated with the odds of severe psychological distress.

With respect to differences in moderate psychological distress outcomes, female gender was not a significant predictor of moderate psychological distress among those with three- and four-waves of mental health data, though it was associated with higher odds of moderate distress among those with five and six timepoints worth of mental health data. Moreover, while higher levels of education were not a protective factor for moderate psychosocial distress in analyses with the six-wave sample, each additional year of education did significantly reduce—albeit slightly—the odds of experiencing moderate mental distress among the three-, four-and five-wave sample. These findings are noteworthy given that the majority of those with fewer than five timepoints were female (62.3% of three-wave respondents were female compared with 42.1% among those who were respondents for all six survey waves) and had significantly lower levels of education than their six-wave counterparts. No differences were observed in terms of age, employment class, and marital status: younger age, declining employment quality (i.e., membership in class 2), and single/unmarried or divorced/separated/widowed status were all associated with greater odds of moderate psychological distress symptoms.

Table 19. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining Millennials' likelihood of experiencing severe and moderate[a] psychological distress, among respondents with mental health data for three, four, and five survey waves

Characteristic	3 Data Points (n=1017)		4 Data Points (n=907)		5 Data Points (n=671)	
	Severe	Moderate or greater	Severe	Moderate or greater	Severe	Moderate or greater
Age	0.96 (0.92-1.00)	0.97 (0.95-0.99)**	0.95 (0.91-0.99)*	0.96 (0.95-0.98)**	0.96 (0.91-1.01)	0.97 (0.95-0.99)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.65 (0.97-2.81)	1.27 (0.96-1.66)	1.54 (0.89-2.70)	1.23 (0.93-1.63)	1.51 (0.82-2.78)	1.53 (1.12-2.11)**
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	2.17 (1.20-3.92)*	1.47 (1.03-2.11)*	2.43 (1.31-5.00)**	1.59 (1.09-2.31)**	2.48 (1.25-4.93)*	1.64 (1.07-2.50)*
Class 3	0.51 (0.20-1.32)	1.06 (0.70-1.60)	0.34 (0.11-1.04)	0.97 (0.63-1.50)	0.24 (0.06-0.92)*	0.95 (0.59-1.52)
Education (in years)	0.86 (0.79-0.94)**	0.97 (0.95-0.99)**	0.84 (0.77-0.92)***	0.98 (0.95-0.99)*	0.84 (0.76-0.93)**	0.97 (0.95-0.99)*
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	2.26 (1.37-3.72)**	1.62 (1.31-2.00)***	2.54 (1.47-4.37)**	1.77 (1.41-2.21)***	1.62 (0.82-3.18)	1.57 (1.20-2.05)**
Widowed, divorced, separated	5.07 (2.73-9.39)***	1.99 (1.46-2.71)***	4.81 (2.45-9.44)***	1.90 (1.37-2.63)***	3.45 (1.57-7.59)**	1.67 (1.15-2.42)**
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.05 (0.61-1.79)	1.28 (0.97-1.69)	0.96 (0.54-1.69)	1.23 (0.92-1.65)	0.90 (0.47-1.72)	1.05 (0.75-1.47)
Non-white, non-black	1.21 (0.51-2.90)	1.33 (0.87-2.04)	1.06 (0.41-2.72)	1.30 (0.82-2.04)	0.97 (0.35-2.70)	1.26 (0.76-2.08)
Random Effects						
Var (_cons)	1.98 (1.66-2.37)	1.74 (1.59-1.89)	1.99 (1.65-2.39)	1.81 (1.56-1.87)	1.91 (1.54-2.37)	1.66 (1.50-1.84)
Model fit						
Wald chi2, prob>chi2[a]	69.21, p<0.001	80.53, p<0.001	68.65, p<0.001	78.30, p<0.001	48.17, p<0.001	52.28, p<0.001

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

[a]Note that those with total distress scores consistent with severe distress are included in the moderate distress cutoff of 5 or higher

6.3.4. Results from Mixed-Effects Linear Regression: Examining Total Psychological Distress by EQ Class

Given the low frequency of participants in the study who cited symptoms consistent with psychological distress—and the resulting quality issues of the models fitted to examine these severe distress outcomes—additional, mixed effects linear regression models were fitted to explore the effect of employment quality class on participants' total Kessler-6 psychological distress scores.[46] The same set of models were fitted as for the severe and moderate psychological distress models: the first model included all covariates that were found to be marginally significant (p<0.10) in bivariate analyses between total psychological distress score and each sociodemographic variable (like for the logistic regressions in the previous section, age, sex, class, race, marital status, and parental education were all found to be significant in bivariate analyses). The second model dropped parental education as a covariate given its very high p-value in model 1. Model 3, the most parsimonious model, only included age, sex, education, employment quality class, and marital status as predictors.

Coefficients from these mixed-effects regression models are presented in Table 20, below. Of note is the similarity between risk and protective factors for total psychological distress score and those for moderate psychological distress. Namely, in models 2 and 3, each additional year of age is predictive of a 0.05 decrease in total psychological distress score, while female gender is predictive of nearly a 0.75-point decrease in these models. In addition—and as was the case in the models fitted for moderate psychological distress—the predicted total psychological distress score was approximately 0.85 points lower for those in the declining

---

[46] Arguably I could have relied on the moderate psychological distress analyses given the data quality issues surrounding the severe psychological distress analyses; however, the moderate distress cutoff value of 5 was not assigned by the creator of the Kessler-6 scale but rather by another researcher who found this cutoff value to be valid in a particular study (the cutoff value of 5 from this study has been cited and leveraged by other researchers as justification for a 5-point cutoff, though again, this was not the original guidance accompanying the scale).

employment quality subgroup compared to those in the stagnant employment quality subgroup. Finally, study participants who are single, never married have a predicted total psychological distress score that is approximately a half point higher than participants who are married/cohabitating; those who are widowed, divorced, or separated have more than a 0.75-point increase in total psychological distress score compared to their married/cohabitating counterparts. Years of education, race, and parental education levels were not significant predictors of total psychological distress score in any of the models.

Table 20. Coefficients (and 95% confidence intervals) from mixed-effects regression models examining Millennials' total psychological distress scores based on EQ class and sociodemographic characteristics, among Millennials with six psychological distress data points (n=572)

Characteristic	Model 1	Model 2	Model 3
Mean age	-0.03 (-0.06-0.00)	-0.05 (-0.08, -0.02)*	-0.05 (-0.08, -0.02)**
Sex			
Male	(reference)	(reference)	(reference)
Female	0.77 (0.18-1.36)*	0.73 (0.24-1.22)**	0.76 (0.29-1.24)**
Education (in years)	-0.00 (-0.05-0.05)	-0.02 (-0.05- 0.03)	-0.1 (-0.05-0.02)
EQ class			
Class 1	(reference)	(reference)	(reference)
Class 2	0.58 (-0.20-1.37)	0.83 (0.19-1.48)*	0.89 (0.25-1.52)**
Class 3	-0.46 (-1.26-0.33)	-0.32 (-1.03-0.40)	-0.33 (-1.04-0.39)
Race			
White	(reference)	(reference)	-
Black	-0.01 (-0.61-0.58)	0.11 (-0.38-0.60)	-
Non-white (non-black)	0.60 (-0.22-1.43)	0.48 (-0.22-1.19)	-
Marital status			
Married/ cohabitating	(reference)	(reference)	(reference)
Single, never married	0.35 (-0.08-0.77)	0.51 (0.15-0.87)**	0.48 (0.12-0.83)**
Widowed, divorced, separated	0.37 (-0.28-1.02)	0.77 (0.26-1.27)**	0.77 (0.26-1.27)**
Parental education			
Less than college	(reference)	-	-
College or higher	-0.20 (-0.76-0.36)	-	-
Random Effects			
Var (_cons)	5.52 (4.63-6.59)	2.48 (2.30-2.66)	2.47 (2.30-2.65)
Var (residual)	7.62 (7.14-8.12)	2.88 (2.81-2.96)	2.89 (2.81-2.96)
Model fit			
Wald chi2, prob>chi2[a]	30.73, p<0.001	62.74, p<0.001	62.74, p<0.001

**p<0.05, **p<0.01, ***p<0.001*

6.3.5. Diagnostics for Mixed Models

Where appropriate, Stata postestimation commands were used following fitted regression models to test the robustness of each model, examine model assumptions, analyze residuals, and make predictions.

Mixed Effects Logistic Regression Models: As normal distribution of residuals and homoscedasticity are issues pertaining to linear regression, postestimation for the mixed-effects *logistic regressions* involved 1) exploring AIC and BIC; 2) examining the Receiver-Operating Characteristics (ROC) curve and corresponding Area Under the Curve (AUC) values; and 3) plotting the predicted successes against the observed successes (overlaid on a diagonal line). This latter step was done to determine whether there were particular ranges of predicted risk where the model fit was not good.

For each set of models fitted for severe and moderate psychological distress outcomes, AIC and BIC statistics as well as AUC values were compared. These statistics are presented in Table 21, below. As reflected in the table, model 1 for severe psychological distress had the lowest AIC and BIC values; however, as discussed in the preceding sections, the miniscule number of respondents endorsing severe levels of psychological distress (e.g., fewer than five individuals across the study period in the increasing EQ subgroup) render the results from this model questionable. Indeed, the high standard errors for model 1 reflected in Table 18 (p. 116) suggest that the lower fit statistics associated with this model do not necessarily indicate better fit. A comparison of fit statistics for the second and third models fitted for psychological distress offer conflicting results: model 2, which includes race as a covariate, has a lower AIC than model 3 (995.9 versus 1004.9 for models 2 and 3, respectively) but a higher BIC (1063.4 for model 2 versus 1060.1 for Model 3)—based on point differential alone, the difference in BIC levels is approximately 2 points, whereas there is nearly a 10-point difference between the two models' AIC values. Beyond this point differential in favor of model 2, theory would also suggest the importance of including race as a covariate in a model exploring the role of employment quality on severe psychological distress outcomes. AUC values across the three models are nearly identical as reflected in Table 21, below, and Figure 10 on the following page: each model is able to discriminate cases with severe psychological distress outcome (1) from those without this outcome (0)—i.e., the discriminatory power of these models is excellent. Finally, in plots depicting, for each percentile of predicted risk, the predicted successes (x-axis) by the observed successes (y-axis), models 2 and 3 appear to have better fit than model 1: As shown in Figure 11 on the following page, the plots of the number of predicted versus observed successes are much closer to the diagonal line for models 2 and 3 than for model 1.

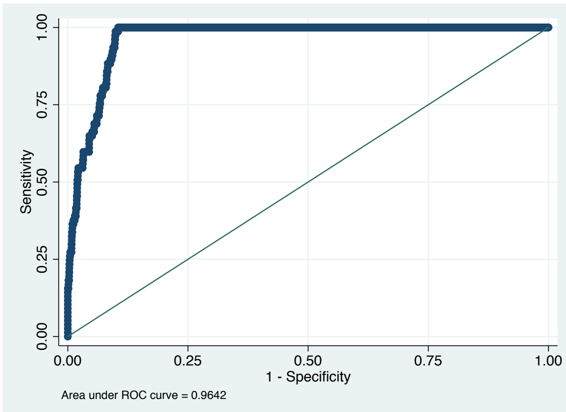
Table 21. Diagnostics for mixed effects logistic regression models assessing predictors of severe and moderate psychological distress outcomes (n=572)

	Severe psychological distress			Moderate (or higher) psychological distress		
Model diagnostics	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
AIC	619.17	995.94	1004.88	2618.44	3871.77	3887.27
BIC	687.96	1063.45	1060.15	2687.22	3939.27	3942.52
Area under the curve (AUC)	0.96 (0.95-0.97)	0.96 (0.96-0.97)	0.965 (0.958-0.972)	0.887 (0.874-0.900)	0.890 (0.880-0.901)	0.890 (0.880-0.900)

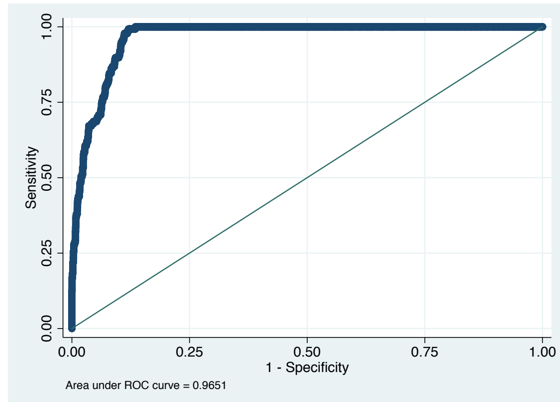
Postestimation analyses for the moderate psychological distress outcomes produce similarly mixed findings. The AUC values are virtually identical for models 1-3 (ROC curves are also presented in Figure 12), meaning all three models are quite capable of distinguishing moderate psychological distress cases from non-moderate psychological distress cases. With respect to the models' fit statistics, the AIC and BIC values for model 1 are substantially

Figure 10. ROC curves for severe psychological distress models

Model 1



Model 2



Model 3

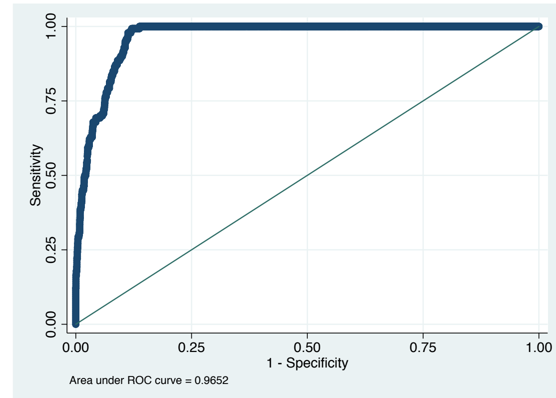
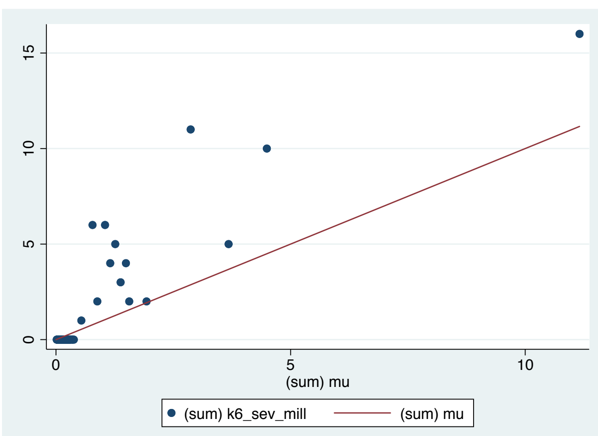
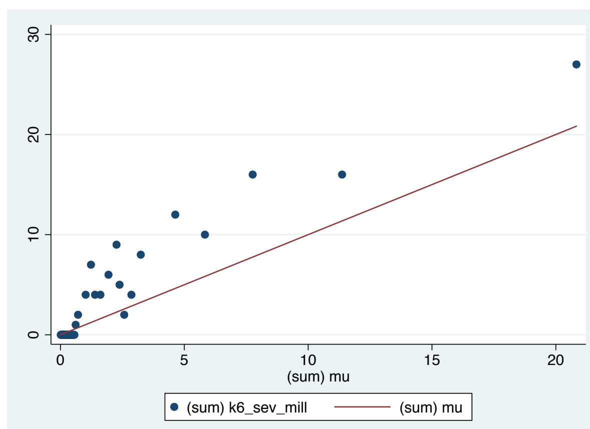


Figure 11. Plots of the number of predicted versus observed successes for severe psychological distress models

Model 1



Model 2



Model 3

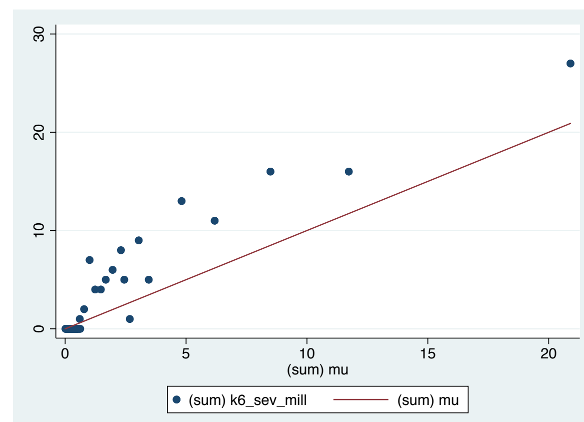


Figure 12. ROC curves for moderate psychological distress models

Model 1 Model 2 Model 3

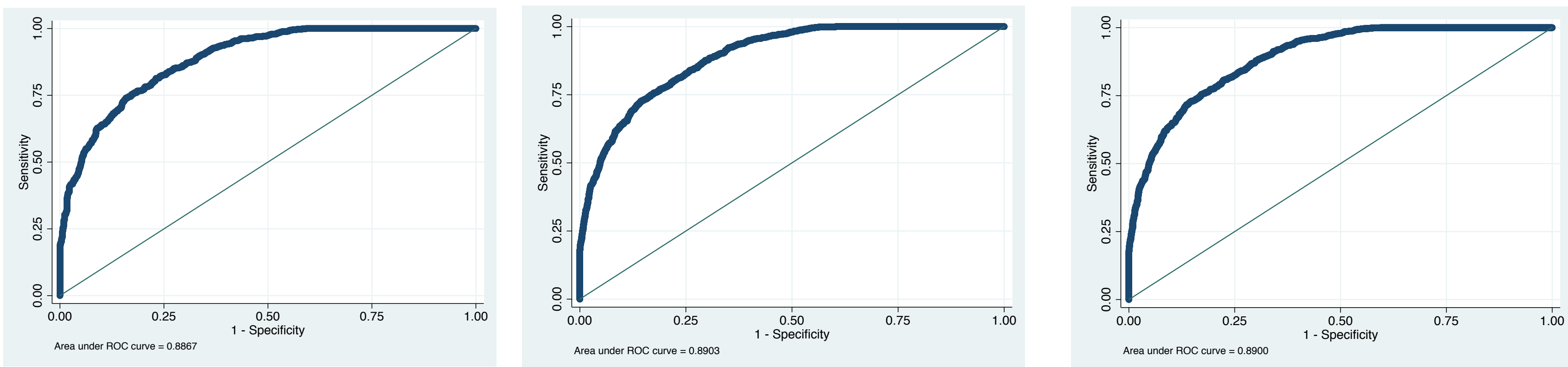
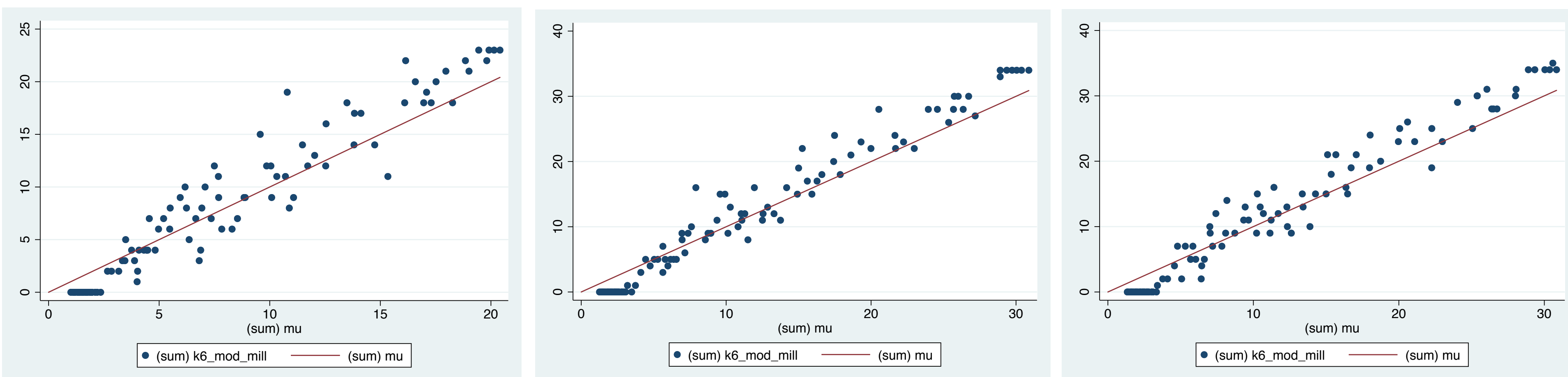


Figure 13. Plots of the number of predicted versus observed successes for moderate psychological distress models

Model 1 Model 2 Model 3



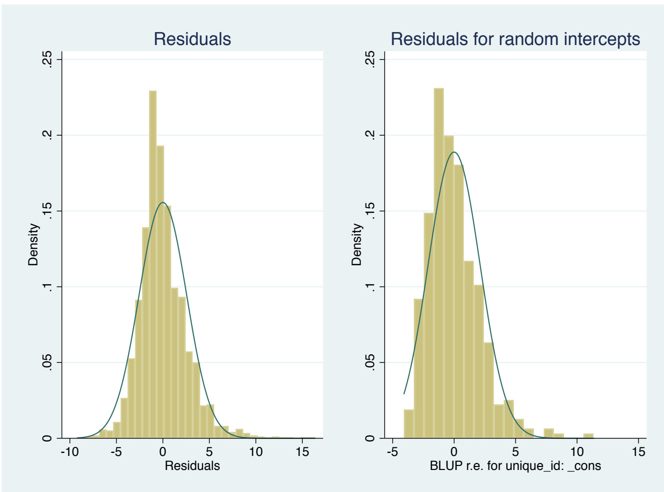
lower than models 2 and 3; however, upon examining plots of the number of predicted versus observed successes for moderate psychological distress outcomes (Figure 13), models 2 and 3 appear to have better model fit: the points are far more scattered in the plot for model 1, whereas they are closer to the diagonal line in models 2 and 3. The slightly lower fit statistics values for model 2 compared to model 3 in addition to theoretical soundness of model 2 (theory would suggest race is an important covariate to include in the model) is the best-fitting for modelling moderate psychological distress outcomes.

Mixed Effects Linear Regression Models: Diagnostic tests for the three mixed effects linear regression models—models where total psychological distress score was the outcome— assessed for 1) normality of residuals (level-1 and level-2 residuals) and 2) homoscedasticity. Figure 14 on the following page displays the distribution of residuals at higher (i.e., random effects/residuals for random intercepts) and lower levels (i.e., residuals at the observation level). As reflected in the histograms, the residuals and residuals for random intercepts are approximately normally distributed, and these distribution patterns are virtually identical across all three models. Meanwhile, the assumption of homoscedasticity is met for the fixed portion of the linear predictions (Figure 15) but not for the fixed portion linear prediction plus contributions based on predicted random effects (Figure 16)— the variance of the residuals is not constant in these latter scatterplots.

