Article

AMERICAN SOCIOLOGICAL ASSOCIATION

Journal of Health and Social Behavior
2021, Vol. 62(1) 53–68

DOI: 10.1177/0022146520984136
jhsb.sagepub.com
SAGE

Changes in Mental Health and Treatment, 1997–2017

Amy L. Johnson[1]

Abstract

Mental health outcomes have shown dramatic changes over the past half-century, yet these trends are still underexplored. I utilize an age-period-cohort analysis of the National Health Interview Survey from 1997 to 2017 (N = 627,058) to disentangle trends in mental health outcomes in the United States over time. Specifically, I leverage the contrast between reported psychological distress and rates of mental health treatment to isolate which has changed, how, and for whom. There is little evidence that psychological distress is worsening over time. Yet, treatment seeking has increased over the past 20 years. The increase in treatment seeking is best modeled as a period effect, providing initial evidence that the historical context has influenced responses to mental health over time for Americans of all ages and birth cohorts. I conclude with potential mechanisms and implications for future mental health research.

Keywords

APC analysis, medicalization, mental health treatment, psychological distress, sociology of mental health

Over the past several decades, there have been enormous changes in how Americans think about and respond to subjective experiences such as sadness, worry, and other negative emotions. Specifically, Americans are now far more likely to seek mental health treatment (Druss et al. 2006; Olfson et al. 2014) and be diagnosed with a mental illness such as depression (Batstra and Frances 2012; Weinberger et al. 2018) than they were in the past. These changes are at least partly due to a process of medicalization, in which medical frames are increasingly applied to mental health experiences (Conrad 2007). Yet how, why, and for whom mental health outcomes are changing over time remain empirical questions. Considering mental health is a key yet understudied component of population well-being (World Health Organization 2004), explaining these trends is of central importance to medical sociology.

Current research has often focused on the extent to which more recent birth cohorts drive mental health trends because more recent cohorts report more depressive symptoms and poorer overall mental health and have higher rates of mental health disorders than previous cohorts (Bell 2014; Kessler et al. 2007; Twenge 2011; Yang 2007). Working from the framework of cohort analysis (Ryder 1965), these studies often discuss how social contextual change—such as the rise of social media and other historical events—may be affecting recent cohorts' mental health outcomes. In doing so, they direct scholarly and popular attention to the effect of social and cultural change on mental health. In parallel, media coverage has demonstrated extensive concern over young people's worse mental health (Denizet-Lewis 2017), especially college (Hunt and Eisenberg 2010; Zivin et al. 2009) and high school students (Twenge 2017a). This perspective, which blends the potential role of age and age-related factors (e.g., cognitive development) with a cohort interpretation, has contributed to a lay belief that mental health has worsened over time, particularly for American youth.

[1]Stanford University, Stanford, CA, USA

Corresponding Author:
Amy L. Johnson, Sociology Department, Stanford University, 450 Jane Stanford Way, Building 120, Room 160, Stanford, CA 94305, USA.
Email: aljohnson@stanford.edu

Notably, this emergent work makes salient a long-standing sociological assumption: Context and cultural change influence mental health outcomes and behaviors over time. And cultural change may be particularly influential for certain groups of people, notably young people and/or more recent cohorts. Yet by focusing only on a subset of the population, age- and cohort-based analyses may be unnecessarily limiting. Taking one step back and considering whether and how social and cultural change may be affecting mental health outcomes across the population as well as for specific ages and cohorts allows one to apply the sociological lens beyond explaining only certain groups' outcomes. By broadening the analytical approach and considering the entire American population over time, one can assess whether and how mental health and associated behaviors are changing for all Americans and start to understand the sociocultural mechanisms driving trends.

This analysis explores how and why mental health outcomes have changed over time, looking above and beyond individual factors and across the entire American population. I compare time trends in both subjective mental health (proxied through psychological distress) and treatment seeking. Because underlying mental health and treatment follow divergent trends over time (Kessler et al. 2005), different mechanisms may influence each, resulting in unique patterns of change. Additionally, to illuminate who or what is driving change in both of these outcomes—whether more recent cohorts, young people, or other factors—a methodological approach that separates these drivers is necessary. Thus, I used an age-period-cohort (APC) analysis to answer the following questions:

Research Question 1: How and for whom have psychological distress and mental health treatment seeking changed over the past two decades?
Research Question 2: Do trends in psychological distress and treatment seeking parallel each other?
Research Question 3: Are these patterns driven by certain birth cohorts or age groups?

I found no evidence that psychological distress has changed over time at the population level. However, I found an increase over time in mental health treatment seeking across all ages and birth cohorts in spite of stable levels of psychological distress. In other words, I observed a *period* change affecting the entire population. In contrast to most mental health scholarship, which focuses on age and cohort patterns in outcomes (Gaydosh et al. 2019; Miech and Shanahan 2000; Thomson and Katikireddi 2018; Wickrama et al. 2008; Yang 2007), this finding recommends attention to factors that influence all individuals regardless of age or birth cohort. Additionally, the gap between trends in psychological distress and treatment is evidence that Americans may be seeking treatment at increasing rates due to cultural changes rather than merely idiosyncratic individual experiences. Thus, the finding of period trends in mental health treatment suggests a need to attend to changing sociocultural norms around mental health and treatment.

BACKGROUND

Explaining Mental Health Trends: The Current Approach

Existing analyses of mental health trends extend a strong tradition in health research of using age and birth cohort as key units of analysis to explain time trends at the population level (Harris 2010). Both approaches focus on the mental health outcomes of certain birth cohorts, often during their youth, using either age- or cohort-related factors as explanations. Based on the theory of cohort replacement, the different health outcomes of more contemporary cohorts, especially while they are young, can lead to wide-scale changes in outcomes at the population level as these cohorts grow older and replace earlier cohorts (Glenn 1977; Ryder 1965). Although some work from the United Kingdom finds that mental health is improving across cohorts over time (Thomson and Katikireddi 2018), the general consensus is that more recent cohorts have poorer mental health outcomes (Bell 2014; Kessler et al. 2007; Twenge 2011) and are more likely to seek treatment than their predecessors (Kadison and DiGeronimo 2004; Kruisselbrink Flatt 2013). Current explanations for these cohort patterns highlight aspects of the social context that may be particularly influential for certain cohorts' mental health. For example, the poorer mental health outcomes of more contemporary cohorts are often attributed to cultural changes such as increased use of smartphones and social media (Twenge 2017b) or other aspects of contemporary life (Bell 2014).

Applying a cohort-based theory of change leads to two empirical predictions about trends in mental health outcomes at the population level over the past two decades. First, one might predict that mental health has worsened over time and that this trend is at least partially the result of more recent cohorts

experiencing poorer mental health. Although the cohort-based research previously described supports this prediction, there is also evidence that mental health is not worsening over time (Mojtabai and Jorm 2015). Second, one would also predict that rates of mental health treatment have increased over time, which does seem to be the case (Kessler et al. 2005; Mojtabai and Jorm 2015), although less work has focused on why and whether this is a product of cohort differences.

Importantly, two key issues add uncertainty to these predictions. First, population-level time trends could be due to any combination of age, period, and cohort effects (Glenn 1977). In other words, changes at the population level over time could be the result of young people's or more contemporary cohorts' different outcomes, but they could also be the result of a secular trend unrelated to any specific cohort or age group (a period effect). Although some work uses methods designed to separate these effects (Bell 2014; Yang 2007), cohort- and age-related explanations dominate the conversation and are often used interchangeably. Nevertheless, theories on how aspects of modern life may be influencing mental health outcomes need not be limited to explaining the outcomes of certain groups, and a potential period effect should be seriously considered. A second point of uncertainty touches on a central debate in the sociology of mental health: what the very notion of mental health means and how to measure it (Horwitz 2002b). In other words, one must unpack the implications of change in mental health outcomes by attending to what, precisely, the outcome measure is capturing.