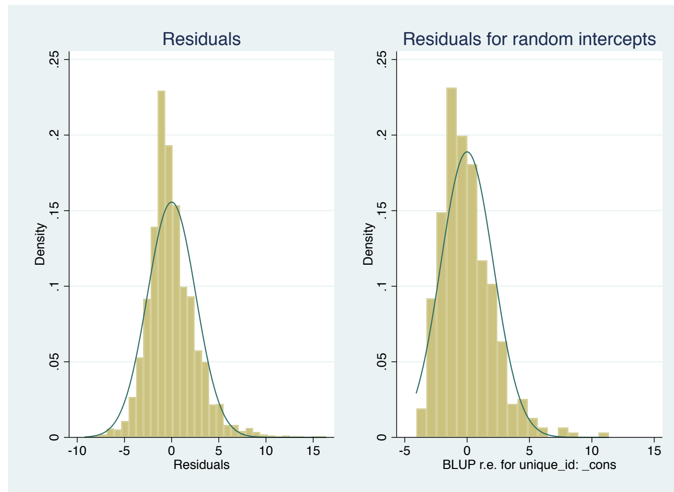
.

Figure 14. Residuals versus residuals for random intercepts for mixed effects linear regressions exploring predictors of psychological distress score among Millennials (n=572)

Model 1.



Model 2.



Model 3.

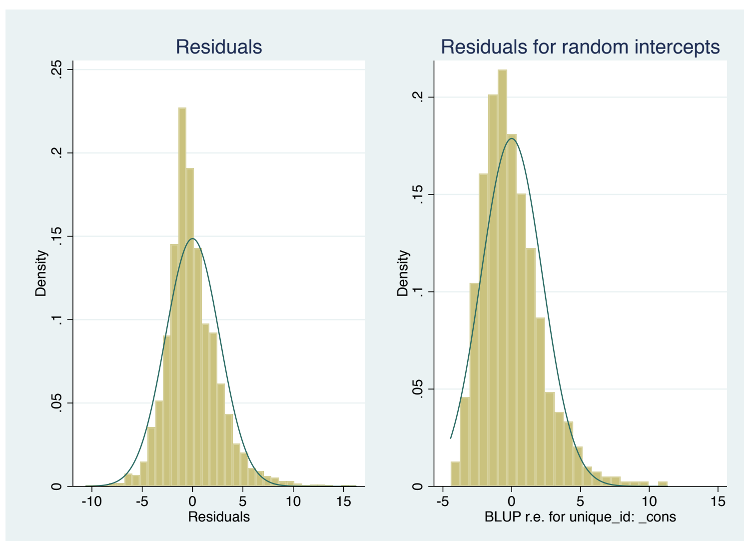


Figure 15. Scatterplot of residuals versus fitted values for the fixed portion of the linear mixed models

Model 1 Model 2 Model 3

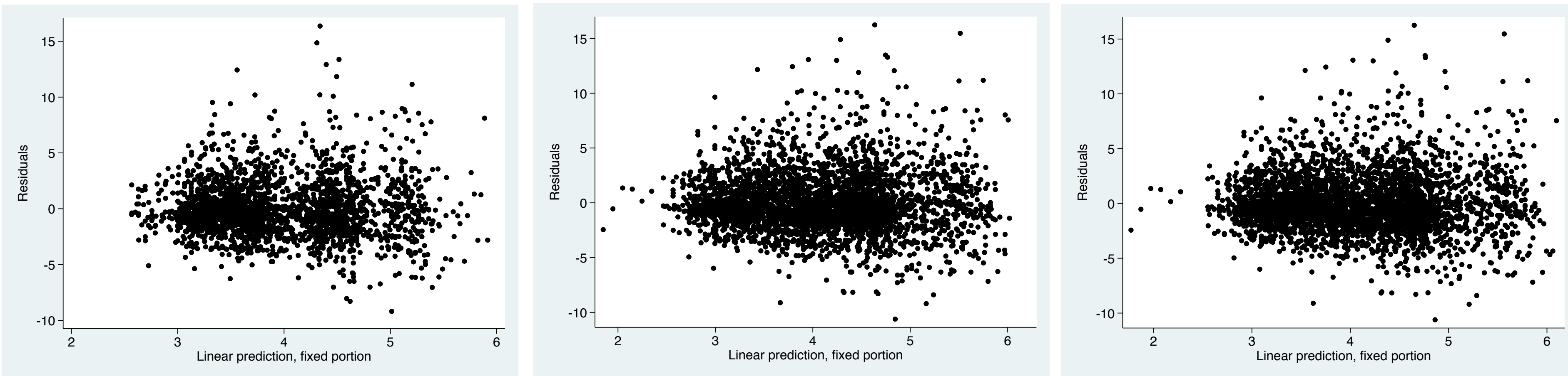
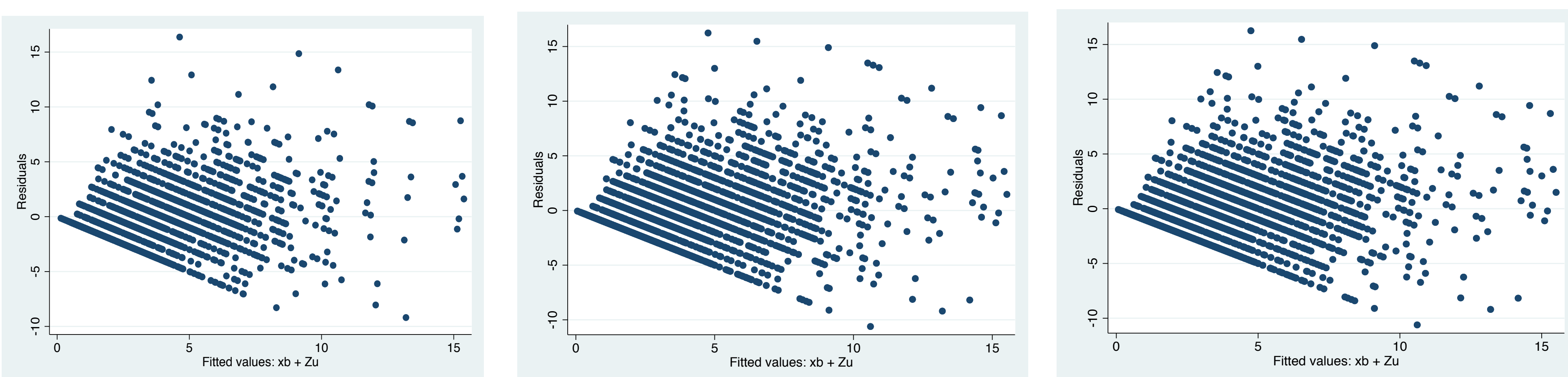


Figure 16. Scatterplot of residuals versus fitted values for three linear mixed models predicting total psychological distress score

Model 1 Model 2 Model 3



6.3.5. Summary of Research Aim 2 Findings

The purpose of this research aim was to understand how, if at all, membership in each employment quality trajectory class was associated with severe and moderate psychological distress outcomes. Analyses were initially carried out on the sample of Millennials with mental health data across all six study waves. Within this sample, fewer years of education and widowed/divorced/separated marital status (compared to married/cohabitating status) were associated with higher odds of severe psychological distress. In models examining moderate psychological distress outcomes, age, sex, EQ class, and marital status were significantly associated with moderate mental distress. Specifically, Millennials who were younger, female, experiencing declining EQ over time, and single/never married or divorced/separated/widowed had higher odds of endorsing symptoms of moderate mental distress compared to their counterparts (i.e., Millennials who were older, male, experiencing stagnant EQ over time, and identified as married/cohabitating). When the analyses were re-run to include a larger sample (those with mental health data from only three, four, and five survey waves), education and marital status remained significant predictors of severe psychological distress, and membership in class 2 (declining EQ) also emerged as a significant predictor of this outcome. Findings for the expanded sample moderate mental distress models were quite similar to the six-survey wave sample: age (older), employment quality class (stagnant compared to declining), education (greater years of education), and marital status (single/never married and divorced/widowed/separated compared to married/cohabitating) were significant predictors.

Finally, given the quality issues surrounding the frequency distribution of severe mental health outcomes in the sample of Millennials with mental health data for all six survey waves (too few individuals with severe psychological distress in certain employment quality categories, particularly for the increasing EQ class), mixed effects linear models were fitted to explore predictors of total psychological distress score. Age, female gender, declining employment quality, and both single/never married and divorced/widowed/separated marital statuses were associated with increased total psychological distress scores. Having established that worsening employment quality over time (compared to stagnant employment quality) has implications for psychological distress outcomes, the next section will explore if and how three social welfare policies moderate the strength of the relationship between membership in the declining employment quality class and psychological distress outcomes.

6.4. Research Aim 3: Moderating Effects of Social Protection Policies

6.4.1. Inclusion of Social Welfare Policy as a Predictor Variable

Prior to fitting models that included an interaction term between the respective social welfare policy and EQ class, each social welfare policy was included as a predictor variable in the model. Results of these analyses are presented in Table 22. Neither minimum wage, nor EITC refund rate, nor unemployment insurance were significant predictors of severe or moderate psychological distress outcomes; however, the inclusion of these social welfare policy variables in the model did alter the relationship between EQ class membership and severe mental health outcomes. Specifically, in severe psychological distress models that did not include social policy variables, membership in class 2 (worsening EQ over time) was associated with higher odds of severe psychological distress compared to membership in class 1 (the stagnant EQ growth class). Upon including minimum wage, EITC refund rate, and UI replacement rate as covariates in their respective models, membership in class 3 (compared to class 1) emerged as a significant protective factor in the odds of experiencing severe psychological distress, while membership in class 2 (compared to class 1) was no longer significant in this model. In each severe

Table 22. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the effect of three social welfare policies on Millennials' likelihood of experiencing severe and moderate[a] psychological distress, among Millennials with six data points (n=572)

Characteristic	Minimum Wage		EITC rate		Unemployment Insurance	
	Severe	Moderate (or higher)	Severe	Moderate (or higher)	Severe	Moderate (or higher)
Age	0.96 (0.91-1.02)	0.95 (0.93-0.98)**	0.97 (0.91-1.02)	0.95 (0.93-0.98)***	0.98 (0.92-1.03)	0.96 (0.94-0.99)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.44 (0.74-2.81)	1.60 (1.12-2.29)*	1.44 (0.74-2.81)	1.60 (1.12-2.29)*	1.44 (0.74-2.81)	1.61 (01.12-2.31)*
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	1.98 (0.94-4.19)	1.63 (1.02-2.58)*	1.98 (0.94-4.19)	1.62 (1.02-2.58)*	1.96 (0.93-4.14)	1.61 (1.01-2.55)*
Class 3	0.17 (0.04-0.84)*	0.90 (0.53-1.53)	0.17 (0.04-0.84)*	0.89 (0.52-1.51)	0.18 (0.04-0.85)*	0.91 (0.54-1.54)
Education (yrs)	0.81 (0.69-0.94)**	0.99 (0.96-1.02)	0.81 (0.69-0.94)**	0.99 (0.96-1.02)	0.81 (0.70-0.94)**	0.99 (0.96-1.02)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	1.66 (0.78-3.56)	1.55 (1.13-2.11)**	1.64 (0.76-3.52)	1.54 (1.13-2.09)**	1.65 (0.77-3.54)	1.55 (1.14-2.11)***
Widowed, divorced, separated	2.64 (1.03-6.76)*	1.54 (1.00-2.37)*	2.60 (1.01-6.68)*	1.52 (0.99-2.34)	2.66 (1.04-6.81)*	1.54 (1.00-2.37)*
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.28 (0.61-2.68)	1.13 (0.78-1.64)	1.26 (0.60-2.63)	1.13 (0.78-1.63)	1.30 (0.62-2.72)	1.14 (0.79-1.65)
Non-white, non-black	0.90 (0.28-2.84)	1.52 (0.88-2.65)	0.90 (0.28-2.87)	1.51 (0.87-2.62)	0.92 (0.29-2.92)	1.56 (0.90-2.70)
Social welfare policy	1.10 (0.87-1.38)	1.05 (0.95-1.17)	1.00 (0.99-1.02)	1.00 (0.99-1.01)	1.02 (0.97-1.08)	1.01 (0.99-1.04)
Random Effects						
Var (_cons)	3.72 (2.33-5.92)	2.72 (2.16-3.42)	3.74 (2.34-5.97)	3.04 (2.56-3.62)	3.72 (2.33-5.94)	3.03 (2.55-3.61)
Model fit						
Wald chi2, prob>chi2[a]	34.31, p<0.001	50.14, p<0.001	34.16, p<0.001	82.23, p<0.001	34.48, p<0.001	84.04, p<0.001

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

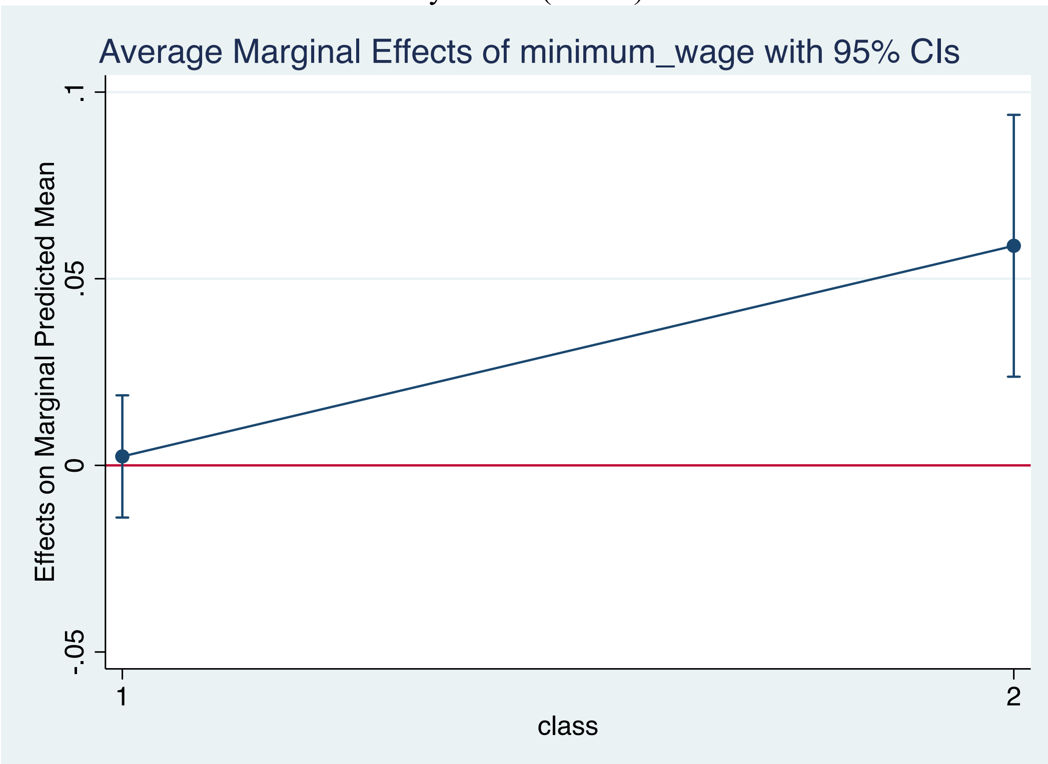
[a]Note that those with total distress scores consistent with severe distress are included in the moderate distress cutoff of 5 or higher

psychological distress model where one of these social welfare policies was included as a covariate, individuals in class 3 had 80% lower odds of experiencing severe psychological distress compared to those in class 1. With respect to moderate psychological distress outcomes, no differences were observed in the effect of covariates when social welfare policies were added to these models. In other words, the same associations were observed between sociodemographic variables and EQ class regardless of the inclusion of a social welfare policy in the model.

6.4.2. Testing the Interaction Effect between EQ Class and Social Welfare Policies

Minimum Wage: No interaction effect was observed between minimum wage and EQ class for the severe mental distress model (Table 23). Moreover, upon adding an interaction term to the model, employment quality class was no longer significant in the model. In contrast, an interaction effect was observed for the moderate psychological distress model: while employment class as a predictor was no longer significant in the interaction model, the class 2-minimum wage interaction term was significant at the $p<0.05$ level (odds ratio of 1.4). Increasing values for minimum wage enhance the effect of declining employment quality (compared to stagnant employment quality) on moderate mental distress. Figure 16, below, depicts the marginal effects of minimum wage on the probability of moderate psychological distress, depending on EQ class membership: Paradoxically, as minimum wage increases so too does the probability of moderate psychological distress for those in the declining EQ trajectory class compared to the stagnant EQ growth class.

Figure 16. Average marginal effects (with 95% confidence intervals) of EQ class, depending on minimum wage, on probability of moderate psychological distress, among Millennials with mental health data from six survey waves (n=572)



EITC Refund Rate: No interaction effect was observed between ETIC refund rate and EQ class for the severe or moderate mental distress models (Table 23). Inclusion of an interaction term in the models only slightly adjusted the significance of predictors in the model. Specifically, marital status (widowed/divorced/separated compared to married/cohabitating status) was no longer significant when an interaction term was included in the severe psychological distress model, while EQ class (class 2 compared to class 1) was no longer a significant variable in the moderate psychological distress model.

Unemployment Insurance: No interaction effect was observed between unemployment insurance replacement percentage and EQ class for the severe or moderate mental distress models (Table 23). Inclusion of an interaction term in the models only slightly adjusted the significance of predictors in the model. Specifically, EQ class (class 2 compared to class 1) was no longer significant when an interaction term was included in the severe and moderate psychological distress models. Moreover, inclusion of an interaction term in the moderate distress model yielded a significant association between unemployment insurance replacement rate and moderate distress outcomes.

As was the case for the severe psychological distress models fitted for research aim 2, the low frequencies of severe distress, particularly for certain categories of employment quality, marital status, etc., compromised the robustness of the interaction models. Indeed, the wide ranging 95% confidence intervals for all moderation analyses where severe psychological distress was the outcome suggests that findings for these models should be interpreted with great caution. Caution should also be applied to the interaction models for moderate psychological distress outcomes. For example, in the model assessing for an interaction effect between EQ class and unemployment insurance replacement rate, the 95% confidence intervals for EQ classes two and three are 0.71-248.2 and 0.57-1478.2, respectively. Given these problematic estimates, moderation analyses were re-run using a larger sample size (Millennials with data from three-, four-, and five survey waves) and using total psychological distress score as the outcome variable. The following two sub-sections present findings from these additional moderation analyses.

Table 23. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the moderating effect of three social welfare policies on Millennials' likelihood of experiencing severe and moderate psychological distress, among Millennials with six data points (n=572)

Characteristic	Minimum Wage		EITC rate		Unemployment Insurance	
	Severe	Moderate (or higher)	Severe	Moderate (or higher)	Severe	Moderate (or higher)
Age	0.96 (0.91-1.02)	0.95 (0.93-0.98)**	0.97 (0.91-1.02)	0.95 (0.93-0.98)***	0.98 (0.92-1.03)	0.96 (0.94-0.99)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.45 (0.74-2.83)	1.61 (1.12-2.31)*	1.49 (0.76-2.93)	1.60 (1.11-2.29)*	1.45 (0.74-2.84)	1.60 (1.11-2.30)*
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	2.38 (0.06-94.03)	0.13 (0.01-1.18)	2.73 (1.20-6.20)*	1.53 (0.94-2.49)	8.03 (0.03-2022.29)	13.36 (0.72-249.27)
Class 3	0.93 (0.00-4582.61)	2.21 (0.26-18.81)	0.49 (0.08-3.07)	0.87 (0.48-1.58)	0.00 (0.00-6634.46)	29.15 (0.58-1471.14)
Education (in years)	0.81 (0.69-0.94)**	0.99 (0.96-1.02)	0.80 (0.69-0.94)**	0.99 (0.96-1.02)	0.81 (0.69-0.94)**	0.99 (0.96-1.02)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	1.64 (0.76-3.54)	1.51 (1.10-2.05)*	1.66 (0.77-3.58)	1.53 (1.12-2.09)**	1.66 (0.77-3.57)	1.54 (1.13-2.10)**
Widowed, divorced, separated	2.62 (1.02-6.74)*	1.49 (0.97-2.29)	2.54 (0.98-6.55)	1.52 (0.99-2.34)	2.64 (1.03-6.77)*	1.55 (1.01-2.38)*
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.29 (0.61-2.69)	1.15 (0.79-1.66)	1.24 (0.59-2.60)	1.13 (0.78-1.63)	1.31 (0.63-2.76)	1.15 (0.79-1.67)
Non-white, non-black	0.90 (0.28-2.86)	1.53 (0.88-2.67)	0.92 (0.29-2.92)	1.51 (0.87-2.62)	0.93 (0.29-2.96)	1.57 (0.90-2.73)
Social welfare policy	1.12 (0.86-1.45)	1.03 (0.91-1.16)	1.01 (0.99-1.02)	1.00 (0.99-1.01)	1.03 (0.96-1.10)	1.03 (1.00-1.06)*
Social welfare policy##EQ class						
Policy -class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Policy-class 2	0.98 (0.62-1.55)	1.38 (1.05-1.81)*	0.96 (0.91-1.01)	1.01 (0.99-1.02)	0.97 (0.86-1.09)	0.95 (0.90-1.02)
Policy-class 3	0.81 (0.28-2.35)	0.89 (0.69-1.16)	0.85 (0.63-1.14)	1.00 (0.98-1.02)	1.16 (0.81-1.67)	0.93 (0.85-1.01)

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

6.4.2. Comparing Interaction Effects across Three-, Four-, and Five-Wave Samples

The same series of models described above (introduction of social welfare policy as a predictor followed by its inclusion as an interaction term) were fitted for the three-, four-, and five-survey wave samples. Tables presenting the findings for each social policy across the three samples (i.e., participants with corresponding mental health data for three, four, and five survey waves) are presented on pages 201-209 in Appendix H. In summary, unemployment insurance replacement rate was the only social protection policy that was significantly associated with psychological distress: For each percent increase in UI replacement rate the odds of experiencing moderate psychological distress increased by 6% and 7% among Millennials with mental health data from three and four survey waves, respectively. Regardless of sample size, no interaction effects were observed between EQ class and minimum wage nor between EQ class and EITC rate on severe or moderate psychological distress outcomes. For models testing the moderating effect of UI replacement rate, an interaction effect was observed on moderate psychological distress outcomes among the four- and five-wave samples; however, the inflated standard errors and confidence intervals for class 2 and 3 upon the inclusion of an interaction term (95% CI of 1.2-146.3 for class 2 and 1.4 to 982.4 for class 3) suggest that an interaction term does not improve model fit and should be interpreted with great caution.

As was the case for the six-wave sample, the introduction of each social policy to its respective regression model did not substantially alter the relationship between other covariates (namely, age, education, and marital status) on distress outcomes. However, the association between EQ class and severe and moderate psychological distress outcomes was no longer significant upon the inclusion of an interaction term for the minimum wage and unemployment insurance models. For the EITC models, membership in class 2 (compared to class 1) remained a significant predictor of severe distress outcomes when an interaction term was included in the model but was not a significant predictor of *moderate* distress outcomes.

6.4.3. Comparing Interaction Effects with Total Psychological Distress as Outcome Variable

Prior to exploring the combined effect of EQ class and social welfare policy on psychological distress score, each social welfare policy was explored as a predictor in linear mixed-effects regression models. In contrast with the models fitted for severe and moderate psychological distress outcomes among the participants with six waves of mental health data (where none of the policies were significantly associated with the odds of experiencing severe or moderate distress), both minimum wage and state EITC rate were significant predictors of total psychological distress score. Paradoxically, higher minimum wage and EITC rates were associated with higher psychological distress scores. Specifically, every dollar increase in minimum wage was associated with a 0.20-point increase in psychological distress score. Each additional percent increase in EITC rate (i.e., each additional percent increase in the percentage of the federal credit offered by states) was associated with a very small but significant 0.01-point increase in psychological distress score. The addition of each social welfare policy in regression models did not alter the relationships between other covariates and total psychological distress score: age, sex, EQ class membership, and marital status remained significant predictors of total psychological distress scores.

Table 26. Coefficients (and 95% confidence intervals) from mixed-effects linear regression models examining the effect of three social welfare policies on **Millennials' psychological distress (PD) scores**, among Millennials with six data points (n=572)

Characteristic	Minimum Wage	EITC rate	Unemployment Insurance
Age	-0.10 (-0.13, -0.06)***	-0.08 (-0.12, -0.05)***	-0.07 (-0.10, -0.04)***
Sex			
Male	(reference)	(reference)	(reference)
Female	0.60 (0.31-0.89)***	0.59 (0.33-0.89)**	0.60 (0.31-0.89)***
EQ class			

Class 1	(reference)	(reference)	(reference)
Class 2	0.83 (0.46-1.19)***	0.80 (0.44-1.17)***	0.80 (0.43-1.16)***
Class 3	-0.34 (-0.74-0.07)	-0.36 (-0.76, 0.05)	-0.32 (-0.72-0.09)
Education (in years)	-0.02 (-0.05-0.01)	-0.02 (-0.05, 0.01)	-0.02 (-0.05, 0.01)
Marital status			
Married/ cohabitating	(reference)	(reference)	(reference)
Single, never married	0.81 (0.48-1.14)***	0.81 (0.49, 1.14)***	0.84 (0.51-1.16)***
Widowed, divorced, separated	1.16 (0.67-1.66)***	1.16 (0.69, 1.66)***	1.17 (0.68-1.67)***
Race			
White	(reference)	(reference)	(reference)
Black	0.13 (-0.16-0.42)	0.08 (-0.21-0.37)	0.08 (-0.21-0.37)
Non-white, non-black	0.22 (-0.25-0.69)	0.22 (-0.25-0.69)	0.27 (-0.19-0.74)
Social welfare policy	0.20 (0.08-0.32)**	0.01 (0.00-0.02)**	0.17 (-0.01-0.04)

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

As reflected in Table 27, below, no interaction effect was observed for any of the social welfare policies in the mixed effect linear regression models. Minimum wage and EITC rate remained significant predictors of total psychological distress in their respective interaction models. However, EQ class was no longer a significant predictor of total psychological distress in interaction models for minimum wage and unemployment insurance.

Table 27. Coefficients (and 95% confidence intervals) from mixed-effects linear regression models examining the moderating effect of three social welfare policies on Millennials' psychological distress (PD) scores, among Millennials with six data points (n=572)

Characteristic	Minimum Wage	EITC rate	Unemployment Insurance
Age	-0.10 (-0.13, -0.06)***	-0.08 (-0.12, -0.05)***	-0.07 (-0.10, -0.04)***
Sex			
Male	(reference)	(reference)	(reference)
Female	0.60 (0.31-0.89)***	0.60 (0.31-0.89)***	0.59 (0.30-0.89)***
EQ class			
Class 1	(reference)	(reference)	(reference)
Class 2	-0.80 (-3.37-1.75)	0.94 (0.52, 1.35)***	0.82 (-2.55-4.19)
Class 3	0.42 (-2.16-3.01)	-0.39 (-0.91, 0.13)	2.95 (-0.85-6.75)
Education (in years)	-0.02 (-0.05-0.01)	-0.02 (-0.05, 0.01)	-0.02 (-0.05-0.01)
Marital status			

Married/ cohabitating	(reference)	(reference)	(reference)
Single, never married	0.81 (0.48-1.13)***	0.82 (0.49, 1.14)***	0.83 (0.50-1.16)***
Widowed, divorced, separated	1.15 (0.65-1.64)***	1.16 (0.66-1.66)***	1.18 (0.68-1.67)***
Race			
White	(reference)	(reference)	
Black	0.13 (-0.16-0.42)	0.07 (-0.21-0.36)	
Non-white, non-black	0.22 (-0.25-0.68)	0.22 (-0.24-0.69)	
Social welfare policy	0.19 (0.05-0.32)**	0.01 (0.00-0.02)**	0.03 (-0.01-0.06)
Social welfare policy## EQ class			
Policy#class 1	(reference)	(reference)	(reference)
Policy#class 2	0.21 (-0.11-0.53)	-0.01 (-0.03-0.01)	-0.00 (-0.07-0.07)
Policy#class 3	-0.09 (-0.41-0.22)	0..00 (-0.02-0.03)	--0.07 (-0.15-0.01)

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

6.4.4. Summary of Research Aim 3 Findings

The purpose of this research aim was to assess whether certain social welfare policies moderated the relationship between employment quality class and moderate and severe psychological distress outcomes. In contrast with this study's hypothesis that more generous welfare measures (e.g., higher levels of minimum wage, higher UI replacement rate percentages, etc.) would temper the adverse effects of EQ on psychological distress outcomes, these analyses generally revealed no interaction effects. Moreover, in the case of the minimum wage moderation analyses, the probability of moderate psychological distress actually increased with rising levels of minimum wage for those in the declining EQ class compared with the stagnant EQ class. Finally, no interaction effects were observed in analyses where total psychological distress score was the outcome variable; however, both minimum wage and state EITC rate were significant predictors of total psychological distress score, whereby higher minimum wage and EITC rates were associated with higher psychological distress scores.

Chapter 7. Discussion

The goal of this dissertation study was to identify and characterize patterns of employment quality among Millennial workers in the post-Great Recession period, to understand how these patterns (subgroups) of employment quality are associated with severe and moderate psychological distress outcomes, and to ascertain whether certain social welfare policies moderate the relationship between these employment quality patterns and psychological distress outcomes. The following pages reflect on the main findings from these study objectives, drawing parallels to and highlighting deviations from the extant literature on employment precarity of young workers where appropriate. Study limitations and avenues for future research are also discussed.

7.1. Employment quality: Reflections on overall score and particular items

A few points regarding the trends in employment quality score are worth raising. First, while it is true that that the employment quality score gradually rose over the course of the study period (2009-2019), the average score never surpassed 2.8, out of a total possible score of 5—the highest median value for the study sample of 2.2 (at timepoint 6) was more than a half point lower than the mean EQ score. These average EQ figures are consistent with two other studies that leveraged nationally-representative panel data from the United States to understand trends in employment quality, though these studies were focused on the experiences of older rather than younger adults. For example, in a study examining intersectional differences in EQ among older adults, Andrea et al. (2021) cited EQ scores ranging from 0 to 4.85 (uncentered scores), with an average of 2.14. Oddo et al. (2021) examined trends in precarious employment among workers between the years 1988 and 2016, noting that precarious employment increased by 9% over the course of the study period, with an average precarious employment score of 3.1 out of 7. As higher PE scores were indicative of worse employment quality in their study, reverse coding of their PE measure would yield an average employment quality score of 3.9 out of 7, which is nearly equivalent to 2.8 out of 5. Importantly, neither of these studies centered around EQ trends among *Millennial workers,* hindering the ability to contextualize the average EQ scores presented here with prior studies on the EQ characteristics of young adults specifically.

In short, while employment quality did steadily rise following its Great Recession-related nadir in 2011, overall, employment quality remained low even once EQ scores had "bounced back" to pre-Recession levels. In terms of the specific dimensions comprising employment quality, on average, Millennial workers enjoyed greater employment *stability* and *material rewards* (e.g., higher incomes) over the course of the study period. Fewer than 10% of the sample was unemployed at the time of the 2019 survey compared to a high of 21% in 2011. In addition, median income, adjusted for inflation, increased by 50% between 2009 ($26,824) and 2019 ($40,000). While these improvements are appreciable, the low levels of workers' rights and protections and collective bargaining arrangements are concerning: it is striking, for example, that across the study period less than 10% of Millennial workers endorsed having their contracts covered by a collective bargaining arrangement *or* belonging to a union, a finding which tracks with the decline in union density in the wake of deindustrialization. Moreover, 5% or fewer of Millennial respondents indicated that they would be paid for overtime hours, a provision that would be more likely to exist for bargaining[47] compared with non-bargaining workers.

Consistent with the extant literature (Benach et al., 2014; Eisenberg-Guyot et al., 2020; Puig-Barrachina et al., 2013), marked differences in employment quality trends were also observed across gender and educational lines. Specifically, the decline in EQ in the wake of the

[47] Bargaining workers refers to those who are covered by a collective bargaining agreement.

Great Recession was slightly steeper for female compared with male Millennials, and the pace of recovery for female respondents was slower compared to their male counterparts. This is consistent with research on the impacts of the Great Recession on men and women, which has shown that while the unemployment rate increased more for men than women at the outset of the Recession, men gained more jobs than women in the first two years of the recovery (Kalleberg and von Wachter, 2017). With respect to average EQ trends by education level, EQ scores between timepoints 1 and 3 suggest that non-college-educated Millennials experienced greater setbacks in employment quality due to the Great Recession than their college-educated peers (though it is worth noting that the discrepancy in average EQ score existed at the start of the study period); this gap in average EQ score persisted across the decade following the Great Recession. Given the narrowing of opportunities in the workforce for those without a college degree—indeed, one quarter of non-college-educated Americans between the ages 25 to 64 were not in the labor force in 2017 compared to 10% among those holding a bachelor's degree (Case and Deaton, 2020)—and the ballooning "earnings premium"[48] (80% by 2000 (James, 2012)) associated with a college degree, it is unsurprising that Millennials in this study who do not have a college degree would experience lower levels of EQ than their college-educated peers.

7.2. Reflections on the prevalence of moderate and severe psychological distress

The Kessler-6 psychological distress scale, widely used in both practice and research settings, is a reliable screener for mental health disorders, particularly affective disorders like anxiety and depression. The recommended cutoff value of 13 or higher on the K-6 scale to

---

[48] Here, the earnings premium refers to the ratio of median hourly wages for full-time, full-year workers with a college degree to the median hourly earnings for those with a high school diploma but no additional education (James, 2012).

.

indicate the likelihood of serious psychological distress was ultimately a rare occurrence among this study sample. The percentage of participants endorsing symptoms of severe distress ranged from 1.9% in 2011 to 3.5% in 2015, rates that are mostly consistent with recent analyses investigating the distribution of psychological distress on a population level in the United States in the last two decades. Specifically, Tomitaka and colleagues (2019) examined K-6 data from the National Health Interview Survey for the years 1997 to 2017, finding a prevalence of severe distress ranging from 2.9% to 4.2%.

The low frequency of severe psychological distress at any one point during the study period—a total of 140 instances of severe distress were observed across the study period, ranging 17 respondents at timepoint 2 to 27 individuals at timepoints 1 and 3—became problematic once regression models were fitted to account for the role of employment quality class (as well as other categorical covariates) on the probability of severe psychological distress outcomes. Ultimately, a larger sample size would be required to draw conclusions about the role of employment quality on severe psychological distress outcomes, a limitation which is addressed later in this chapter (“Limitations” subsection).

In contrast, a much larger percentage of Millennials met this study’s threshold for moderate psychological distress—approximately one-third of respondents across the study period met the criteria for the moderate distress (a cut-off value of 5 or higher). While this substantial number of respondents meeting the threshold for moderate distress does confer greater certainty in the estimates yielded by the aforementioned regression models, it also raises the question of whether 5 or higher is an appropriate cut-off value. That this mental health screener would flag *one out of three* respondents as possibly experiencing moderate mental distress is cause for reconsidering the appropriate threshold for moderate distress. While this study relied upon the work of other researchers in the field of occupational health who had determined the cutoff score of 5 or higher to be valid (Prochaska et al., 2012; Eisenberg-Guyot et al., 2020), future studies might consider alternative approaches to capturing distress outcomes that do not meet the criteria for a "severe" diagnosis, but would still warrant clinical follow-up/further assessment—this point is also raised in the limitations subsection.

7.3. Reflections on the characteristics of workers in identified EQ subgroups

Based on statistical and conceptual considerations, the three-class quadratic growth model was identified as the best-fitting model, yielding one group—to which nearly three-quarters of the sample belonged—with stagnant EQ growth, a second with negative growth, and a third with appreciably positive growth. The EQ trajectory of each of these subgroups mostly aligned with the hypotheses outlined in chapter 4. Specifically, one might expect similar EQ scores in the immediate aftermath of the Great Recession given that this generation of workers was just entering the workforce or in the early stages of their careers in 2007/2008. Though the question of how young workers in particular fared in the wake of the Great Recession has to-date been understudied, existing literature suggests labor entrants experienced significant earnings and employment losses during the Recession, with lasting impacts on earnings and wealth (Rinz, 2022).

Over the course of the decade following the Great Recession, one would also expect to see the types of divergent EQ trajectories among subgroups of Millennials yielded by this study. Upon inspection of the sociodemographic characteristics of Millennials in each identified EQ subgroup for this study, much higher percentages of workers in the stagnant and declining EQ growth subgroups were women, persons of color, low-skill workers (both blue and white collar), and workers with lower levels of education. Numerous studies on the economic and social consequences of the Great Recession have underscored how these groups of workers were more vulnerable to prolonged unemployment and lasting reductions in earnings and wealth than others (Addo & Darity, 2021; Compton, Giedeman, & Muller, 2018; Hout & Cumberworth, 2012; Kochhar, 2011). With respect to gender dynamics, for example, research has found that men gained appreciably more jobs than women during the recovery period (between 2010 and 2014 men gained 5.5 million jobs compared to 3.6 million among women (Wething, 2014)). As Kalleberg and von Wachter (2017) note, the fact that unemployment rates fell for men but rose for women in the wake of the Recession led some to dub the period a "he-covery." Consistent with the extant literature, in this study, three-quarters of respondents in the negative EQ growth class were female compared to 58% in the stagnant growth class and less than half (48%) in the positive growth class.

While the education divide preceded the 2008 financial crisis, the Great Recession further exacerbated this gap in employment opportunities between those with and without college degrees (Berghammer & Adserà, 2022). According to a 2016 report published by the Georgetown University Center on Education and the Workforce, a staggering 95% of jobs created during the recovery required at least some college education. Meanwhile, workers with a high school diploma or less lost 5.6 million jobs during the recession and gained only 80,000 jobs in the recovery period (Georgetown University Center on Education and the Workforce, 2016). Indeed, gaps in EQ class membership by education level were a key finding in this study: among those in the negative growth EQ class, 50% had a high school diploma or less (compared to 30% in the stagnant growth class and 23% in the positive growth class). In contrast, 44% of those in the positive EQ growth class were college degree holders, compared to just 20% in the negative growth class.

Related to this gap in employment opportunities along educational lines, research has also highlighted growing job polarization in the U.S. labor market, which refers to the hollowing-out of middle-skills occupations and the increasing concentration of employment opportunities for low- and high-skill workers (Jaimovich & Sieu, 2012; Foote & Ryan, 2015). Many middle-wage workers who lost their jobs during the Great Recession (Millennials would have been among this group of laid-off workers) were reemployed as low-wage workers, with reduced wages that persisted for years following the economic downturn (Mitchell & Nichols, 2012; Zago, 2020). In line with these national trends, low-skill workers (both blue- and white-collar) in this study were more concentrated in the negative EQ growth class at the final timepoint (2019): 20% of respondents in this negative growth class were blue-collar, low-skill workers compared to less than 10% in the stagnant and positive EQ growth classes. Similarly, the highest percentage of low-skill, white-collar workers was observed in the negative EQ growth class: nearly half (48%) of respondents in this EQ class were white-collar, low-skill workers, compared to 38% and 37% in the stagnant and positive growth classes, respectively. White-collar, high-skill workers, in contrast, were well-represented in the stagnant and positive EQ growth classes (comprising 41% of respondents in each of these categories)—only one-fifth (21%) of respondents in the negative growth class were white-collar, high-skill workers. While beyond the scope of this study, further exploration is warranted to understand if and how *transitions* between high-skill and low-skill profiles contributed to this decline in employment quality in the post-Great Recession period.

Finally, research has highlighted the disproportionate effects of the Great Recession on persons of color: Black and Latino workers were more likely to lose their jobs, to default on their mortgages, and to face foreclosures on their homes than their white counterparts (Addo & Darity, 2020; Pfeffre, Danziger, & Schoeni, 2013). A greater percentage of Black respondents in this study were concentrated in the negative EQ growth class (24%) compared to the stagnant growth class (13%) and the high growth class (18%). However, chi-squared tests did not reveal significant associations between race and EQ class. It is worth noting that survey weights were used to describe the sociodemographic characteristics of the EQ subgroups and to explore bivariate relationships between these characteristics and EQ class. In analyses performed without use of the survey weights, race was significantly associated with EQ class membership, a finding likely explained by the fact that the original PSID sample consisted of both a nationally representative sample as well as an oversample of low-income families, drawn from areas with high proportions of minorities (Brown, 1996).

7.4. Key takeaways on the relationship between EQ and psychological distress

Consistent with previous studies that have leveraged multidimensional measures of precarious employment to elucidate the mental health consequences of work precarity (Demiral et al., 2022; Eisenberg-Guyot et al., 2021; Pollack et al., 2022) this study found significant associations between consistently poor employment quality and psychological distress outcomes. Specifically, in models adjusted for key sociodemographic characteristics, respondents in the negative EQ growth class had approximately 2.1 and 1.7 times the odds of experiencing severe and moderate psychological distress, respectively, compared to respondents in the stagnant growth class. Contrary to expectations, Millennials in the stagnant growth class did not have significantly higher odds of experiencing severe or moderate psychological distress compared to their counterparts who enjoyed appreciable EQ growth over the study period. It is possible that certain dimensions of employment quality that remained the same over the study period (e.g., lack of collective bargaining agreement, lack of employer health insurance, etc.) were less salient to mental distress than other dimensions such as unemployment or income. As such, it may be the case that the decision to equally weight all dimensions (and each sub-dimensions) of EQ when constructing the EQ measure masked some of the effects of certain employment quality indicators on mental distress outcomes. Next, two important dimensions of EQ were excluded from the EQ measure due to dataset limitations: training and employment opportunities (the opportunities available to advance one's skills/position in workplace) and interpersonal power relations (the degree of decision-making power held by worker). It is unclear how, if at all, the inclusion of these items in the EQ measure might have affected the relationship between stagnant EQ class membership and severe and moderate psychological distress.

Due to the low frequencies of severe psychological distress in the study sample, additional analyses explored psychological distress outcomes using an expanded sample of Millennials (Millennials who were survey respondents for three, four, and five survey waves) and using total psychological distress score as the outcome variable. Each of these analyses—adjusted for key sociodemographic variables—yielded similar results with respect to psychological distress outcomes. Specifically, when exploring mental health outcomes among the three-, four-, and five-wave samples, membership in the declining EQ class was associated with endorsement of severe and moderate psychological distress. Similarly, those in the declining employment quality subgroup had predictably lower total psychological distress scores (0.85 points lower) compared to those in the stagnant employment quality subgroup. That findings regarding the role of EQ class membership on psychological distress outcomes were comparable using these larger sample sizes and total psychological distress score as the outcome variable (rather than its binary counterpart) suggest that despite the high standard errors yielded by models fitted using the six-wave sample (n=572), the model fit is sound.

Mixed effects models adjusted for key sociodemographic variables underscored the protective role of several factors against psychological distress. Marital status, specifically single/never married and divorced/separated/widowed statuses, emerged as the variable most consistently associated with moderate and severe psychological distress outcomes. Indeed, among the six-wave sample, divorced/separated/widowed respondents had nearly three times the odds of severe psychological distress and 1.5 times the odds of moderate psychological distress compared to their married/cohabitating counterparts. Single/never married respondents, meanwhile, had 1.8 and 1.5 times the odds of severe and moderate psychological distress, respectively, when holding all other variables equal. The degree to which marriage protects mental health in this study, while striking, is consistent previous studies that have explored the role of marriage on mental health (Horwitz, White, & Howell-White, 1996), particularly in times of economic precarity (Jace & Makridis, 2021). Research has shown that having a partner in times of economic and social uncertainty (e.g., the Great Recession, COVID-19) can help provide a sense of stability—both a financial sense of stability (e.g., in the event one partner has lost his/her job) as well as a psychological sense of safety and stability (e.g. having a partner to weather the periods of social isolation during the COVID-19 pandemic). While beyond the scope of this study, it would be worth probing whether this lower likelihood of psychological distress is attributable to companionship itself or whether the job-related income of a partner alleviates any distress associated with poor employment quality/job precarity—this would best be accomplished through a qualitative or mixed-methods study.

Sex and education level also emerged as significant predictors of psychological distress when adjusting for employment quality. Specifically, female sex was associated with higher odds of moderate psychological distress, and each additional year of education conferred protection against severe psychological distress (as well as moderate psychological distress when analyses were expanded to the three-, four-, and five-wave samples). Both findings are consistent with previous epidemiological studies on risk factors for psychological distress. Indeed, several studies, including those leveraging nationally-representative datasets, have underscored that women are more likely to self-report psychological distress symptoms than their male counterparts (Drapeau et al., 2010; Viertiö et al., 2021; Weissman, Russell, & Mann; 2020). The rationale for these sex-specific differences, however, remains murky: Many cite greater role-related stress experienced by women as opposed to “intrinsic” differences in the experience of psychological distress (Drapeau et al., 2012), while others have posited that differences in how men versus women express emotion might lead women to more frequently endorse certain items on psychological distress scales (Drapeau et al., 2010; Leach, Christensen, & Mackinnon, 2008).

As for differences in psychological distress according to education level, here too a robust literature has emerged over the years highlighting the protective role of education against mental health problems (Molarius & Granström, 2018; Bauldry, 2015; McFarland & Wagner, 2015). Among the mechanisms by which education has been found to confer this protective status include lower likelihood of unemployment, greater financial stability, and higher capacity to complete job-related tasks (Muñoz & Santos-Lozada, 2021). It is therefore noteworthy that in this study education remained an important protective factor even after adjusting for EQ class membership: A higher concentration of college-educated Millennials was observed in the positive EQ growth class, which suggests that mechanisms unrelated to employment quality explain the relationship between education level and psychological distress in this study. Such a line of inquiry was beyond the scope of this study but would be worth exploring through a qualitative or mixed-methods approach.