Mental Health Outcomes as Socially Constructed and Influenced

Challenges regarding the operationalization and interpretation of mental health stem from the foundational idea that mental health is socially constructed. Mental health itself as well as cultural ideas about how to define and respond to mental health issues change over time (Horwitz 2002a; for a review, see Aneshensel, Phelan, and Bierman 2012). Understandings of and behaviors around mental health can and do shift according to the cultural beliefs of a given historical moment, and the line between mental health and "illness"—between "normal" psychological experiences and those considered "deviant"—is context dependent (Pescosolido 2013; Scheff 1966; Szasz 1970, 1974). One hypothesized reason why mental health and treatment seeking are changing so dramatically is the broad process of medicalization that began to shift cultural understandings of mental health in the late twentieth century. Peter Conrad (1992:211) defines medicalization as a sociocultural process that "occurs when a medical frame or definition has been applied to understand or manage a problem." In the context of mental health, medicalization pushed psychological experiences (such as what is now referred to as anxiety and depression), once considered personal problems, into the realm of medical issues requiring professional treatment (Conrad 2007). In 1980, the publication of the third edition of the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM-III*) epitomized the medicalization process by explicitly converting psychological symptoms into medical diagnoses (Mayes and Horwitz 2005; Scheid and Brown 2010). As mental health issues became more clearly articulated and labeled, the category of "normal" shrank; now, almost any negative emotion can be diagnosed as a mental health problem (Horwitz and Wakefield 2007; Sweet and Decoteau 2018).

The social construction of mental health underscores the need to attend to the implications of change in any particular outcome. As the boundaries around mental health shift and as mental health experiences are further categorized, diagnosed, and medicalized, mental health outcomes and behaviors are shaped not only by individuals' subjective experience but also by social and cultural frames. Thus, outcome measures may show change unrelated to worsening mental health at the individual level. For example, Americans have become increasingly willing to seek mental health treatment due to a reduction in perceived stigma, although this attitudinal change varies across socioeconomic and racial-ethnic groups as well as birth cohort (Mojtabai 2007).[1] Policy change, which frequently reflects broader social change, may also have contributed to change over time in mental health behaviors. Legislation such as the Affordable Care Act (ACA) and Medicaid expansion may have made mental health treatment more accessible, thereby increasing rates of treatment. More recent legislation designed to address the opioid epidemic, such as the 21st Century Cures Act, the Comprehensive Addiction and Recovery Act, and the Support Act, may have both increased access and worked to reduce the stigma surrounding mental health treatment by bringing some mental and behavioral health issues under federal oversight. In sum, broader social and cultural processes can lead to changes in mental health outcomes that should not necessarily be interpreted as worsening mental health.

Diagnostic changes in mental health issues such as major depressive disorder (MDD) and autism illuminate the extent to which mental health outcomes themselves are socially influenced (King and Bearman 2009; Wakefield and Horwitz 2015). In both cases, changes in diagnostic practices led to an increase in prevalence of the disorder; over time, the likelihood that any given person will be diagnosed with a mental health problem such as autism or MDD has increased. By demonstrating that mental health measures are not static over time, this research highlights a key challenge for mental health researchers interested in explaining trends. In this analysis, I focus on measures in which any change over time can be attributed to a real change in the outcome and not measurement change.

To capture changes in mental health outcomes, this analysis offers two key strategies to address gaps in prior research. First, rather than taking a cohort-based approach, I separate between the different drivers of change in mental health experiences and treatment—age, period, and cohort—and leave room for the possibility that social and cultural influences on mental health affect the entire population. And second, I address the social construction of mental health through careful selection of outcome measures and attention to how each may be separately influenced by social and cultural change.