7.5. Reflections on paradoxical moderation analyses findings

Having established that declining employment quality is associated with symptoms of psychological distress, this study's final research aim sought to determine whether certain social welfare policies might mitigate the adverse effects of poor employment quality on mental health outcomes. Here findings were contrary to expectations: None of the examined social welfare policies—minimum wage, EITC, and unemployment insurance—acted as a buffer against the deleterious effects of declining EQ on severe psychological distress among the six-wave sample of Millennials (n=572). Similarly, no interaction effect was observed for EITC or unemployment insurance when examining moderate psychological distress as the outcome variable. An interaction effect was observed between employment quality class and minimum wage in the moderate psychological distress models; however, the direction of the relationship ran counter to this study's hypotheses. Specifically, increasing values of minimum wage exacerbated the negative effect of declining EQ class membership on moderate distress (i.e., as minimum wage increased, so too did the probability of moderate psychological distress for those in the declining EQ trajectory class). While this finding is perplexing, one possible explanation could be that states with higher minimum wages are also states where the cost of living is high, causing more stress and anxiety for an individual experiencing declining employment quality. Persistently low wages, unstable employment, and a lack of employer-provided health care are more likely to provoke symptoms of distress in places where it costs more to make ends meet.

Additional analyses using the three-, four-, and five-wave samples as well as using total psychological distress score as the outcome variable yielded similarly paradoxical results. Specifically, unemployment insurance replacement rate was significantly associated with psychological distress outcomes, whereby each percent increase in UI replacement rate yielded a

6% and 7% *increase* in the odds of experiencing moderate psychological distress among respondents with three- and four-waves of mental health data, respectively. Similarly, no interaction effects were observed for analyses using total psychological distress score as the outcome variable, but both minimum wage and state EITC rate emerged as significant predictors of total psychological distress score: Higher minimum wages and EITC rates were associated with *higher* psychological distress scores. As noted above, these findings, while perplexing, could be explained by the fact that states with higher minimum wages, EITC state-to-federal rates, and unemployment insurance replacement rates are ones with higher costs of living—it is plausible that persistently poor employment quality in these settings would be a source of distress. These possible explanations aside, replications studies are warranted prior to concluding that these social policies fail to buffer the negative effects of precarious employment on worker mental health. Moreover, while these policies may not yield mental health benefits per se, they have demonstrable benefits with respect to poverty reduction (Center on Budget and Policy Priorities, 2023), food insecurity (Lenhart, 2022; Raifman et al., 202), and housing instability (Pilkauskas & Michelmore, 2019).

It is also worth relativizing the degree of social protection in these more "generous" states compared to the social welfare systems of other countries. How protective is a 12- or 15-dollar minimum wage in a country like the United States where there is no universal healthcare, state support for child care, or parental leave? The median monthly salary for workers in France is €2000 Euro (far lower than the United States); however, all French residents are entitled to state-supported healthcare, maternity leave, and subsidized childcare—do these robust social protection policies buffer any negative mental health consequences of these relatively low (compared to the United States) wages? An international comparative study (or series of studies) would be best suited to better understand the role of welfare systems in mitigating the effects of poor employment quality on mental health. The proliferation of panel datasets across the European Union in recent years would facilitate such an endeavor.

7.6. Study Limitations

A number of limitations of the present study are worth delineating here. First and foremost, given that this study relied exclusively on secondary data, there were limitations due to the *availability of variables* of interest (namely, employment and key sociodemographic variables), the *process* in which PSID data were collected, and the *completeness* of the available data.

First, as was the case for other researchers who have attempted to map indicators from their respective datasets onto the seven theorized dimensions of employment quality, this study could only locate variables within the PSID dataset that corresponded with five of the seven dimensions of employment quality. Specifically, only employment stability, material rewards, working time arrangements, workers' rights and protections, and collective bargaining could be "measured" in the present study. Importantly, variables corresponding with the employment quality dimensions of "promotions" and "interpersonal relations" could not be located within the PSID datasets, which raises concerns about the reliability and content validity of the constructed scale. While EQ remains an imperfect measure at this current juncture in occupational health research, the theory undergirding the construct is sound and rooted in dimensions of employment precarity that have been identified as salient by both occupational health researchers and the labor movement.

As for the availability of other variables of interest, this study could not find a reliable measure of immigrant status. The variable in the PSID datasets denoting whether the respondent's family was drawn from the immigrant sample (a sample drawn in the late 1990s) does not accurately reflect the immigrant status of Millennials in the study—in all likelihood it is not the Millennial respondent who is an immigrant but the respondent's parent or grandparent.

Beyond the unavailability of certain dimensions of employment quality, there were limitations regarding the variables that were ultimately included in the six-item employment quality measure. For example, up until 2017, there was no variable in the datasets for "income from main current job." Rather, respondents were asked to provide an income figure for all jobs worked in the previous year, limiting this study's understanding of how, if at all, income from primary jobs changed over the course of the study period. In other words, it is difficult to know whether a figure of $60,000 a year is attributable to one decent-paying job or one poorly paying job plus two side jobs. In addition, with respect to the dimension of worker protections, this study relied on a measure of whether respondents would be paid overtime as there was no item within the PSID questionnaires that assesses experienced workplace discrimination or policies in place to prevent/address discrimination. Finally, it would have been ideal if the PSID dataset included questions pertaining to respondents' desired working arrangements: Research in the wake of the Great Recession has found high rates of workers involuntarily working part-time, (Kalleberg & von Wachter, 2017); however, this phenomenon could not be assessed using existing PSID variables. In short, dataset limitations threaten the reliability of the EQ measure, as the items selected for the EQ measure in this study are slightly different than the items other researchers have opted for given the variables available in their respective datasets.

With respect to the process with which data were collected, here too this secondary data analysis encountered a number of limitations. The study design of the PSID precludes the availability of psychological distress data for both household members with employment-related data. Specifically, only the survey respondent answers the survey's mental health questions, which ultimately limited the sample size for the mental health analyses to less than half of the sample for the employment quality trajectory analyses. Attempts were made to overcome this limitation by widening the sample for mental health analyses to those with three-, four-, and five-timepoints worth of mental health data, and findings from the analyses did not significantly change when the sample size was expanded. Indeed, employment quality class (declining employment quality class compared to stagnant employment quality class) remained a significant predictor of moderate and severe mental health; education, marital status, and age were also significant covariates in these expanded analyses. Another limitation due to study design involves the possibility of recall bias. PSID respondents were asked to recall very intricate details regarding their income (weekly, monthly, and yearly basis), expenditures, debts, and health over a two-year period. As with all surveys that rely on self-report, it is probable that there was some degree of error in the responses provided by participants. Nevertheless, the frequency with which respondents are interviewed (every two years) makes the PSID's study design far superior to a purely retrospective study, which would introduce a far greater likelihood of recall bias.

A few limitations of the study *methods* also warrant scrutiny. First, a number of trajectory modeling techniques for longitudinal data could have been leveraged for Research Aim 1 (identifying employment quality trajectories). Among these possible statistical approaches include repeated measures latent class analysis (as the name would suggest, an extension of latent class analysis involving repeated measures), group-based trajectory modeling, and latent transition analysis. Repeated measures latent class analysis is arguably the preferable approach given that it does not require distilling employment quality into a composite linear score (which might obscure the pernicious effects of certain combinations of employment conditions on mental health outcomes). It is unclear given the study's opted approach (growth mixture modeling) what profile of work conditions is especially detrimental to mental health—is it the low salary plus job instability? Is it the lack of employer-covered health care and long working hours in spite of the high salary? Ultimately, repeated measures latent class analysis could not be used for the present study given the large number of employment quality indicators and their corresponding response categories—repeated measures latent class analysis models would have failed to converge given that they would have included 36 indicators (6 items at each timepoint), with at least 4 response option indicators per item.

The choice to create a binary moderate psychological distress variable was based on previous social epidemiological and occupational health studies (Eisenberg-Guyot et al., 2020; Prochaska et al., 2012**)** that relied on a cutoff score of 5 or higher to signify possible moderate distress. While this scoring approach has been found to be valid and consistent across diverse ethnic/racial groups, it is possible that this cutoff value is too sensitive, over-diagnosing individuals with moderate distress. After all, the creator of the K-6 psychological distress scale only ever identified one cut-off value—13—to denote serious psychological distress. Were it the case that this study's threshold for moderate distress (5 or higher) was not sufficiently discriminatory, then the observed relationships between certain variables and moderate (but not severe) psychological distress—namely age and sex—might not in fact be significant.

Finally, there are several key individual-, family-, and community-level predictors of mental health that were not included in the mixed-effects models. Pertinent risk factors at the individual-level include trauma history, childhood mental health diagnoses, and low self-esteem. At the family-level, parental mental health and substance abuse, financial difficulties, and parental separation are salient risk factors for mental health. Other important drivers of mental health at the school-, neighborhood-, and community-level include peer relations, poverty, and community violence. That none of these well-established risk factors of mental health were included in the models is a function of the types of variables available in the PSID dataset.

7.7. Study Strengths

Having acknowledged the limitations of this secondary data analysis, there are several strengths of the present study that merit attention. First, this study contributes to a still nascent research literature that leverages *longitudinal* data to explore the relationship between precarious employment and mental health and constitutes. Among the handful of studies that have analyzed precarious employment and mental health trends across time, this is—to this author's knowledge—the only panel study to date that has explored this phenomenon among Millennial workers. This generational cohort of workers faced unique challenges in securing stable employment upon entering the labor market and their employment trajectories and mental health outcomes of this subpopulation were deserving of scholarly attention. Using nationally representative data from the world's longest running household panel survey, this study confirms that the employment quality of the vast majority of Millennial workers has remained virtually unchanged since the financial crisis. Given that this subpopulation has not enjoyed any meaningful gains in work conditions in the decade following their entry into the workforce, it should come as no surprise that many Millennials have yet to meet major milestones such as marriage, homeownership, and having children.

Next, this study is the first to have explored the interaction of specific U.S. social protection programs on the association between precarious employment and mental health. This line of inquiry is an essential one in an economic climate marked by the erosion of standard employment arrangements and the rise of the gig economy. Policies designed to support workers, such as the minimum wage, state EITC, and unemployment insurance, should be evaluated for their potential to temper the mental health consequences of precarious work. While findings from the moderation analyses ultimately ran counter to this study's hypotheses, this exercise was nevertheless an important first step in understanding the strengths and limitations of current social protection policies in shielding beneficiaries from the mental health-related consequences of these shifting labor market dynamics. Indeed, this study makes an important contribution to the efforts of social welfare scholars and practitioners working at the intersection of labor market and occupational health policies and should serve as a stepping stone to future studies that aim to identify policies that support the health and wellbeing of those engaged in precarious work.

This study also merits a few words on the strength of its methodological approach. Specifically, this dissertation leverages an innovative statistical technique—growth mixture modeling—to identify underlying subgroups in a panel dataset. This method for identifying multiple unobserved subpopulations is not one often used in social work research but could, depending on the research question, be a useful method for social work researchers working with longitudinal data. For example, researchers working on geriatric social work issues might leverage GMM to identify multiple unobserved subpopulations of dementia progression, examining differences in symptom progression among each unobserved subpopulation and how social support might be associated with membership in each subgroup. Another example might be the use of GMM to identifying underlying patterns of substance abuse among adolescents and the role of peer- and family-level factors on membership in each subgroup. While no statistical technique is without its limitations (and as noted in the discussion section, such techniques offer only a small window of understanding into a much more nuanced phenomenon), GMM provides a much more complete picture of patterns in individual responses than traditional regression techniques.

7.8. Implications for Social Work Policy and Practice

This ambitious yet necessary exploration of the post-Great Recession employment quality trajectories of Millennials has important implications for social work policy and practice. With respect to implications for social work policy, several takeaways from this study are of import to those working on economic and health policy. First, this study has demonstrated that improvements in employment quality in the post-Great Recession period were not shared equally among Millennial workers. Instead, the vast majority of Millennials in this study experienced stagnant or declining employment quality over the course of the decade following the recession, with a mere 10% of respondents enjoying a boost in employment quality during the study period. While it is true that Millennials in the positive EQ growth class compared to the negative growth class tended to have higher levels of education, to be high-skilled workers, and to be men, the sociodemographic characteristics of those in the stagnant growth class (to which nearly three-quarters of the sample belonged) were not appreciably different from those of the positive growth class. In other words, this study found that stagnant employment quality affected virtually all workers in this study regardless of sex, race/ethnicity, education, and job skill level.

This finding alone is an important one for policy makers to grapple with, especially in light of the proliferation of more precarious types of work arrangements (e.g., gig-work) in the post-Great Recession period.

The mental health implications of such sluggish—and in some cases negative—growth is also crucial for policymakers to consider. It is unsurprising that poor employment quality in what should otherwise be one's prime working years would be a source of consternation and psychological distress for Millennial workers in this study. Research has demonstrated that poor mental health can affect one's ability to work effectively, which means persistently poor employment can create a vicious cycle where workers' health and ultimately their livelihoods deteriorate. Policymakers, particularly those working at the intersection of labor and health policy, will need to evaluate how best to support the mental health of young workers as they navigate a labor market that is wholly disconnected from the proverbial "American dream." Expanding access to behavioral health care services could be an important step toward ensuring that those struggling with the mental health implications of poor employment conditions can receive appropriate services. State and federal agencies should continue to address the many barriers that obstruct receipt of behavioral health services, including issues of affordability (i.e., cost of mental health services), availability of services (i.e., ability to receive services in a timely manner), accessibility of services (i.e., location of services—a real problem in rural America), and acceptability of services (i.e., tailored to the specific needs of the client).

That none of the social welfare policies examined in this study mitigated the effects of poor employment quality on psychological distress speaks to the need for policymakers to invest in research to understand what policies—if any—might serve lessen the blow of precarious employment on mental health outcomes. Some American cities have begun experimenting with the concept of a universal basic income (UBI), with promising results for the mental health of recipients. Indeed, while a UBI might be one possible policy tool, it is incumbent upon policy makers to explore other measures that might support worker wellbeing. International comparative studies would also be worthwhile to understand how different welfare *systems* promote worker wellbeing in contexts of precarious employment.

Finally, from a social work practice standpoint, it is my hope that this research will be valuable to social workers advocating for worker protections in labor organization and policy-making circles. In keeping with social work's mission to promote social justice and social change, such advocates can draw upon this study's findings regarding the inequalities in employment outcomes in the post-Great Recession period as well as the mental health implications of these inequalities to make the case for better conditions for workers. For those clinically-trained, this research will highlight the need for mental health practitioners to place greater emphasis on the employment conditions of their clients when assessing contributing factors for mental health disorders. Glaring examples of adversity in a client's life (e.g., child abuse/neglect, domestic violence, etc.) often shape the practitioner's biopsychosocial assessment of the client; however, as this study has demonstrated, persistently poor/stagnant employment quality—innocuous as it may seem when dealing with childhood trauma cases—can play a major role in a client's wellbeing. Clinical social workers might consider including questions related to clients' employment conditions in their intake assessments and working with clients to shift blame away from themselves to the macro-level forces that contribute to employment precarity.

In addition, caseworkers at mental health agencies, when feasible, could provide referrals to local American Job Centers[49] for clients struggling to find/maintain employment opportunities.

7.9. Future Research

This study contributes to a still nascent research literature that leverages *longitudinal* data to explore the relationship between precarious employment and mental health. Study results are consistent with previous labor studies that underscored the particularly poor employment prospects faced by Millennials in the immediate aftermath of the Great Recession as well as the stagnant employment quality conditions faced by this generation of workers in the decade following the financial crisis. Moreover, findings support the literature's general thesis that poor employment quality is associated with worse mental health outcomes, though this study stopped short of identifying social protection policies that might weaken the deleterious effect of poor EQ on psychological distress. In light of these findings, and in the hopes of further advancing the knowledge base on the connection between precarious work and mental health, there are several possible avenues for future research worth detailing here.

First, as the purpose of this study was to ascertain the employment quality trajectories of a particular subset of the greater population (Millennials), future studies might aim to understand how the trajectories of Millennials are distinct from those of their older and younger employment-age counterparts. For example, to what extent, if any, were Gen X-ers (born 1965-1980) and Boomers (born 1946-1964) spared the employment-related consequences of the Great Recession? As the oldest members of the Gen X cohort are approaching retirement age, it will be

---

[49] American Job Centers are designed to assist job seekers by providing a range of services such as career counseling, training opportunities, and job listings. These centers also assist businesses in finding qualified workers by organizing job fairs, assisting with recruitment needs, and job referrals.

important to examine whether their employment quality trajectories in recent years have afforded them the financial security needed to retire. In addition, have members of Generation Z (those born from 1997 onward) suffered a similar fate as their Millennial counterparts? In short, is stagnant employment quality the name of the game for the vast majority of the American workforce or a fate reserved only for the Millennial workers unfortunate enough to enter the workforce at the outset of the Great Recession? These are important queries, and this study has laid the foundation for such an endeavor. Indeed, data from the Panel Study on Income Dynamics could easily be pulled for older and younger cohorts and analyses replicated for these respondents.

Next, the study methods employed here preclude the kind of contextualization of findings that would be possible through qualitative research: what are the mechanisms underlying the relationship between precarious employment and mental health? What aspects of precarious work in particular are most distress-inducing for Millennials? Is it the quality of employment opportunities or the mismatch between employment expectations versus reality that are most destructive to mental wellbeing? Quantitative analyses are certainly an important starting point for understanding precarious employment and mental health at a population level; however, these kinds of questions can only be explored through qualitative work, such as in-depth interviews and focus group discussions. Moreover, the information gleaned from qualitative research on the characteristics of current employment conditions that induce distress or the coping strategies young workers employ to manage unmet career expectations would have important implications for social work practice. For example, if certain aspects of employment quality (e.g., job benefits, working-time arrangements, or income) were consistently identified by respondents as contributing to distress, policy makers working at the intersection of health and labor issues could push for policy changes to address these specific employment concerns. Or, if qualitative work sheds light on how Millennials make meaning of their precarity to preserve their mental health, such findings might be important for clinical social workers working with clients whose jobs are a source of great stress and mental anguish. Indeed, much can be gleaned from probing the relationship between precarious employment and mental health though qualitative methods, with important implications for social work research and practice.

Given the significant association between employment quality and mental health highlighted in this study, it is my hope that labor studies and mental health scholars will no longer consider issues of employment and mental health in isolation. There is great value in incorporating measures of mental health as well as well-established risk and protection factors for mental health in large-scale labor market studies. Likewise, mental health researchers should consider including items pertaining to the employment conditions of respondents when designing their respective study instruments. Moreover, this study underscores the importance of continued investment in nationally-representative datasets, such as the PSID, that measure key outcomes such as labor market participation/employment outcomes as well as reliable and valid measures of mental health.

Finally, it will be important for future research to interrogate what elements of the welfare system can support the mental health of workers in times of economic precarity. An international comparative study that could identify welfare state typologies and specific policies that support worker wellbeing was beyond the scope of this study but would be a worthwhile next-step. Ongoing panel studies in Germany (the German Socio-Economic Panel) and Sweden (the Longitudinal Integration Database for Health Insurance and Labor Market Studies) collect the requisite employment and mental health data that would allow for such a comparative study.

Moreover, each of these countries represents a different welfare state typology: Sweden would be characterized as a social democratic regime (high levels of decommodification, cross-class solidarity, and universal welfare benefits), while Germany is consistent with the "continental model" of welfare capitalism (solidarity stratified by occupational status, welfare benefits predicated on earnings, and social welfare policies that seek to preserve traditional family values). Indeed, this dissertation project constitutes the mere first step in an effort to understanding how the welfare state can best protect the mental health of workers in a political and economic climate marked by accelerating technological advances, growing inequality, and rising labor contentiousness.

References

Abramovitz, M., & Zelnick, J. (2015). Privatization in the human services: Implications for direct practice. *Clinical Social Work Journal, 43*, 283-293.

Addo, F.R., & Darity, W.A. (2021). Disparate recoveries: Wealth, race, and the working class after the Great Recession. *The ANNALS of the American Academy of Political and Social Science, 695*(1), 173-192. https://doi.org/10.1177/00027162211028822

Albæk, K., & Andrade, S.B. (2023) Involuntary temporary work and mental health medications: A longitudinal study in Denmark. P*LOS Glob Public Health, 3*(11), e0002634. https://doi.org/10.1371/journal.pgph.0002634

Allan, B.A., Autin, K.L., Wilkins-Yel, K.G. (2021). Precarious work in the 21st century: A psychological perspective. *Journal of Vocational Behavior*, 126, 103491.

Allmang, S. (2019). Emerging adults in uncertain employment: an examination of the dimensions and consequences of precarious work in the United States. UCLA Electronic Thesis and Dissertations.

Andrea, S.B., Eisenberg-Guyot, J., Oddo, V.M., Peckham, T., Jacoby, D., Hajat, A. (2021). Intersectional trends in employment quality in older adults in the United States. *SSM Population Health, 15,* 100868.

Artazcoz, L., Benach, J., Borrell, C., Cortes, I. (2005). Social inequalities in the impact of flexible employment on different domains of psychosocial health. *J. Epidemiol. Community Health* 59(9):761–67.

Asahina, Y. (2019). Insecure millennials: coming of age in Seoul and Tokyo. University of Hawaii at Manoa (dissertation).

Bardasi, E., & Francesconi, M. (2004). The impact of atypical employment on individual wellbeing: evidence from a panel of British workers. *Social Science & Medicine,* 58(9), 1671-1688.

Bartley, M., Ferrie, J., Montgomery, S.M., (2011). Health and labour market disadvantage: unemployment, non-employment, and job insecurity. In: In: Marmot, M., Wilkinson, R.G. (Eds.), Social Determinants of Health, vol. 2006. Oxford University Press, Oxford, pp. 78–96.

Bauldry, S. (2015). Variation in the protective effect of higher education against depression. *Society and Mental Health, 5*(2), *145-161.*

Beale, N., & Nethercott, S. (1985). Job-loss and family morbidity: a study of a factory closure. *The Journal of the Royal College of General Practitioners*, *35*(280), 510–514.

Béland, D., de Chantal, F.V., & Waddan, A. (2002). Third way social policy: Clinton's legacy? *Policy & Politics, 30*(1), 19-30.

Benach, J., Vives, A., Amable, M., Vanroelen, C., Tarafa, G., & Muntaner, C. (2014). Precarious employment: Understanding an emerging social determinant of health. *Annual Review of Public Health, 35,* 229-53.

Berghammer, C., & Adserà, A. (2022). Growing inequality during the Great Recession: Labour market institutions and the education gap in unemployment across Europe and in the United States. *Acta Sociologica*, *65*(4), 374-397. https://doi.org/10.1177/00016993221083226

Bialik, K., & Fry, R. (2019). Millennial life: How young adulthood today compares with prior generations. Pew Research Center. Retrieved from https://www.pewresearch.org/social-trends/2019/02/14/millennial-life-how-young-adulthood-today-compares-with-prior-generations-2/

Blue Cross Blue Shield. (2019). https://www.bcbs.com/sites/default/files/file-attachments/health-of-america-report/HOA-Millennial_Health_0.pdf

Bosmans, K., Lewchuck, W., De Cuyper, N. Hardonk, S., Van Aerden K., & Vanroelen, C. (2017). The experience of employment strain and activation among temporary agency workers in Canada. *Society, Health & Vulnerability, 8*(1). https://doi.org/10.1080/20021518.2017.1306914

Brockner, J. (1988). The effects of work layoffs on survivors: Research, theory, and practice. In B.M. Staw & L.L. Cummings (Eds.), Research in Organizational Behavior, 10, 213-255.

Brown, C. (1996). Notes on the “SEO” or “Census” Component of the PSID. Survey Research Center-Institute for Social Research at the University of Michigan (Technical Series Paper#96-03). https://psidonline.isr.umich.edu/publications/Papers/tsp/1996-03_Notes_on_the_SEO_C_Brown.pdf

Brown, R.L., Richman, J.A., & Rospenda, K.M. (2017). Research stressors and psychological distress: exploring age cohort variation in the wake of the Great Recession. *Stress and Health, 33,* 267-277.

Burgard, S.A., & Seelye, S. (2017). Histories of perceived job insecurity and psychological distress among older U.S. adults. *Soc Ment Health, 7*(1), 21-35.

Canivet, C., Aronsson, G., Berhnard-Oettel, C., Leineweber, C., Moghaddassi, M., Stengard, J., westerlund, H., Östergren, P.O. (2017). The negative effects on mental health of being in a non-desired occupation in an increasingly precarious labour market. *SSM- Population Health, 3,* 516-524.

Carcasson, M. (2006). Ending welfare as we know it: President Clinton and the rhetorical transformation of the anti-welfare culture." *Rhetoric & Public Affairs,* 9(4), 655-692.

Case, A., & Deaton, A. (2020). *Deaths of despair and the future of capitalism*. Princeton University Press.

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, 13, 195-212.

Center on Budget and Policy Priorities. (2023, April). *The Earned Income Tax Credit: Policy Brief.* https://www.cbpp.org/sites/default/files/atoms/files/policybasics-eitc.pdf

Clarke, M., Lewchuk, W., de Wolff, A., & King, A. (2007). 'This just isn't sustainable': Precarious employment, stress and workers' health. *Psychiatry, 30(4-5), 311-326.*

Cobb, S. & Kal, S.V. (1977). Termination: the consequences of job loss. Cincinnati, National Institutes for Occupational Safety and Health. (DHEW-NIOSH Publication No. 77-224).

Collins, J.L., and Mayer, V. (2010). *Both hands tied: Welfare reform and the race to the bottom in the low-wage labor market.* The University of Chicago Press.

Compton, R., Giedeman, D., & & Muller, L. (2018). Racial diffrentials in the wealth effects of the financial crisis and Great Recession. *Journal of economics, race, and policy, 1*(2)*, 126-141.*

Culatta, E., & Clay-Warner, J. (2021). Falling behind and feeling bad: Unmet expectations and mental health during the transition to adulthood. *Society and Mental Health*, *11*(3), 251–265.

Davenport & Friedman (2021). Bipartisan infrastructure deal omits big climate measures. https://www.nytimes.com/2021/06/24/climate/biden-climate-infrastructure.html

Dawson, C., Veliziotis, M., Pacheco, G., & Webber, D. J. (2015). Is temporary employment a cause or consequence of poor mental health? A panel data analysis. *Social science & medicine (1982)*, *134*, 50–58. https://doi.org/10.1016/j.socscimed.2015.04.001

De Moortel, D., Vandenheede, H., Vanroelen, C. (2014). Contemporary employment arraignments and mental well-being in men and women across Europe: a cross-sectional study. *International Journal for Equity in Health, 13,* 90.

Deloitte Global. *The Deloitte Global Millennial Survey 2019: Societal discord and technological transformation create a "generation disrupted."* 2019. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/global/Documents/About-Deloitte/deloitte-2019-millennial-survey.pdf

Deloitte Global. *Millennials, Gen Z and mental health: Managing mental health in the workplace.* June 2020. Retrieved from https://www2.deloitte.com/global/en/pages/about-deloitte/articles/millennials-gen-z-and-mental-health-2020.html

Dimock, M. (2019). Defining generations: Where Millennials end and Generation Z begins. Pew Research Center. Retrieved from https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/

Domenighetti, G., D'Avanzo, B., & Bisig, B. (2000). Health effects of job insecurity among employees in the Swiss general population. *International journal of health services : planning, administration, evaluation*, *30*(3), 477–490. https://doi.org/10.2190/B1KM-VGN7-50GF-8XJ4

Drapeau, A., Beaulieu-Prévost, D., Marchand, A., Boyer, R., Preville, M., & Kairouz, S. (2010). A life-course and time perspective on the construct validity of psychological distress in women and men. Measurement invariance of the K6 across gender. *BMC Med Res Methodol* **10**, 68. https://doi.org/10.1186/1471-2288-10-68

Drapeau, A., Marchand, A., & Beaulieu-Prevost, D. (2012). Epidemiology of psychological distress. In *Mental Illnesses- Understanding, Prediction and Control.* L'Abate L. (Ed.). doi: 10.5772/1235

Easton, S.D., Safadi, N.S., Wang, Y., & Hasson 3rd, R.G. (2017). The Kessler psychological distress scale: translation and validation of an Arabic version. *Health Qual Life Outcomes,* 15(1), 215.

Economic Research Service. (2023). Rural employment and unemployment. US Department of Agriculture. https://www.ers.usda.gov/topics/rural-economy-population/employment-education/rural-employment-and-unemployment/

Ehrman, J. (2005). *The eighties: America in the age of Reagan*. Yale University Press.

Eisenberg-Guyot, J. Peckham, T., Andrea, S.B., Oddo, V., Seixas, N., & Hajat, A. (2020). Life-course trajectories of employment quality and health in the U.S.: A multichannel sequence analysis. *Social Science & Medicine, 264,* 113327.

Erola, J., Jalonen, S., & Lehti H. (2016). Parental education, class and income over early life course and children's achievement. *Research in social stratification and mobility, 33-43.*

Feldman, B., Maysyn, K.E., & Conger, R.D. (2009). New approaches to studying problem behaviors: A comparison of methods for modeling longitudinal, categorical adolescent drinking data. *Developmental Psychology, 45*(3), 652-676.

Ferrie JE. 2001. Is job insecurity harmful to health? *J. R. Soc. Med.* 94(2):71–76

Ferrie, J.E. (1999). Health consequences of job insecurity. In. M.G. Marmot , J. Griffiths, & E. Ziglio (Eds.), *Labour Market Changes and Job Insecurity: A Challenge for Social*

Welfare and Health Promotion (p. 59-99). Copenhagen: WHO. Reg. Publ., Eur. Ser. No. 81.

Ferrie, J. E., Shipley, M. J., Stansfeld, S. A., & Marmot, M. G. (2002). Effects of chronic job insecurity and change in job security on self reported health, minor psychiatric morbidity, physiological measures, and health related behaviours in British civil servants: the Whitehall II study. *Journal of epidemiology and community health*, *56*(6), 450–454. https://doi.org/10.1136/jech.56.6.450

Ferrie, J.E., Westerlund, H., Virtanen, M., Vahtera, J., & Kivimaki, M. (2008). Flexible labor markets and employee health. *Scand. J. Work Environ Health,* Suppl. 6, 98-110.

Fitzpatrick, S., Coughlin, J.W., Appel, L.J., Tyson, C., Stevens, V.J., … & Hill-Briggs, F. (2015). Application of latent class analysis to identify behavioral patterns of response to behavioral lifestyle interventions in overweight and obese adults. *Int J Behav Med,* 22(4), 471-480.

Folbre, N. (2021). Gender inequality and bargaining in the U.S. labor market: Why care work is undervalued. Economic Policy Institute. https://www.epi.org/unequalpower/publications/gender-and-bargaining-in-the-u-s-labor-market/

Foote, C.L., & Ryan, R.W. (2015). Labor market polarization over the business cycle. *NBER Macroeconomics Annual, 29, 371-413.* https://doi.org/10.1086/680656

Fry, R. (2020). Millennials overtake Baby Boomers as America's largest generation. Pew Research Center. Retrieved from https://www.pewresearch.org/fact-tank/2020/04/28/millennials-overtake-baby-boomers-as-americas-largest-generation/

Georgetown University Center on Education and the Workforce. (2016). America's Divided Recovery: College Haves and Have-Nots. https://cew.georgetown.edu/wp-content/uploads/Americas-Divided-Recovery-web.pdf

Gevaert, J., Van Aerden, K., De Moortel, D., & Vanroelen, C. (2021). Employment quality as a health determinant: Empirical evidence for the waged and self-employed. *Work and Occupations, 48*(2), 146-183.

Gilek, M. (2020). Mental health among young workers, the impact of job quality. University of Strathclyde (Business School). Retrieved from https://stax.strath.ac.uk/concern/theses/t435gd06n

Global 2019 Diseases and Injuries Collaborators. (2020). Global burden of 369 diseases and injuries in 204 countries and territories, 1990-2019: a systematic analysis for the Global Burden of Disease Study 2019.

Gray, B.J., Grey, C.N.B., Hookway, A., Homolova, L., Davies, A.R. (2021). Differences in the impact of precarious employment on health across population subgroups: a scoping review. *Perspectives in Public Health, 141,* 1.

Guest, D.E., Oakley, P., Clinton, M., & Budjanovcanin, A. (2006). Free or precarious? A comparison of the attitudes of workers in flexible and traditional employment contracts. *Human Resource Management Review, 16*, 107-124.

Han, K.M., Chang, J., Won, E., Lee, M.S., Ham, B.J. (2017). Precarious employment associated with depressive symptoms and suicidal ideation in adult wage workers. *Journal of Affective Disorders, 218,* 201-209.

Harvey, D. (2007). *A brief history of neoliberalism*. Oxford University Press.

Hasenfield, Y., & Garrow, E.E. (2012). Nonprofit human-service organizations, social rights, and advocacy in a neoliberal welfare state. *Social Service Review, 86*(2), 295-322.

Holmlund, B. (2013). What do labor market institutions do? *IZA Discussion Papers, No. 7809.* Institute for the Study of Labor (IZA), Bonn. Retrieved from https://www.econstor.eu/bitstream/10419/90120/1/dp7809.pdf

Hout, M., Cumberworth, E. (2012). The Labor Force and the Great Recession: *Inequality Research Brief.* New York: Russell Sage Foundation and Stanford Center on Poverty.

International Labour Organization. *Youth and Covid-19: Impacts on jobs, education, rights, and mental well-being.* Survey Report 2020. Retrieved from https://www.ilo.org/wcmsp5/groups/public/---ed_emp/documents/publication/wcms_753026.pdf

Irvine, A., & Rose, N. (2022). How does precarious employment affect mental health? A scoping review and thematic synthesis of qualitative evidence from western economies. *Work, employment, and society, 38*(2). https://doi.org/10.1177/09500170221128698

Jace, C.E., & Makridis, C.A. (2021). Does marriage protect mental health? Evidence from the COVID-19 pandemic. *Soc Sci Q.* https://doi.org/10.1111/ssqu.13063

Jaimovich, N., & Siu, H.E. (2012). Job polarization and jobless recoveries. *Working paper 18334.* National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w18334/w18334.pdf

Jalovaara, M., & Andersson, G. (2018). Disparities in children's family experiences by mother's socioeconomic status: The case of Finland. *Population Research and Policy Review, 37,* 751-768.

James, J. (2012). The college wage premium. *Economic Commentary*, 2012-10, August 8, Research Department of the Federal Reserve Bank of Cleveland.

Janz, N. (n.d.). Advanced handling of missing data: One-day workshop. Social Sciences' Research Methods Center, University of Cambridge.

Jonsson, J., Matilla-Santander, N., Kreshpai, B., Johansson, G., Kjellberg, K., Burström, B., Östergren, P.O., Nilsson, K., Strömdahl, S., Orellana, C., & Bodin, T. (2021a). Precarious employment and general, mental and physical health in Stockholm, Sweden: a cross-sectional study. *Scand J Public Health, 49*(2), 228-236.

Jonsson, J., Muntaner, C., Bodin, T., Alderling, M., Rebeka, R., Burström, B., Davis, L., Gunn, V., Hemmingsson, T., Julià, M., Kjellberg, K., Kreshpaj, B., Orellana, C., Padrosa, E., Wegman, D. H., & Matilla-Santander, N. (2021b). Low-quality employment trajectories and risk of common mental disorders, substance use disorders and suicide attempt: a longitudinal study of the Swedish workforce. *Scandinavian journal of work, environment & health*, *47*(7), 509–520. https://doi.org/10.5271/sjweh.3978

Julià, M., Belvis, F., Vives, A., Tarafa, G., Benach, J. (2019). Informal employees in the European Union: working conditions, employment precariousness and health. *J Public Health*, *41*(2), e141-e151.

Kalleberg, A.L. (2018). Job insecurity and well-being in rich democracies. *Econ Soc ev (Irel), 49*(3), 241-258.

Kalleberg, A.L., & Vallas, S.P. (2018), Probing precarious work: Theory, research, and politics. Kalleberg, A.L. & Vallas, S.P. (Eds.) *Precarious Work* (*Research in the Sociology of Work, Vol. 31*), Emerald Publishing Limited, Leeds, pp. 1-30.

Kalleberg, A.L., & von Wachter, T.M. (2017).The U.S. labor market during and after the Great Recession: Continuities and transformations. *RSF, 3*(3), 1-19. doi: 10.7758/rsf.2017.3.3.01

Kauhanen, M., & Nätti, J. (2015). Involuntary temporary and part-time work, job quality and well-being at work. *Social Indicators Research, 120*(3), 783–799. https://doi.org/10.1007/s11205-014-0617-7

Kessler, R.C., Berglund, P.A., Zhao, S., Leaf, P.J., Kouzis, A.C., Bruce, M.L., Friedman, R.M., Grossier, R.C., Kennedy, C., Narrow, W.E., Kuehnel, T.G., Laska, E.M., Manderscheid, R.W., Rosenheck, R.A., Santoni, T.W., & Schneier, M. (1996) The 12-month prevalence and correlates of serious mental illness In *Mental Health, United States, 1996*, Manderscheid R.W., Sonnenschein M.A. (eds) pp. 59–70, Washington, DC, US Government Printing Office

Kessler, S. (2018). *Gigged: The gig economy, the end of the job and the future of work.* Random House.

Kim, S. (2012). Sample size requirements in single-and multiphase growth mixture models: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal,* 19(3), 457-476.

Kochhar, R. (2011). Two years of economic recovery: Women lose jobs, men find them. *Pew Research Center.* https://www.pewresearch.org/social-trends/2011/07/06/two-years-of-economic-recovery-women-lose-jobs-men-find-them/

Korupp, S.E., Ganzeboom, H.B.G., Van Der Lippe, T. (2002). Do mothers matter? A comparison of models of the influence of mothers' and fathers' educational and occupational status on children's educational attainment. *Quality and Quantity, 36*(1), 17-42.

Kreshpaj, B., Orellana, C., Burström, B., Davis, L., Hemmingsson, T., Johansson, G., Kjellberg, K., Jonsson, J., Wegman, D. H., & Bodin, T. (2020). What is precarious employment? A systematic review of definitions and operationalizations from quantitative and qualitative studies. *Scandinavian journal of work, environment & health*, *46*(3), 235–247.

LaPonsie, M. (2021). How much does it cost to raise a child? U.S. News. Retrieved from https://money.usnews.com/money/personal-finance/articles/how-much-does-it-cost-to-raise-a-child

Larrison, C.R., Hack-Ritzo, S., Koerner, B.D., Schoppelrey, S.L., Ackerson, B., & Korr, W.S. (2015). Economic grand rounds: state budget cuts, health care reform, and a crisis in rural community mental health agencies. *Psychiatric Services, 62*(11), 1255-1257.

Leach, L.S., Christenesen, H., & Mackinnon, A.J. (2008). Gender differences in the endorsement of symptoms for depression and anxiety: are gender-biased items responsible? *J Nerv Men Dis, 196*(2), 128-35.

Lenhart, O. (2022). The earned income tax credit and food insecurity. *American Journal of Agricultural Economics, 105*(5), 1543-1570.

Lewis, J., & Surender R. (2004). *Welfare state change: towards a third way?* Oxford University Press.

Loewe, M., Zintl, T., & Houdret, A. (2021). The social contract as a tool of analysis: Introduction to the special issue on “Framing the evolution of new social contracts in Middle Eastern and North African countries.” *World Development,* 145, 104982.

Lore, H., Nguefack, N., Page, G.M., Katz, J., Choiniere, M., Vanasse, A., Dorais, M., Samb, O.M., Lacasse, A. (2020). Trajectory modeling techniques useful to epidemiological research: A comparative narrative review of approaches. *Clinical Epidemiology, 12,* 1205-1222.

McFarland, M.J., & Wagner, B.G. (2015). Does a college education reduce depressive symptoms in American young adults? *Social Science & Medicine, 146,* 75-84.

McHugh M. (1998). Rationalization as a key stressor for public sector employees: an organizational case study. *Occupational medicine (Oxford, England)*, *48*(2), 103–112. https://doi.org/10.1093/occmed/48.2.103

Mewton, L., Kessler, R. C., Slade, T., Hobbs, M. J., Brownhill, L., Birrell, L., Tonks, Z., Teesson, M., Newton, N., Chapman, C., Allsop, S., Hides, L., McBride, N., & Andrews, G. (2016). The psychometric properties of the Kessler Psychological Distress Scale (K6) in a general population sample of adolescents. *Psychological Assessment, 28*(10), 1232–1242.

Molarius, A., & Granström, F. (2018). Educational differences in psychological distress? Results from a population-based sample of men and women in Sweden in 2012. *BMJ Open, 8*(4), e021007.

Mont Pelèrin Society. (1947). Statement of Aims. https://www.montpelerin.org/statement-of-aims/

Moscone, F., Tosetti, E., Vittadini, G. (2016). The impact of precarious employment on mental health: the case of Italy. *Social Science & Medicine, 158,* 86-95.

Munoz, I.G., & Santos-Lozada, A.R. (2021). Educational attainment and psychological distress among working-age adults in the United States. *SSM- Mental Health, 1.*

Muthén, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), Handbook of quantitative methodology for the social sciences (pp. 345–368). Newbury Park, CA: Sage.

Muthén, L.K., & Muthén, B.O. (1998-2017). Mplus User's Guide. Eighth Edition. Los

Angeles, CA: Muthén & Muthén

Neufeind, M., O'Reilly, J., & Ranft, F. (Eds.). (2018). Work in the digital age: challenges of the fourth industrial revolution. London: Rowman & Littlefield.

Oddo, V. M., Zhuang, C. C., Andrea, S. B., Eisenberg-Guyot, J., Peckham, T., Jacoby, D., & Hajat, A. (2021). Changes in precarious employment in the United States: A longitudinal analysis. *Scandinavian journal of work, environment & health*, *47*(3), 171–180. https://doi.org/10.5271/sjweh.3939

OECD. *In it together: Why less inequality benefits all*. (2015). Paris, France: OECD Publishing. Retrieved from http://www.oecd-ilibrary.org/employment/in-it-together-why-less-inequality-benefits-all_9789264235120-en.

Paul, K.I., & Moser, K. (2009). Unemployment impairs mental health: meta-analyses. *J. Vocat. Behav*, *74*, 264–282 2009.

Pew Research Center. (2012). Young, underemployed and optimistic. Retrieved from https://www.pewresearch.org/social-trends/2012/02/09/young-underemployed-and-optimistic/

Pew Research Center. (2015). The whys and hows of generations research. Retrieved from https://www.pewresearch.org/politics/2015/09/03/the-whys-and-hows-of-generations-research/

Pew Research Center. (2018). The generation gap in American politics. Retrieved from file:///Users/leiladalsanto/Downloads/03-01-18-Generations-release2.pdf

Pfeffer, F.T., Danziger, S., Schoeni, R.F. (2013). Wealth disparities before and after the Great Recession. *Annals of the American Academy of Political and Social Science, 650*(1), 98–123.

Phillips-Fein, K. (2009). Business conservatives and the Mont Pèlerin Society. In P., Mirowski & D., Plehwe (Eds.), *The road from Mont Pèlerin: The making of the neoliberal thought* collective (pp. 280–301). Harvard University Press.

Phillips-Fein, K. (2017). *Fear city: New York's fiscal crisis and the rise of austerity politics*. Henry Holt and Company.

Pförtner, T.K., Pfaff, H., Hower, K.I. (2019). Trends in the association of different forms of precarious employment and self-rated health in Germany. An analysis of the German Socio-Economic Panel between 1995 and 2015. *J Epidemiol Community Health, 73,* 1002-1011.

Pierson, P. (1994). *Dismantling the welfare state: Reagan, Thatcher, and the politics of retrenchment.* Cambridge University Press.

Pirani, E., & Salvini, S. (2015). Is temporary employment damaging to health? A longitudinal study on Italian workers. *Social Science & Medicine, 124,* 121-131.

Pollack, R., Kreshpaj, B., Jonsson, J., Bodin, T., Gunn, V., Orellana, C., Östergren, P.O., Muntaner, C., Matilla-Santander, N. (2022). Low-quality employment trajectories and the risk of common mental health disorders among individuals with Swedish and foreign background – a register-based cohort study. *Scand J Work Environ Health, 48*(5), 351-360.

Popham, F., Gray, L., Bambra, C. (2012). Employment status changes and the prevalence of self-rated health: findings from UK individual level repeated cross-sectional data from 1978 to 2004. *BMJ Open 2*, e001342. https://doi.org/10.1136/bmjopen-2012- 001342.

Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillis, M.R., & Rahman, A. (2007). No heath without mental health. *The Lancet, 370,* 859-877.

Prochaska, J.J., Sung, H., Max, W., Shi, Y., & Ong, M. (2012). Validity study of the K6 scale as a measure of moderate mental distress based on mental health treatment need and utilization. *International Journal of Methods in Psychiatric Research\, 21*(2), 88-97.

Puig-Barrachina, V., Vanroelen, C., Vives, A., Martinez, J.M., Muntaner, C., et al. (2014). Measuring employment precariousness in the European working conditions survey: the social distribution in Europe. *Work, 49*(1), 143-161.

Quesnel-Vallée, A., DeHaney, S., & Ciampi, A. (2010). Temporary work and depressive symptoms: a propensity score analysis. *Social science & medicine (1982)*, *70*(12), 1982–1987. https://doi.org/10.1016/j.socscimed.2010.02.008

Raifman, J., Bor, J., & Venkataramani, A. (2021). Association Between Receipt of Unemployment Insurance and Food Insecurity Among People Who Lost Employment During the COVID-19 Pandemic in the United States. *JAMA network open*, *4*(1), e2035884. https://doi.org/10.1001/jamanetworkopen.2020.35884

Ram, N., & Grimm, K.J. (2009). Growth mixture modeling: a method for identifying differences in longitudinal change among unobserved groups. *Int J Behav Dev,* 33(6), 565-576.

Reich, M., Gordon, D.M., & Edwards, R.C. (1973). Dual labor markets: A theory of labor market segmentation. *American Economic Association, 63*(2), 359-365.

Reisch, M. (2013). What is the future of social work? *Critical and Radical Social Work,* 1(1), 67-85.

Reynolds, J.R., & Baird, C.L. (2010). Is there a downside to shooting for the stars? Unrealized educational expectations and symptoms of depression. *American Sociological Review,* 75(1), 151-172.

Rinz, K. (2022). Did timing matter ? Life cycle differences in effects of exposure to the Great Recession. *Journal of labor economics, 40*(3). https://doi.org/10.1086/716346

Ruiz, M.E., Vives, A., Martinez-Solanas, Julia, M., Benach, J. (2017). How does informal employment impact population health? Lessons from the Chilean employment conditions survey. *Safety Science, 100,* 57-65.

Scott, L., & O'Hara, M. W. (1993). Self-discrepancies in clinically anxious and depressed university students. *Journal of abnormal psychology*, *102*(2), 282–287. https://doi.org/10.1037//0021-843x.102.2.282

Seong, Y., Lee, E.S., & Park, S. (2021). The association between unstable employment and suicidal behavior in young-adult precarious workers. *Psychiatry Investig,* 18(7), 661-669.

Sijbrandij, J.J., Hoekstra, T., Almansa, J., Peeters, M., Bultmann, U., & Reijneveld, S.A. (2020).Variance constraints strongly influenced model performance in growth mixture modeling: a simulation and empirical study. *BMC Medical Research Methodology*, 20(276).

Silla, I., Gracia, F. J., & Peiró, J. M. (2005). Job Insecurity and Health-Related Outcomes among Different Types of Temporary Workers. *Economic and Industrial Democracy*, *26*(1), 89-117. https://doi.org/10.1177/0143831X05049404

Soss, J., Fording, R.C., & Schram, S.F. (2011). *Disciplining the poor: Neoliberal paternalism and the persistent power of race.* University of Chicago Press.

Strauman T. J. (1989). Self-discrepancies in clinical depression and social phobia: cognitive structures that underlie emotional disorders?. *Journal of abnormal psychology*, *98*(1), 14–22. https://doi.org/10.1037//0021-843x.98.1.14

Sverke M, Hellgren J, Na¨swall K. (2002). No security: a meta-analysis and review of job insecurity and its consequences. *J. Occup. Health Psychol.* *7*(3):242–64

Tefft, N. (2011). Insights on unemployment, unemployment insurance, and mental health. *J. Health Econ. 30*, 258–264.

Thelen, K. (2014). *Varieties of liberalization and the new politics of social solidarity*. Cambridge University Press.

United States Department of Labor. (2022). Wage and Hour Division. Changes in basic minimum wages in non-farm employment under state law: selected years 1968 to 2021. Retrieved from https://www.dol.gov/agencies/whd/state/minimum-wage/history

University of California, Los Angeles. (n.d.). Mixed effects logistic regression: Stata data analysis examples. Advanced Research Computing, Statistical Methods and Data Analytics: UCLA. Retrieved from https://stats.oarc.ucla.edu/stata/dae/mixed-effects-logistic-regression/

University of Wisconsin Center for Tobacco Research and Intervention (UW-CTRI). (n.d.). Behavior change analysis. Retrieved from https://ctri.wisc.edu/researchers/behavior-change-analysis/

Vahtera, J., Kivimäki, M., & Pentti, J. (1997). Effect of organisational downsizing on health of employees. *Lancet (London, England)*, *350*(9085), 1124–1128. https://doi.org/10.1016/S0140-6736(97)03216-9

Van Aerden, K., Puig-Barrachina, V., Bosmans, K., & Vanroelen, C. (2016). How does employment quality relate to health and job satisfaction in Europe? A typological approach. *Social Science & Medicine, 158,* 132-140.

Viertiö, S., Kiviruusu, O., Piirtola, M., Kaprio, J., Korhonen, T., Marttunen, M., & Suvisaari, J. (2021). Factors contributing to psychological distress in the working population, with a special reference to gender difference. *BMC Public Health, 21*(1), 611.

Virtanen M, Kivimäki M, Ferrie JE, Elovainio M, Honkonen T, et al. (2008). Temporary employment and antidepressant medication: a register linkage study. *J. Psychiatr. Res.* 42(3):221–29

Vives, A., Vanroelen, C., Amable, M., Ferrer, M., Moncada, S., Llorens, C., Muntaner, C., Benavides, F.G., & Benach, J., (2011). Employment precariousness in Spain: prevalence, social distribution, and population-attributable risk percent of poor mental health. *Int J Health Serv, 41*(4)*,* 625-46.

Vives, A., Amable, M., Ferrer, M., Moncada, S., Llorens, C., Muntaner, C., Benavides, F.G., & Benach, J. (2013). Employment precariousness and poor mental health: evidence from Spain on a new social determinant of health. *Journal of Environmental and Public Health, 2013*:978656.

Vives, A., Benmarhnia, T., Gonzalez, F., & Benach, J. (2020). The importance of using a multi-dimensional scale to capture the various impacts of precarious employment on health: Results from a national survey of Chilean workers. *PLoS One, 15*(9), e0238401.

Wacquant, L. (2009). Punishing the poor: The neoliberal government of social insecurity. Duke University Press.

Weissman, J., Russell, D., & Mann, J.J. (2020). Sociodemographic characteristics, financial worries and serious psychological distress in US adults. *Community mental health journal, 56*, 606-613.

Wething, H. (2014). Job growth in the Great Recession has not been equal between men and women. Economic Policy Institute. https://www.epi.org/blog/job-growth-great-recession-equal-men-women/

Williams, C. (2020). Millennials were already putting off having children. Then the pandemic hit. Morning Consult. Retrieved from https://morningconsult.com/2020/09/28/millennials-economy-children-poll/

Wilson, N. (2021). U.S. Millennials: Home ownership and the growing chasm between aspiration and reality. Forbes. Retrieved from https://www.forbes.com/sites/nigelwilson/2021/08/18/us-millennials-home-ownership-and-the-growing-chasm-between-aspiration-and-reality/

Won, M.J., & Hae, L.S. (2015). Validation of the K6/K10 Scales of Psychological Distress and their optimal cutoff scores for older Koreans. *International Journal of Aging and Human Development, 80*(3), 264-282.

Zago, R. (2020). Job polarization, skill mismatch and he Great Recession. *Working paper series no. 755.* Banque de France. https://publications.banque-france.fr/en/job-polarization-skill-mismatch-and-great-recession

Appendix A. Mental Health Items and Coding Scheme

Table A1. Mental health items collected by PSID and proposed coding scheme

Item	PSID Coding	Proposed coding scheme
In the past 30 days, about how often did you feel…		
So sad nothing could cheer you up	1=All of the time 2=Most of the time 3=Some of the time 4=A little of the time 5=None of the time 8=DK 9=NA; refused	0=None of the time 1=A little of the time 2=Some of the time 3=Most of the time 4=All of the time .=DK/NA
Nervous	1=All of the time 2=Most of the time 3=Some of the time 4=A little of the time 5=None of the time 8=DK 9=NA; refused	0=None of the time 1=A little of the time 2=Some of the time 3=Most of the time 4=All of the time .=DK/NA
Restless or fidgety	1=All of the time 2=Most of the time 3=Some of the time 4=A little of the time 5=None of the time 8=DK 9=NA; refused	0=None of the time 1=A little of the time 2=Some of the time 3=Most of the time 4=All of the time .=DK/NA
Hopeless	1=All of the time 2=Most of the time 3=Some of the time 4=A little of the time 5=None of the time 8=DK 9=NA; refused	0=None of the time 1=A little of the time 2=Some of the time 3=Most of the time 4=All of the time .=DK/NA
That everything was an effort	1=All of the time 2=Most of the time 3=Some of the time 4=A little of the time 5=None of the time 8=DK 9=NA; refused	0=None of the time 1=A little of the time 2=Some of the time 3=Most of the time 4=All of the time .=DK/NA
Worthless	1=All of the time 2=Most of the time 3=Some of the time 4=A little of the time 5=None of the time 8=DK 9=NA; refused	0=None of the time 1=A little of the time 2=Some of the time 3=Most of the time 4=All of the time .=DK/NA
Moderate psychological distress-binary	-	1=K-6 score ≥5 0=K-6 score <5
Severe psychological distress-binary	-	1=K-6 score ≥13 0=K-6 score <13

Appendix B. Employment Quality Items and Coding Scheme

Table B1. Employment quality items collected by PSID and proposed coding scheme*

Dimension	Item	PSID Coding	Proposed coding scheme
Employment stability	Laid off in past year (Variable=ER42338)	1=Yes 5=No 8=DK 9=Refused	0=Laid off in past year (employment instability) 1=Not laid off in past year (employment stability)
Material rewards	Salary amount (Variable=ER72211)	.01-9,999,996.99=Actual amount 9,999,997.00=$9,999,997 or more 9,999,998.00=Don't know 9,999,999.00=NA; refused 0.00=Inap. (not currently employed; not salaried)	0=Looking for work/unemployed 1=NILF 2=Quartile 1 3=Quartile 2 4=Quartile 3 .=DK/Refused
	Employer-provided health insurance (Variable=ER34804)	[*Asked of those who have health insurance at time of interview]* 1=Employer provided health insurance 2=Private health insurance purchased 3=Medicare 4=Medi-Gap/Supplemental 5=Medicaid/[STATEMEDPROG] 6=Military health care 7=Tricare/Champus/ChampVA 8=Indian Health Insurance 11=Veterans Administration 97=Other-specify	*[Denominator will be all respondents in study sample, not just those who are insured]* 0=Looking for work/unemployed 1=NILF 2=Yes 3=No .=DK/Refused
Workers' rights and protections	Would be paid for overtime work (Variable=ER72213)	1=Yes 5=No 8=DK 9=NA	0=Looking for work/unemployed 1=NILF 2=Yes 3=No .=DK/Refused

		0=Inap. (not currently working for money; not salaried; DK/NA/RF how paid on main job)	
Working-time arrangements	Average hours worked per week on current main job	1-112=Amount of hours worked 998=DK 999=NA; refused 0=Inap. (not currently employed)	0=Looking for work/unemployed 1=NILF 2=Quartile 1 3=Quartile 2 4=Quartile 3 .=DK/Refused
Collective organization	Whether respondents belong to a union *OR* hold jobs covered by a union contract Variable 72207= Respondent's job covered by union contract Variable 72208= Respondent belongs to union	<u>Var 72207</u> 1=Yes 5=No 8=DK 9=NA; refused 0=Inap (not currently employed; works for self) <u>Var 72208</u> 1=Yes 5=No 8=DK 9=NA; refused 0=Inap. (not currently employed; DK, NA, RF whether working for money now; works for self only or for both someone else and self; DK, NA, RF whether self-employed or worked for someone else; current job not covered by union contract; DK, NA, RF whether job covered by union contract)	0=Looking for work/unemployed 1=NILF 2=Yes 3=No .=DK/Refused

*Note: "Current employment status" (ER72164) will be used to first categorize respondents into wage-earners versus non-wage earners. PSID codes this variable as follows: 1=working now; 2=only temporarily laid off/sick leave/maternity leave; 3=looking for work/unemployed; 4=retired; 5=permanently disabled/temporarily disabled; 6=keeping house; 7=student; 8=other).
I will recategorize non-wage-earners as either looking for work/unemployed OR not in the labor force (collapsing temporarily laid off/sick leave/maternity leave, temporarily disabled, keeping house, student, and other). The indicators included in this table will only

pertain to those who respond "working now" to variable ER72164, and "looking for work/unemployed" and "NILF" will be included as additional categories for each indicator to account for the presence of non-wage earners in the sample.

Appendix C. Sociodemographic Items and Coding Scheme

Table C1. Sociodemographic items collected by PSID and proposed coding scheme

Item	PSID Coding	Proposed coding scheme
Sex of respondent (Var=ER2018)	1=Male 2=Female	0=Male 1=Female
Marital status (Var=ER77601)	1=Married or permanently cohabitating 2=Single, never legally married 3=Widowed and no spouse 4=Divorced and no spouse 5=Separated 9=DK	0= Married or permanently cohabitating 1=Single, never married 2=Divorced, widowed, separated .=DK
Ethnicity/race (Var=ER9060)	1=White 2=Black 3=American Indian, Aleut, Eskimo 4=Asian, Pacific Islander 5=Mentions Latino origin or descent 6=Mentions color other than black or white 7=Other 8=DK 9=NA; refused	0=White 1=Black 2=Non-white, non-black
Education (Var=ER77599)	0=Completed no grades of school 1-17=Actual number 99=DK; NA	0=Less than high school 1=High school 2=Some college 3=College +
Immigrant status (Var=ER77001)	1=Reference person screened as immigrant 2=Spouse/partner screened as immigrant 3=Both reference person and spouse/partner screened as immigrants 4=Individual screened as immigrant was a mover out at time of the interview Inap. (FU Is not part of the immigrant 2017/2019)	0=No (respondent not an immigrant) 1=Yes (immigrant)
Region (ER77591)	1=Northeast 2=North Central	0=Northeast 1=Midwest

	3=South 4=West 5=Alaska, Hawaii 6=Foreign country 9=DK; NA	2=South 3=West .=DK/NA
Metro/Nonmetro Indicator	1=Metropolitan area 2=Non-metropolitan area 9=NA 0=Inap. (foreign country)-	0=Metropolitan area 1=Non-metropolitan area .=NA/Inap.
Highest level of mother's/father's education	1=Completed 0-5 grades 2=Completed 6-8 grades (grade school) 3=Completed 9-11 grades (some high school) 4=Completed 12 grades 5=Completed 12 grades plus nonacademic training 6=Completed 13-14 years (some college); Associates 7=Completed 15-16 years; college BA 8=Completed 17 or more years (advanced professional degree, some graduate work) 99=DK/NA	0=Less than high school 1=High school 2=Some college 3=College +
Blue collar-white collar status	0=No job 1=Management occupations (*white, high skill*) 2=Business and financial operations occupations (*white, high skill*) 3=Computer and mathematical occupations (*white, high skill*) 4=Architecture and engineering occupations (*white, high skill*) 5=Life, physical and science occupations (*white, high skill*) 6=Community and social service occupations (*white, high skill*) 7=Legal occupations (*white, high skill*) 8=Education, training and library" (*white, high skill*) 9=Arts, design, entertainment, sports, media (*white, high skill*)	0=Blue collar, low-skill 1=Blue collar, high-skill 2=White collar, low-skill 3=White collar, high-skill

10=Healthcare practitioners and technical occupations (*white, high skill*)
11=Healthcare support occupations (*white, low skill*)
12=Protective service occupations (*white, low skill*)
13=Food prep and serving related occupations (*white, low skill*)
14=Building and grounds cleaning and maintenance (*blue, low skill*)
15=Personal care and service occupation (*white, low skill*)
16=Sales and related occupations (*white, low skill*)
17=Office and administrative support occupations (*white, low skill)*
18=Farming, fishing, and forestry occupations (*blue low skill)*
19=Construction and extraction occupations (*blue, high skill)*
20=Installation, maintenance and repair occupation (*blue, high skill*)
21=Production occupations (*blue, high skill)*
22=Transportation and material moving occupations (*blue, low skill*)
23=Military specific occupations
24=Don't know, refused, n/a

Appendix D. Moderating Variables and Proposed Coding Scheme

Table D1. Proposed data sources and coding scheme for moderator variables

Social welfare policy	Data source	Proposed coding scheme
Minimum wage	US Department of Labor's historical tables recording changes in basic minimum wages in non-farm employment	Year-specific minimum wage levels will be generated for each state, such that each state has a value for the years 2009, 2011, 2013, 2015, 2017, and 2019. State- and year-specific values will then be assigned to individuals based on the state in which they resided at the first study period included in the analysis (i.e., 2009).
Cash assistance	DHHS: Office of Family Assistance website: https://www.acf.hhs.gov/ofa/programs/tanf/data-reports	Maximum cash assistance values will be generated for each state by multiplying the number of months the benefit is extended by the value of the benefit (e.g., $900 if the maximum monthly value a state would offer is $300 over a period of 3 months). Each state will have a maximum cash assistance value for the years 2009, 2011, 2013, 2015, 2017, and 2019. State- and year-specific cash assistance values will then be assigned to individuals based on the state in which they resided at the first study period included in the analysis (i.e., 2009).
Unemployment insurance	U.S. Department of Labor's online "Unemployment Insurance Chartbook" (https://oui.doleta.gov/unemploy/chartbook.asp	Maximum unemployment insurance values will be generated for each state by multiplying the number of weeks the UI benefit is extended by the % of salary that is provided by the state (e.g., 26 weeks X 0.5 if the state covers 50% of a participant's income prior to unemployment). Each state will have a maximum unemployment insurance value for

		the years 2009, 2011, 2013, 2015, 2017, and 2019. State- and year-specific unemployment insurance values will then be assigned to individuals based on the state in which they resided at the first study period included in the analysis (i.e., 2009).

Appendix E. Frequency Distribution of Mental Health Scores among Millennials with Three Mental Health Data Points

Table E1. Frequency Distribution of Kessler-6 Psychological Distress Scores by Survey Wave (2009-2019), Among Millennial Reference Persons with 3 Mental Health Data Points (n=1017)

	2009 % /mean (SE)	**2011** % /mean (SE)	**2013** % /mean (SE)	**2015** % /mean (SE)	**2017** % /mean (SE)	**2019** % /mean (SE)
Sadness in past 30 days						
None of the time	71.64	75.93	79.06	76.93	74.41	78.51
A little of the time	15.89	12.19	10.84	11.04	12.60	10.49
Some of the time	9.84	9.72	9.18	9.56	11.40	9.79
Most of the time	1.32	1.42	7.60	2.25	0.99	0.77
All of the time	1.31	0.73	0.16	0.22	0.60	0.44
Nervous in past 30 days						
None of the time	39.20	39.39	40.36	42.08	38.49	41.37
A little of the time	26.38	22.21	21.46	21.51	23.56	19.33
Some of the time	28.46	35.20	33.72	31.75	33.18	34.96
Most of the time	3.73	2.24	2.87	3.33	3.04	2.51
All of the time	2.22	0.95	1.59	1.32	1.73	1.83
Restless in past 30 days						
None of the time	40.81	46.28	41.61	42.39	41.67	42.41
A little of the time	23.42	16.98	21.85	18.76	19.73	18.19
Some of the time	27.72	30.64	30.05	32.90	31.74	33.01
Most of the time	4.23	3.56	3.62	3.78	4.04	3.68
All of the time	3.82	2.53	2.87	2.18	2.81	2.71
Hopeless in past 30 days						
None of the time	80.24	85.36	82.88	8.39	80.05	81.27
A little of the time	11.38	7.65	0.85	7.34	10.59	8.67
Some of the time	7.08	5.54	7.91	7.17	7.66	8.51
Most of the time	0.71	1.16	0.58	1.01	1.03	1.08
All of the time	0.59	0.30	0.12	0.57	0.67	0/47
Everything effort in past 30 days						
None of the time	49.40	52.39	5.51	57.99	54.22	55.95
A little of the time	19.84	17.22	16.94	13.74	16.88	15.29
Some of the time	20.53	20.75	20.24	19.12	19.68	22.04
Most of the time	4.90	5.05	3.55	4.88	5.98	2.52
All of the time	5.32	4.58	4.16	4.27	3.24	4.20
Worthless in past 30 days						
None of the time	84.61	87.44	88.53	88.26	86.64	83.73
A little of the time	8.68	5.70	5.80	5.77	5.78	9.64
Some of the time	4.98	5.45	4.91	4.41	6.85	5.86
Most of the time	1.03	0.70	0.56	0.98	0.51	0.64
All of the time	0.70	0.71	0.21	0.58	0.22	0.13

Average total score	4.05 (0.15)	3.78 (0.11)	3.70 (0.13)	3.73 (0.13)	3.94 (0.13)	3.83 (0.15)

Table E2. Kessler-6 Psychological Distress Thresholds by Survey Wave (2009-2019), among Millennials with 3 mental health data points (n=1017)

	2009	**2011**	**2013**	**2015**	**2017**	**2019**
	%	%	%	%	%	%
Severe mental distress (K-6 score $\geq$13)						
Yes	2.94	2.32	3.26	3.80	3.46	2.57
No	97.06	97.68	96.74	96.20	96.54	97.43
Moderate mental distress (K-6 score $\geq$5)						
Yes	35.47	32.39	30.05	30.97	33.60	65.70
No	64.53	67.61	69.95	69,03	66.40	34.30

Appendix F. Missingness among Millennial Heads and Spouses with Three Mental Health Data Points

Table F1. Frequency distribution of missing psychological distress values among Millennial heads of household and spouses with mental health data for 3 survey waves, 2009-2019, (n=1017)

Number of missing K-6 indicators	**Timepoint**					
	2009 % (n)	**2011 % (n)**	**2013 % (n)**	**2015 % (n)**	**2017 % (n)**	**2019 % (n)**
0	99.21 (1009)	99.51 (1012)	99.41 (1011)	99.80 (1015)	99.61 (1013)	99.61 (1013)
1	0.10 (1)	0.00 (0)	0.20 (2)	0.20 (2)	0.00 (0)	0.10 (1)
3	0.00 (0)	0.00 (0)	0.00 (0)	0.00 (0)	0.00 (0)	0.10 (1)
6	0.69 (7)	0.49 (5)	0.39 (4)	0.00 (0)	0.39 (4)	0.20 (2)

Appendix G. Fit Statistics and Model Results for Growth Mixture Models

Table G1. Two-Class Linear Model: Fit Statistics and Model Results

	Model 1: 2 Class GMM (default)	Model 2a: 2 Class GMM with random intercept for class 1	Model 3: 2 class GMM with random intercepts	Model 4: 2 Class GMM with random intercepts, random slope C1*	Model 5: 2 Class GMM full free *
Fit statistics					
AIC	14439.608	14623.487	14486.41	14410.59	14259.72
BIC	14512.022	14685.56	1455365	14483.00	14337.31
Entropy	0.799	0.887	0.687	0.685	0.733
Counts and proportions					
	C1: 95.8% (n=1248) C2: 4.2% (n=55)	C1=96.2% (n=1253) C2=3.8% (n=50)	C1=15.0% (n=196) C2=85.0% (n=1107)	C1=79.6% (n=1037) C2=20.4% (n=266)	C1=77.6% (n=1011) C2=22.4% (n=292)
Model results					
Class1					
Means					
Intercept	1.798 (0.031), p<0.001	1.794 (0.025), p<0.001	1.158 (0.063), p<0.001	1.638 (0.03), p<0.001	1.646 (0.02), p<0.001
Slope	0.030 (0.007), p<0.001	0.038 (0.006), p<0.001	0.299 (0.022), p<0.001	0.066 (0.01), p<0.001	0.061 (0.01), p<0.001
Variances					
Intercept	0.344 (0.032), p<0.001	0.297 (0.016), p<0.001	0.369 (0.052), p<0.001	0.277 (0.02), p<0.001	0.276 (0.02), p<0.001
Slope	0.010 (0.002), p<0.001	0	0	0.014 (0.001), p<0.001	0.015 (0.001), p<0.001
Class2					
Means					
Intercept	1.119 (0.197), p<0.001	0.734 (0.096), p<0.001	1.876 (0.030), p<0.001	2.245 (0.03), p<0.001	2.145 (0.045), p<0.001
Slope	0.362 (0.033), p<0.001	0.399 (0.043), p<0.001	0.000 (0.008), p=0.982	0.003 (0.01), p=0.727	0.030 (0.01), p<0.001
Variances					
Intercept	0.344 (0.032), p<0.001	0	0.263 (0.017), p<0.001	-0.034 (0.004), p<0.001	0.031 (0.01), p<0.001
Slope	0.010 (0.002), p<0.001	0	0	0	-0.005 (0.001), p<0.001

***Mplus output indicates the models could not converge, suggesting the instability of this model**

Table G2. Three-Class Linear Model: Fit Statistics and Model Results

	Model 1: 3 Class GMM (default)	Model 2: 3 Class GMM-random intercept C1	Model 3: 3 Class GMM-random intercepts C1+2	Model 4: 3 Class GMM-all random intercepts*	Model 5: 3 Class GMM- random intercepts, slope C1*	Model 6: 3 class GMM with random intercepts; slopes C1-2*	Model 7: 3 class GMM fully free*
Fit statistics							
AIC	14339.90	14509.11	14390.16	14365.12	14199.37	14174.79	14146.29
BIC	14427.833	14586.70	14472.92	14453.06	14292.47	14273.07	14249.74
Entropy	0.838	0.861	0.493	0.598	0.649	0.667	
Counts and proportions							
	C1=70.6% (n=920) C2=10.4% (n=135) C3=19.0% (n=248)	C1=89.8% (n=1170) C2=37.6% (n=49) C3=6.4% (n=84)	C1=44.7% (n=583) C2=21.1% (n=275) C3=34.1% (n=445)	C1=58.6% (n=764) C2=18.9% (=246) C3=22.5% (n=293)	C1=25.1% (n=327) C2=53.7% (n=700) C3=21.2% (n=276)	C1=60.8% (n=793) C2=24.1% (n=314) C3=15.0% (n=196)	C1=23.9% (n=312) C2=48.1% (n=627) C3=27.9% (n=364)
Model results							
Class1							
Means							
Intercept	1.80 (0.02) p<0.001	1.83 (0.03) p<0.001	1.85 (0.05) p<0.001	1.84 (0.04), p<0.001	2.07 (0.04), p<0.001	1.81 (0.04), p<0.001	2.12 (0.04), p<0.001
Slope	0.06 (0.00), p<0.001	0.015 (0.01), p=0.018	-0.04 (0.01), p=0.01	-0.02 (0.01), p=0.10	0.05 (0.01), p<0.001	-0.01 (0.01), p=0.578	0.04 (0.01), p<0.001
Variances							
Intercept	0.36 (0.02), p<0.001	0.29 (0.02) p<0.001	0.34 (0.03), p<0.001	0.30 (0.02), p<0.001	0.03 (0.00), p<0.001	0.28 (0.03), p<0.001	0.03 (0.01), p<0.001
Slope	0.01 (0.00), p<0.001	0	0	0	-0.005 (0.00), p<0.001	0.01 (0.002), p<0.001	-0.005 (0.001), p<0.001
Class2							
Means							
Intercept	1.88 (0.12), p<0.001	1.72 (0.09) p<0.001	1.17 (0.06), p<0.001	2.19 (0.03), p<0.001	1.84 (0.04), p<0.001	2.10 (0.04), p<0.001	1.98 (0.08), p<0.001
Slope	0.29 (0.02), p<0.001	0.36 (0.02) p<0.001	0.27 (0.02), p<0.001	0.02 (0.01), p=0.006	-0.03 (0.01), p=0.002	0.04 (0.01), p<0.001	-0.03 (0.02), p=0.08

Variances							
Intercept	0.36 (0.02), p<0.001	0	0.39 (0.04), p<0.001	-0.04 (0.00)p<0.001	0.29 (0.02), p<0.001	0.03 (0.00), p<0.001	0.28 (0.03), p<0.001
Slope	0.01 (0.00), p<0.001	0	0	0	0	-0.005 (0.00), p<0.001	0.01 (0.002), p<0.001
Class 3							
Means							
Intercept	1.50 (0.06), p<0.001	0.81 (0.10) p<0.001	2.04 (0.04), p<0.001	1.21 (0.06), p<0.001	1.21 (0.06), p<0.001	1.08 (0.10), p<0.001	1.15 (0.10), p<0.001
Slope	-0.10 (0.01), p<0.001	0.33 (0.03) p<0.001	0.03 (0.01), p<0.001	0.27 (0.02), p<0.001	0.27 (0.02), p<0.001	0.31 (0.03), p<0.001	0.20 (0.03), p<0.001
Variances							
Intercept	0.36 (0.02), p<0.001	0	0	0.35 (0.04), p<0.001	0.38 (0.04), p<0.001	0.36 (0.07), p<0.001	0.18 (0.03), p<0.001
Slope	0.01 (0.00), p<0.001	0	0	0	0	0	0.01 (0.002), p<0.001

***Mplus output indicates the models could not converge, suggesting the instability of this model**

Table G3. Four-Class Linear Model: Fit Statistics and Model Results

	Model 1: 4 Class GMM (default)	Model 2: 4 Class GMM with random intercept C1	Model 3: 4 Class GMM with random intercepts C1+2	Model 4: 4 Class GMM with random intercepts for first 3 classes*	Model 5: 4 Class GMM with random intercepts for all classes*	Model 6: 4 class GMM with random intercepts for all classes; random slope C1*	Model 7: 4 class GMM with random intercepts and random slopes for C1 &2*	Model 8: 4 class GMM with random intercepts and random slopes for C1-3*	Model 9: 4 class GMM fully free*
Fit statistics									
AIC	14315.02	14401.10	14346.35	14309.38	14291.03	14135.25	14117.78	14087.94	14079.25
BIC	14418.47	14494.20	14444.62	14412.82	14399.65	14249.05	14236.74	14212.08	14208.56
Entropy	0.847	0.623	0.552	0.555	0.622	0.652	0.634	0.634	0.632
Counts and proportions									
	C1=3.4% (n=44) C2=70.5% (n=919) C3=6.8% (n=89) C4=19.3% (n=251)	C1=44.7% (n=582) C2=12.2% (n=159) C3=38.2% (n=498) C4=4.9% (n=64)	C1=11.4% (n=148) C2=35.6% (n=464) C3=12.3% (n=160) C4=40.7% (n=531)	C1=40.9% (n=533) C2=23.8% (n=310) C3=16.9% (n=220) C4=18.4% (n=240)	C1=8.6% (n=112) C2=60.6% (n=790) C3=18.3% (n=239) C4=12.4% (n=162)	C1=23.8% (n=310) C2=6.7% (n=88) C3=53.6% (n=699) C4=15.8% (n=206)	C1=45.5% (n=593) C2=25.5$ (n=332) C3=2.8% (n=37) C4=26.2% (n=341)	C1=2.8% (n=36) C2=25.4% (n=331) C3=42.7% (n=556) C4=29.2% (n=380)	C1=41.3% (n=538) C2=30.7% (n=400) C3=25.2% (n=328) C4=2.8% (n=37)
Model results									
Class1									
Means									
Intercept	2.77 (0.76), p<0.001	1.84 (0.05), p<0.001	1.26 (n=0.08), p<0.001	1.90 (0.05), p<0.001	2.31 (0.11), p<0.001	2.10 (0.04), p<0.001	1.31 (0.05), p<0.001	2.99 (0.12), p<0.001	1.94 (0.10), p<0.001
Slope	0.12 (0.18), p=0.48	-0.03 (0.01), p=0.04	0.31 (0.02), p<0.001	-0.06 (0.01), p<0.001	-0.20 (0.03), p<0.001	0.04 (0.01), p<0.001	0.14 (0.02), p<0.001	0.07 (0.03), p=0.012	-0.05 (0.02), p=0.003
Variances									
Intercept	0.30 (0.03), p<0.001	0.40 (0.03), p<0.001	0.45 (0.06), p<0.001	0.39 (0.03), p<0.001	0.45 (0.08), p<0.001	0.03 (0.01), p<0.001	0.22 (0.03), p<0.001	0.01 (0.005), p=0.015	0.21 (0.09), p=0.02
Slope	0.01 (0.001), p<0.001	0	0	0	0	-0.005 (0.001), p<0.001	0.02 (0.003), p<0.001	-0.004 (0.00), p<0.001	0.005 (0.004), p=0.230

Class2									
Means									
Intercept	1.80 (0.03), p<0.001	0.82 (0.06), p<0.001	1.90 (0.05), p<0.001	2.19 (0.03), p<0.001	1.67 (0.06), p<0.001	2.37 (0.13), p<0.001	2.13 (0.04), p<0.001	2.11 (0.04), p<0.001	1.20 (0.09), p<0.001
Slope	0.06 (0.01), p<0.001	0.27 (0.03), p<0.001	-0.06 (0.01), p<0.001	0.02 (0.01), p=0.003	0.04 (0.01), p=0.003	-0.22 (0.03), p<0.001	0.03 (0.01), p<0.001	0.04 (0.01), p<0.001	0.20 (0.03), p<0.001
Variances									
Intercept	0.30 (0.03), p<0.001	0	0.42 (0.04), p<0.001	-0.03 (0.003), p<0.001	0.26 (0.03), p<0.001	0.42 (0.10), p<0.001	0.03 (0.005), p<0.001	0.03 (0.005), p<0.001	0.23 (0.12), p=0.07
Slope	0.01 (0.001), p<0.001	0	0	0	0	0	-0.005 (0.00), p<0.001	-0.005 (0.00), p<0.001	0.01 (0.002), p<0.001
Class 3									
Means									
Intercept	1.35 (0.42), p=0.001	1.98 (0.04), p<0.001	1.09 (0.12), p<0.001	1.19 (0.07), p<0.001	2.21 (0.03), p<0.001	1.69 (0.04), p<0.001	3.24 (0.10), p<0.001	1.29 (0.05), p<0.001	2.12 (0.04), p<0.001
Slope	0.38 (0.05), p<0.001	0.05 (0.01), p<0.0010	0.16 (0.03), p<0.001	0.29 (0.02), p<0.001	0.01 (0.01), p=0.02	0.02 (0.01), p=0.05	0.005 (0.03), p=0.85	0.15 (0.02), p<0.001	0.04 (0.01), p<0.001
Variances									
Intercept	0.30 (0.03), p<0.001	0	0	0.45 (0.04), p<0.001	-0.03 (0.003), p<0.001	0.27 (0.03), p<0.001	-0.020 (0.01), p=0.001	0.22 (0.03), p<0.001	0.03 (0.005), p<0.001
Slope	0.01 (0.001), p<0.001	0	0	0	0	0	0	0.02 (0.003), p<0.001	-0.005 (0.001), p<0.001
Class 4									
Means									
Intercept	1.48 (0.07), p<0.001	1.80 (0.11), p<0.001	2.03 (0.04), p<0.001	1.50 (0.10), p<0.001	1.16 (0.08), p<0.001	1.18 (0.07), p<0.001	2.04 (0.08), p<0.001	2.05 (0.09), p<0.001	2.92 (0.30), p<0.001
Slope	-0.09 (0.01), p<0.001	0.34 (0.02), p<0.001	0.04 (0.01), p<0.001	0.10 (0.02), p<0.001	0.32 (0.02), p<0.001	0.31 (0.02), p<0.001	-0.07 (0.02), p<0.001	-0.08 (0.02), p<0.001	0.09 (0.07), p=0.19
Variances									

Intercept	0.30 (0.03), p<0.001	0	0	0	0.39 (0.05), p<0.001	0.38 (0.05), p<0.001	0.12 (0.04), p=0.001	0.19 (0.04), p<0.001	0.01 (0.01), p=0.27
Slope	0.01 (0.001), p<0.001	0	0	0	0	0	0	0	-0.004 (0.001), p<0.001

***Mplus output indicates the models could not converge, suggesting the instability of this model**

Table G4. Two-Class Quadratic Model: Fit Statistics and Model Results

	Model 1: 2 Class GMM (default)	Model 2: 2 Class GMM with random intercept for class 1	Model 3: 2 class GMM with random intercepts	Model 4: 2 Class GMM with random intercepts, random slope C1*	Model 5: 2 Class GMM fully free*
Fit statistics					
AIC	14324.41	14610.812	14472.38	14395.93	14246.79
BIC	14422.69	14683.226	14549.97	14478.69	14334.72
Entropy	0.901	0.885	0.685	0.685	0.735
Counts and proportions					
	C1=96.8% (n=1261) C2=3.2% (n=42)	C1=96.2% (n=1254) C2=3.8% (n=49)	C1=15.0% (n=196) C2=85% (n=1107)	C1=79.5% (n=1036) C2=20.5% (n=267)	C1=22.5% (n=293) C2=77.5% (n=1010)
Model results					
Class1					
Means					
Intercept	1.832 (0.028), p<0.001	1.830 (0.026), p<0.001	1.190 (0.06), p<0.001	1.684 (0.030), p<0.001	2.153 (0.045), p<0.001
Slope	-0.042 (0.02), p=0.010	-0.010 (0.016), p=0.547	0.260 (0.07), p<0.001	0.002 (0.018), p=0.912	0.026 (0.022), p=0.235
Quad term	0.019 (0.003), p<0.001	0.009 (0.003), p=0.001	0.007 (0.01), p=0.598	0.012 (0.003), p<0.001	0.001 (0.004), p=0.878
Variances					
Intercept	0.360 (0.04), p<0.001	0.297 (0.016), p<0.001	0.369 (0.052), p<0.001	0.278 (0.021), p<0.001	0.030 (0.006), p<0.001
Slope	0.07 (0.02), p<0.001	0	0	0.014 (0.001), p<0.001	-0.005 (0.001), p<0.001
Quad term	0.002 (0.000), p=0.001	0	0	0	0
Class2					
Means					
Intercept	1.035 (0.20), p<0.001	0.847 (0.108), p<0.001	1.920 (0.03), p<0.001	2.243 (0.035), p<0.001	1.690 (0.027), p<0.001
Slope	0.791 (0.18), p<0.001	0.239 (0.125), p=0.056	-0.059 (0.02), p=0.005	0.005 (0.192), p=0.848	0.00 (0.018), p=0.997
Quad term	-0.169 (0.039), p<0.001	0.030 (0.022), p=0.170	0.011 (0.004), p=0.002	-0.001 (0.005), p=0.913	0.012 (0.003), p<0.001
Variances					
Intercept	0.360 (0.038), p<0.001	0	0.262 (0.017), p<0.001	-0.034 (0.004), p<0.001	0.277 (0.021), p<0.001
Slope	0.066 (0.017), p<0.001	0	0	0	0.015 (0.001), p<0.001
Quad term	0.002 (0.000), p<0.001	0	0	0	0

***Mplus output indicates the models could not converge, suggesting the instability of this model**

Table G5. Three-Class Quadratic Model: Fit Statistics and Model Results

	Model 1: 3 Class GMM (default)	Model 2: 3 Class GMM- random intercept C 1	Model 3: 3 Class GMM-random intercepts C1+2	Model 4: 3 Class GMM-all random intercepts*	Model 5: 3 Class GMM- random intercepts, slope C1*	Model 6: 3 class GMM with random intercepts; slopes C1-2	Model 7: 3 class GMM fully free*
Fit statistics							
AIC	14184.82	14487.69	14376.96	14350.06	14286.50	13941.39	13932.81
BIC	14303.78	14580.80	14475.23	14453.51	14395.12	14055.18	14051.78
Entropy	0.888	0.866	0.495	0.599	0.623	0.658	0.649
Counts and proportions							
	C1=72.6%, n=946 C2=15.6%, n=203 C3=11.8%, n=154	C1=89.9%, n=1172 C2=6.5%, n=85 C3=3.5%, n=46	C1=21.4%, n=279 C2=44.7%, n=582 C3=33.9%, n=442	C1=57.9% (n=754) C2=22.6% (n=294) C3=19.6% (n=255)	C1=64.5% (n=84) C2=8.8% (n=115) C3=26.7% (n=348)	C1=31.9% (n=416) C2=38.3% (n=499) C3=29.8% (n=388)	C1=30.5% (n=397) C2=37.0% (n=482) C3=32.5% (n=424)
Model results							
Class1							
Means							
Intercept	1.87 (0.02), p<0.001	1.87 (0.03), p<0.001	1.22 (0.06), p<0.001	1.90 (0.05), p<0.001	1.56 (0.05), p<0.001	1.46 (0.05), p<0.001	2.11 (0.03), p<0.001
Slope	-0.04 (0.02), p=0.01	-0.04 (0.02), p=0.02	0.21 (0.07), p=0.002	-0.09 (0.03), p=0.004	-0.06 (0.02), p=0.02	-0.20 (0.05), p<0.001	-0.01 (0.02), p=0.54
Quad	0.02 (0.00), p<0.001	0.01 (0.00), p=0.001	0.01 (0.01), p=0.33	0.01 (0.01), p=0.014	0.03 (0.005), p<0.001	0.07 (0.01), p<0.001	0.01 (0.004), p=0.008
Variances							
Intercept	0.36 (0.03), p<0.001	0.28 (0.02), p<0.001	0.39 (0.03), p<0.001	0.30 (0.03), p<0.001	0.17 (0.03), p<0.001	0.15 (0.02), p<0.001	0.007 (0.002), p=0.002
Slope	0.10 (0.02), p<0.001	0	0	0	0.02 (0.002), p<0.001	0.02 (0.002), p<0.001	-0.001 (0.000), p=0.041
Quad	0.00 (0.00), p<0.001	0	0	0	0	0	0
Class2							
Means							
Intercept	1.37 (0.07), p<0.001	0.91 (0.10), p<0.001	1.90 (0.05), p<0.001	1.26 (0.06), p<0.001	2.06 (0.13), p<0.001	1.83 (0.06), p<0.001	1.83 (0.06), p<0.001

***Mplus output indicates the models could not converge, suggesting the instability of this model**

Table G6. Four-Class Quadratic Model: Fit Statistics and Model Results

	Model 1: 4 Class GMM (default)	Model 2: 4 Class GMM with random intercept C1	Model 3: 4 Class GMM with random intercepts C1+2	Model 4: 4 Class GMM with random intercepts for first 3 classes*	Model 5: 4 Class GMM with random intercepts for all classes*	Model 6: 4 class GMM with random intercepts for all classes; random slope for C1	Model 7: 4 class GMM with random intercepts and random slopes for C1 &2	Model 8: 4 class GMM with random intercepts and random slopes for C1-3*	Model 9: 4 class GMM fully free*
Fit statistics									
AIC	14103.10	14374.97	14319.03	14288.19	14101.84	13913.53	13771.68	13721.19	13722.78
BIC	14242.76	14488.76	14438.00	14412.32	14231.15	14048.01	13911.34	13866.02	13872.78
Entropy	0.877	0.626	0.644	0.566	0.776	0.815	0.708	0.726	0.725
Counts and proportions									
	C1=14.8% (n=193) C2=12.0% (n=157) C3=3.8% (n=49) C4=69.4% (n=904)	C1=44.1% (n=575) C2=39.1% (n=510) C3=12.1% (n=158) C4=4.6% (n=60)	C1=19.0% (n=247) C2=36.9% (n=481) C3=3.4% (n=44) C4=40.7% (n=531)	C1=36.7% (n=478) C2=16.9% (n=220) C3=25.2% (n=329) C4=21.2% (n=276)	C1=40.0% (n=521) C2=9.0% (n=117) C3=17.8% (n=232) C4=33.2% (n=433)	C1=56.1% (n=731) C2=8.0% (n=104) C3=4.7% (n=61) C4=31.2% (n=407)	C1=23.4% (n=305) C2=28.1% (n=366) C3=15.4% (n=201) C4=33.1% (n=431)	C1=4.4% (n=58) C2=47.7% (n=621) C3=19.3% (n=251) C4=28.6% (n=373)	C1=28.9% (n=376) C2=4.4% (n=57) C3=19.2% (n=250) C4=47.6% (n=620)
Model results									
Class1									
Means									
Intercept	1.55 (0.09), p<0.001	1.88 (0.05), p<0.001	1.20 (0.06), p<0.001	1.91 (0.06), p<0.001	1.80 (0.04), p<0.001	1.66 (0.04), p<0.001	1.80 (0.08), p<0.001	1.53 (0.18), p<0.001	2.10 (0.04), p<0.001
Slope	-0.09 (0.21), p=0.678	-0.08 (0.03), p=0.008	0.19 (0.09), p=0.03	-0.06 (0.04), p=0.17	-0.06 (0.02), p=0.020	-0.04 (0.02), p=0.06	0.300 (0.07), p<0.001	0.86 (0.14), p<0.001	-0.01 (0.02), p=0.73
Quad	0.001 (0.040), p=0.985	0.010 (0.01), p=0.105	0.02 (0.02), p=0.252	0.00 (0.01), p=0.992	0.011 (0.004), p=0.015	0.02 (0.005), p<0.001	-0.06 (0.01), p<0.001	-0.19 (0.03), p<0.001	0.01 (0.004), p=0.02
Variances									
Intercept	0.36 (0.04), p<0.001	0.40 (0.04), p<0.001	0.36 (0.05), p<0.001	0.41 (0.04), p<0.001	0.36 (0.03), p<0.001	0.34 (0.05), p<0.001	0.46 (0.06), p<0.001	0.56 (0.15), p<0.001	0.004 (0.002), p=0.02

Slope	0.09 (0.04), p=0.03	0	0	0	0	0.03 (0.004), p<0.001	0.03 (0.004), p<0.001	0.02 (0.01), p=0.05	0.00 (0.00), p=0.60
Quad	0.003 (0.001), p=0.03	0	0	0	0	0	0	0	0
Class2 Means									
Intercept	1.95 (0.08), p<0.001	2.00 (0.04), p<0.001	1.69 (0.07), <0.001	1.24 (0.07), p<0.001	1.77 (0.12), p<0.001	1.62 (0.14), p<0.001	1.42 (0.05), p<0.001	1.79 (0.05), p<0.001	1.53 (0.18), p<0.001
Slope	0.10 (0.05), p=0.03	0.02 (0.03), p=0.37	-0.13 (0.04), p=0.001	0.22 (0.07), p=0.002	0.34 (0.13), p=0.007	0.04 (0.07), p=0.52	-0.21 (0.05), p<0.001	0.05 (0.03), p=0.04	0.86 (0.14), p<0.001
Quad	0.03 (0.01), p<0.001	0.01 (0.005), p=0.20	0.02 (0.01), p=0.015	0.01 (0.01), p=0.399	-0.10 (0.02), p<0.001	-0.004 (0.01), p=0.80	0.07 (0.01), p<0.001	-0.01 (0.005), p=0.15	-0.19 (0.03), p<0.001
Variances									
Intercept	0.36 (0.04), p<0.001	0	0.18 (0.03), p<0.001	0.45 (0.05), p<0.001	0.36 (0.05), p<0.001	0.00 (0.001), p=0.685	0.18 (0.02), p<0.001	0.28 (0.03), p<0.001	0.56 (0.15), p<0.001
Slope	0.09 (0.04), p=0.03	0	0	0	0	0	0.02 (0.002), p<0.001	0.02 (0.002), p<0.001	0.02 (0.01), p=0.05
Quad	0.003 (0.001), p=0.03	0	0	0	0	0	0	0	0
Class 3 Means									
Intercept	1.06 (0.16), p<0.001	0.96 (0.08), p<0.001	3.04 (0.15), p<0.001	2.18 (0.04), p<0.001	1.35 (0.05), p<0.001	1.67 (0.21), p<0.001	1.79 (0.11), p<0.001	1.42 (0.07), p<0.001	1.42 (0.07), p<0.001
Slope	0.61 (0.35), p=0.08	0.07 (0.07), p=0.32	0.23 (0.08), p=0.007	0.02 (0.03), p=0.44	0.02 (0.05), p=0.727	0.67 (0.15), p<0.001	-0.077 (0.05), p=0.14	-0.29 (0.07), p<0.001	-0.29 (0.07), p<0.001
Quad	-0.15 (0.06), p=0.008	0.04 (0.01), p=0.003	-0.04 (0.01), p=0.001	0.00 (0.005), p=0.95	0.05 (0.01), p<0.001	-0.17 (0.04), p<0.001	0.01 (0.01), p=0.083	0.10 (0.01), p<0.001	0.10 (0.01), p<0.001
Variances									

Intercept	0.36 (0.04), p<0.001	0	0	-0.03 (0.003), p<0.001	0.41 (0.04), p<0.001	0.42 (0.08), p<0.001	0.015 (0.005), p=0.002	0.15 (0.03), p<0.001	0.15 (0.03), p<0.001
Slope	0.09 (0.04), p=0.03	0	0	0	0	0	0	0.02 (0.002), p<0.001	0.02 (0.002), p<0.001
Quad	0.003 (0.001), p=0.03	0	0	0	0	0	0	0	0
Class 4 Means									
Intercept	1.87 (0.03), p<0.001	1.74 (0.11), p<0.001	2.13 (0.04), p<0.001	1.62 (0.08), p<0.001	2.03 (0.04), p<0.001	2.11 (0.04), p<0.001	2.11 (0.03), p<0.001	2.10 (0.04), p<0.001	1.79 (0.05), p<0.001
Slope	-0.04 (0.02), p=0.03	0.48 (0.10), p<0.001	0.02 (0.03), p=0.39	-0.10 (0.06), p=0.12	-0.002 (0.02), p=0.93	-0.02 (0.02), p=0.51	-0.02 (0.02), p=0.340	-0.01 (0.02), p=0.71	0.05 (0.03), p=0.04
Quad	0.02 (0.003), p<0.001	-0.03 (0.02), p=0.15	-0.001 (0.005), p=0.78	0.04 (0.01), p=0.001	0.01 (0.004), p=0.011	0.01 (0.004), p=0.02	0.011 (0.003), p=0.001	0.01 (0.004), p=0.01	-0.008 (0.005), p=0.15
Variances									
Intercept	0.36 (0.04), p<0.001	0	0	0	-0.002 (0.002), p=0.29	0.003 (0.001), p=0.001	0.003 (0.001), p=0.001	0.003 (0.001), p<0.001	0.28 (0.03), p<0.001
Slope	0.09 (0.04), p=0.03	0	0	0	0	0	0	0	0.02 (0.002), p<0.001
Quad	0.003 (0.001), p=0.03	0	0	0	0	0	0	0	0

***Mplus output indicates the models could not converge, suggesting the instability of this model**

Appendix H. Results from mixed-effects models on the effect of three social protection policies on psychological distress outcomes, among Millennials with three-, four-, and five psychological distress data points.

Table H1a. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the effect of minimum wage on Millennials' likelihood of experiencing severe and moderate psychological distress (PD), among Millennials with three, four, and five psychological distress data points

Characteristic	3 Data Points (n=1017)		4 Data Points (n=907)		5 Data Points (n=671)	
	Severe	Moderate	Severe (start here)	Moderate	Severe	Moderate
Age	0.96 (0.92-1.01)	0.96 (0.94-0.98)***	0.95 (0.90-1.00)	0.96 (0.94-0.98)***	0.96 (0.90-1.01)	0.96 (0.93-0.98)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.71 (0.99-2.94)	1.27 (0.97-1.67)	1.61 (0.91-2.82)	1.24 (0.94-1.64)	1.58 (0.85-2.95)	1.54 (1.11-2.12)**
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	2.20 (1.21-3.99)**	1.47 (1.03-2.11)*	2.46 (1.32-4.57)**	1.59 (1.09-2.31)*	2.53 (1.27-5.04)**	1.62 (1.06-2.48)*
Class 3	0.52 (0.20-1.36)	1.05 (0.70-1.59)	0.34 (0.11-1.06)	0.96 (0.62-1.48)	0.24 (0.06-0.93)*	0.95 (0.59-1.53)
Education (in years)	0.86 (0.79-0.94)**	0.97 (0.95-0.99)**	0.84 (0.77-0.92)***	0.98 (0.95-0.99)^	0.83 (0.75-0.92)**	0.98 (0.95-1.00)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	2.27 (1.37-3.76)**	1.62 (1.31-1.99)***	2.53 (1.46-4.38)**	1.76 (1.40-2.20)***	1.59 (0.80-3.13)	1.57 (1.19-2.05)**
Widowed, divorced, separated	4.89 (2.62-9.13)***	2.00 (1.46-2.73)***	4.59 (2.32-9.08)***	1.91 (1.38-2.65)***	3.19 (1.44-7.09)**	1.66 (1.14-2.42)**
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.05 (0.61-1.82)	1.29 (0.98-1.71)	0.98 (0.55-1.75)	1.25 (0.93-1.67)	0.93 (0.48-1.80)	1.09 (0.78-1.52)
Non-white, non-black	1.25 (0.52-3.01)	1.32 (0.86-2.03)	1.08 (0.42-2.79)	1.29 (0.82-2.02)	0.99 (0.36-2.79)	1.24 (0.75-2.06)
Minimum wage	0.95 (0.78-1.17)	1.04 (0.96-1.13)	1.02 (0.83-1.26)	1.05 (0.97-1.15)	1.02 (0.82-1.27)	1.08 (0.98-1.19)

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

Table H1b. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the moderating effect of minimum wage on Millennials' likelihood of experiencing severe and moderate psychological distress (PD), among Millennials with three, four, and five psychological distress data points

Characteristic	3 Data Points (n=1017)		4 Data Points (n=907)		5 Data Points (n=671)	
	Severe	Moderate	Severe	Moderate	Severe	Moderate
Age	0.96 (0.92-1.01)	0.96 (0.94-0.98)**	0.95 (0.90-1.00)	0.96 (0.94-0.98)***	0.96 (0.90-1.01)	0.96 (0.93-0.98)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.70 (0.99-2.93)	1.26 (0.96-1.66)	1.60 (0.91-2.82)	1.23 (0.93-1.63)	1.58 (0.84-2.95)	1.53 (1.11-2.12)**
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	0.49 (0.02-10.69)	0.37 (0.08-1.76)	0.68 (0.03-15.34)	0.34 (0.07-1.76)	0.82 (0.03-23.73)	0.18 (0.03-1.30)
Class 3	13.16 (0.01-30249.94)	2.18 (0.40-11.76)	2.44 (0.00-4018.87)	3.02 (0.50-18.18)	1.09 (0.00-5790.17)	1.63 (0.24-11.19)
Education (in years)	0.86 (0.79-0.94)**	0.97 (0.95-0.99)*	0.84 (0.77-0.92)***	0.98 (0.95-1.00)	0.83 (0.75-0.92)**	0.98 (0.95-1.00)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	2.25 (1.35-3.73)**	1.60 (1.29-1.98)***	2.51 (1.45-4.35)**	1.75 (1.38-2.17)***	1.57 (0.79-3.10)	1.54 (1.17-2.01)**
Widowed, divorced, separated	4.80 (2.57-8.98)***	1.98 (1.45-2.70)***	4.53 (2.29-8.98)***	1.89 (1.36-2.62)***	3.15 (1.42-7.01)**	1.62 (1.11-2.36)*
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.06 (0.61-1.83)	1.31 (0.99-1.73)	0.99 (0.55-1.77)	1.26 (0.94-1.70)	0.93 (0.48-1.82)	1.11 (0.79-1.55)
Non-white, non-black	1.27 (0.53-3.07)	1.33 (0.87-2.04)	1.09 (0.42-2.83)	1.30 (0.82-2.04)	1.00 (0.36-2.81)	1.25 (0.76-2.08)
Minimum wage	0.92 (0.71-1.18)	1.02 (0.93-1.13)	0.98 (0.76-1.27)	1.04 (0.94-1.15)	0.98 (0.75-1.29)	1.05 (0.94-1.18)
Class## Minimum wage						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	1.21 (0.82-1.79)	1.19 (0.98-1.45)	1.18 (0.80-1.74)	1.22 (0.99-1.49)	1.15 (0.76-1.75)	1.32 (1.03-1.69)*

Class 3	0.66 (0.24-1.81)	0.91 (0.74-1.12)	0.78 (0.30-2.01)	0.87 (0.70-1.08)	0.82 (0.28-2.46)	0.93 (0.74-1.18)

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

Table H2a. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the effect of EITC rate on Millennials' likelihood of experiencing severe and moderate psychological distress (PD), among Millennials with three, four, and five psychological distress data points

Characteristic	3 Data Points (n=1017)		4 Data Points (n=907)		5 Data Points (n=671)	
	Severe	Moderate	Severe	Moderate	Severe	Moderate
Age	0.96 (0.92-1.01)	0.96 (0.94-0.98)***	0.95 (0.91-0.99)*	0.96 (0.94-0.98)***	0.96 (0.91-1.01)	0.96 (0.94-0.99)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.72 (0.99-2.96)	1.27 (0.97-1.66)	1.60 (0.91-2.82)	1.23 (0.93-1.63)	1.58 (0.84-2.95)	1.54 (1.11-2.13)**
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	2.20 (1.21-3.99)**	1.47 (1.03-2.10)*	2.46 (1.32-4.57)**	1.58 (1.09-2.30)*	2.53 (1.27-5.05)**	1.61 (1.05-2.47)*
Class 3	0.52 (0.20-1.35)	1.05 (0.70-1.58)	0.34 (0.11-1.06)	0.96 (0.62-1.48)	0.24 (0.06-0.93)*	0.94 (0.58-1.52)
Education (in years)	0.86 (0.79-0.94)**	0.97 (0.95-0.99)**	0.84 (0.77-0.92)***	0.98 (0.95-0.99)*	0.83 (0.75-0.92)**	0.98 (0.95-1.00)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	2.27 (1.37-3.72)**	1.61 (1.31-1.99)***	2.54 (1.46-4.39)**	1.76 (1.40-2.20)***	1.58 (0.80-3.11)	1.55 (1.19-2.04)**
Widowed, divorced, separated	4.89 (2.62-9.13)***	1.99 (1.46-2.72)***	4.59 (2.32-9.09)***	1.90 (1.37-2.64)***	3.17 (1.42-7.05)**	1.65 (1.13-2.40)**
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.06 (0.62-1.83)	1.29 (0.97-1.70)	0.98 (0.55-1.74)	1.24 (0.92-1.66)	0.92 (0.48-1.79)	1.07 (0.76-1.50)
Non-white, non-black	1.25 (0.52-2.99)	1.33 (0.87-2.03)	1.08 (0.42-2.80)	1.29 (0.82-2.03)	0.98 (0.35-2.77)	1.25 (0.75-2.06)
ETIC refund rate	1.00 (0.99-1.01)	1.00 (0.99-1.01)	1.00 (0.99-1.01)	1.00 (0.99-1.01)	1.00 (0.99-1.01)	1.00 (0.99-1.01)

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

Table H2b. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the moderating effect of EITC rate on Millennials' likelihood of experiencing severe and moderate psychological distress (PD), among Millennials with three, four, and five psychological distress data points

Characteristic	3 Data Points (n=1017)		4 Data Points (n=907)		5 Data Points (n=671)	
	Severe	Moderate	Severe	Moderate	Severe	Moderate
Age	0.96 (0.92-1.01)	0.96 (0.94-0.98)***	0.95 (0.91-0.99)*	0.96 (0.94-0.98)***	0.95 (0.90-1.01)	0.96 (0.94-0.99)**
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.73 (1.01-2.98)*	1.26 (0.96-1.65)	1.62 (0.92-2.84)	1.23 (0.93-1.62)	1.60 (0.86-3.00)	1.53 (1.11-2.12)**
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	2.49 (1.32-4.72)**	1.34 (0.92-1.96)	2.84 (1.47-5.50)**	1.45 (0.98-2.15)	2.90 (1.39-6.07)**	1.48 (0.94-2.32)
Class 3	0.80 (0.26-2.45)	1.08 (0.69-1.69)	0.62 (0.17-2.30)	1.00 (0.63-1.60)	0.51 (0.10-2.48)	0.92 (0.54-1.56)
Education (in years)	0.86 (0.79-0.94)**	0.97 (0.95-0.99)**	0.84 (0.77-0.92)***	0.98 (0.95-1.00)^	0.83 (0.75-0.92)***	0.98 (0.95-1.00)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	2.25 (1.36-3.73)**	1.61 (1.31-1.99)***	2.53 (1.46-4.38)**	1.75 (1.40-2.20)***	1.58 (0.80-3.11)	1.55 (1.18-2.03)**
Widowed, divorced, separated	4.79 (2.56-8.95)***	1.99 (1.45-2.72)***	4.52 (2.28-8.95)***	1.89 (1.37-2.63)***	3.11 (1.39-6.94)**	1.65 (1.13-2.40)**
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.06 (0.62-1.84)	1.29 (0.98-1.71)	0.98 (0.55-1.74)	1.24 (0.93-1.67)	0.91 (0.47-1.78)	1.07 (0.77-1.50)
Non-white, non-black	1.25 (0.52-2.99)	1.33 (0.87-2.04)	1.07 (0.42-2.77)	1.29 (0.82-2.03)	0.98 (0.35-2.77)	1.26 (0.76-2.08)
EITC refund rate	1.00 (0.99-1.02)	1.00 (0.99-1.01)	1.01 (0.99-1.02)	1.00 (0.99-1.01)	1.01 (0.99-1.02)	1.36 (0.72-2.55)
Class## refund rate						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	0.98 (0.96-1.02)	1.01 (0.99-1.02)	0.98 (0.95-1.01)	1.01 (0.99-1.02)	0.98 (0.96-1.01)	1.01 (0.99-1.02)
Class 3	0.95 (0.87-1.04)	0.99 (0.98-1.01)	0.92 (0.81-1.05)	1.00 (0.98-1.01)	0.89 (0.74-1.08)	1.00 (0.98-1.02)

*p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05

Table H3a. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the effect of UI rate on Millennials' likelihood of experiencing severe and moderate psychological distress (PD), among Millennials with three, four, and five psychological distress data points

Characteristic	3 Data Points (n=1017)		4 Data Points (n=907)		5 Data Points (n=671)	
	Severe	Moderate	Severe	Moderate	Severe	Moderate
Age	0.97 (0.93-1.02)	0.97 (0.95-0.99)**	0.97 (0.92-1.01)	0.97 (0.95-0.99)**	0.97 (0.92-1.02)	0.97 (0.95-0.99)*
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.69 (0.98-2.90)	1.26 (0.96-1.66)	1.59 (0.90-2.79)	1.23 (0.93-1.63)	1.58 (0.84-2.95)	1.54 (1.11-2.13)**
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	2.20 (1.21-3.99)**	1.48 (1.03-2.11)*	2.46 (1.33-4.58)**	1.59 (1.09-2.31)*	2.51 (1.26-5.01)*	1.60 (1.04-2.45)*
Class 3	0.49 (0.19-1.28)	1.04 (0.69-1.57)	0.33 (0.11-1.03)	0.96 (0.62-1.49)	0.23 (0.06-0.92)*	0.95 (0.59-1.54)
Education (in years)	0.86 (0.79-0.94)**	0.97 (0.95-0.99)**	0.84 (0.77-0.92)***	0.98 (0.95-0.99)*	0.84 (0.75-0.93)**	0.98 (0.95-1.00)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	2.26 (1.36-3.74)**	1.62 (1.31-2.00)***	2.55 (1.47-4.43)**	1.77 (1.41-2.22)***	1.59 (0.81-3.14)	1.57 (1.20-2.06)**
Widowed, divorced, separated	4.88 (2.62-9.12)***	2.00 (1.46-2.73)***	4.65 (2.35-9.22)***	1.91 (1.38-2.65)***	3.25 (1.46-7.22)**	1.66 (1.14-2.42)**
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.17 (0.68-2.03)	1.32 (0.99-1.75)	1.08 (0.60-1.93)	1.26 (0.94-1.69)	0.98 (0.50-1.91)	1.08 (0.77-1.52)
Non-white, non-black	1.24 (0.52-2.97)	1.34 (0.88-2.06)	1.08 (0.42-2.78)	1.31 (0.83-2.06)	0.99 (0.35-2.80)	1.27 (0.77-2.11)
UI rate	1.06 (1.02-1.11)**	1.02 (0.99-1.04)	1.07 (1.02-1.12)**	1.02 (0.99-1.04)	1.04 (0.99-1.10)	1.01 (0.99-1.04)

**p<0.05, **p<0.01, ***p<0.001*

Table H3b. Odds ratios (and 95% confidence intervals) from mixed-effects logistic regression models examining the moderating effect of UI rate on Millennials' likelihood of experiencing severe and moderate psychological distress (PD), among Millennials with three, four, and five psychological distress data points

Characteristic	3 Data Points (n=1017)		4 Data Points (n=907)		5 Data Points (n=671)	
	Severe	Moderate	Severe	Moderate	Severe	Moderate
Age	0.97 (0.93-1.02)	0.97 (0.95-0.99)**	0.97 (0.92-1.01)	0.97 (0.95-0.99)**	0.97 (0.92-1.02)	0.97 (0.95-0.99)*
Sex						
Male	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Female	1.68 (0.98-2.89)	1.27 (0.96-1.66)	1.58 (0.90-2.79)	1.23 (0.93-1.63)	1.57 (0.84-2.95)	1.54 (1.11-2.13)*
EQ class						
Class 1	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2	11.99 (0.12-1148.23)	6.93 (0.74-64.87)	12.28 (0.11-1398.07)	13.46 (1.23-145.63)*	25.80 (0.14-4771.48)	13.97 (0.92-212.15)
Class 3	0.06 (0.00-998.75)	19.55 (0.94-408.56)	0.00 (0.00-367.38)	36.56 (1.36-982.37)*	0.00 (0.00-1567.15)	92.66 (2.67-3214.19)*
Education	0.86 (0.79-0.94)**	0.97 (0.95-0.99)**	0.84 (0.77-0.92)***	0.98 (0.95-0.99)*	0.83 (0.75-0.92)**	0.98 (0.95-1.00)
Marital status						
Married/ cohabitating	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Single, never married	2.27 (1.37-3.76)**	1.62 (1.31-1.99)***	2.57 (1.48-4.46)**	1.76 (1.40-2.20)***	1.60 (0.81-3.17)	1.56 (1.19-2.04)**
Widowed, divorced, separated	4.85 (2.59-9.08)***	2.02 (1.48-2.76)***	4.60 (2.32-9.13)***	1.93 (1.39-2.67)***	3.20 (1.44-7.15)**	1.67 (1.15-2.44)**
Race						
White	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Black	1.18 (0.68-2.05)	1.32 (0.99-1.75)	1.09 (0.61-1.96)	1.27 (0.94-1.71)	1.00 (0.51-1.95)	1.09 (0.78-1.53)
Non-white, non-black	1.25 (0.52-3.00)	1.35 (0.88-2.06)	1.08 (0.42-2.79)	1.32 (0.84-2.08)	0.99 (0.35-2.79)	1.29 (0.78-2.14)
UI rate	1.07 (1.01-1.13)*	1.03 (1.01-1.06)**	1.07 (1.01-1.14)*	1.03 (1.01-1.06)*	1.05 (0.98-1.12)	1.03 (1.00-1.06)*
Class## UI rate						
Class 1, UI rate	(reference)	(reference)	(reference)	(reference)	(reference)	(reference)
Class 2, UI rate	0.96 (0.87-1.06)	0.97 (0.92-1.01)	0.97 (0.87-1.07)	0.95 (0.91-1.00)	0.95 (0.85-1.06)	0.95 (0.90-1.01)
Class 3, UI rate	1.04 (0.85-1.27)	0.94 (0.88-1.00)	1.13 (0.87-1.48)	0.92 (0.86-0.99)*	1.19 (0.84-1.68)	0.90 (0.84-0.98)*

**p<0.05, **p<0.01, ***p<0.001, ^p equals 0.05*

Figure H1. Average marginal effects (with 95% confidence intervals) of UI replacement rate, depending on EQ class, on probability of moderate psychological distress, among Millennials with mental health data from four survey waves (n=572)