DATA AND METHODS

I drew on age-period-cohort analysis as an underutilized window into social and cultural influences on mental health outcomes. As Fosse and Winship (2019:468) stated in a recent review, "the goal of an APC analysis is to understand social and cultural change in a given outcome by identifying the separate contributions of the causal processes associated with each of the three APC variables." As mentioned above, in an APC perspective, change over time is the result of three interrelated processes. On the one hand, it can be a period effect, in which the historical context equally affects everyone. On the other hand, it can also involve cohort effects, in which individuals born in certain years are particularly affected by the historical moment at a given stage of life. Both period and cohort effects are also entangled with age effects, in which outcomes vary throughout the life course. By focusing on trends across the two APC variables that capture the effect of historical context, period and cohort, my approach was uniquely suited to explore the patterns through which social change influences mental health outcomes in the absence of clear measures for "context."

Data

The National Health Interview Survey (NHIS) has used consistent mental health outcome measures since 1997, making it one of the earliest health surveys to include reliable measures of mental health. As a nationally representative, cross-sectional household interview survey, the NHIS also provided the necessary breadth to trace temporal changes in mental health outcomes and behaviors across the United States. I specifically used the Sample Adult portion of the NHIS from 1997 to 2017, limiting my analyses to adults 18 and over. My results were generalizable to the noninstitutionalized adult population; I cannot speak to mental health trends among specific populations, such as college students or the incarcerated.

I obtained my analytical sample through the following process. Beginning with 646,279 observations in the Sample Adult portion of the NHIS from 1997 to 2017, I removed the 17 individuals born in 1912 and the 314 individuals born in 1999 to create equally spaced cohort intervals. I also removed individuals missing on key covariates of race, ethnicity, and/or general health (468). Individuals missing information on health insurance (2,602), college education (5,178), poverty status (97,549), or marital status (2,867) were coded as not having health insurance, as having not attended college, as not poor, and as unmarried, respectively, rather than dropped from analysis due to the high number of missing cases. Finally, I removed the 18,061 individuals missing information on either of the two outcome variables, resulting in a final sample of 627,058 observations.

To ensure that listwise deletion and the coding of health insurance, college education, poverty status, and marital status did not skew my results, I used two strategies. First, given the very high number of individuals missing information on poverty status, I ran separate analyses in which those missing were coded as poor rather than not poor. Although individual-level coefficients, such as that on poverty status, changed slightly in magnitude (but not direction), the period and cohort patterns remained the same. Second, I used multiple imputation to fill in all missing values of relevant covariates. These models, shown in Appendix A in the online version of the article, matched those in the main text. Overall, the results presented were robust to considerations around missing data.

Dependent Variables

I measured subjective mental health through the Kessler 6 index (K6) for nonspecific psychological distress (Kessler et al. 2003). The K6 measures the frequency of six symptoms over the past 30 days—sadness, nervousness, restlessness, worthlessness, hopelessness, and the feeling that everything is an effort—on a scale of 0 to 4 (0 = none of the time, 4 = all of the time). The six items sum to 24, with higher scores indicating poorer mental health and a score of 13 or higher indicating severe mental illness (SMI), which has been used as a proxy for *DSM* diagnosis. This scale has been tested in international survey research and was found to be a valid measure of psychological distress (Furukawa et al. 2003). The K6 was designed for survey research, not as a clinical measure; I used it here as a standardized means of measuring subjective mental health. Importantly, the K6 is a general measure of psychological distress rather than a specific measure of either anxiety or depressive symptoms; this was ideal for my analyses because I aimed to trace broad trends in subjective mental health, as experienced by individuals. Psychological distress offers a window into subjective psychological experience and, in contrast to other measures of mental health such as diagnosis with a psychiatric disorder, is measured consistently over time.

The second outcome, mental health treatment, was measured using a binary indicator of whether the respondent had seen or talked to a mental health professional such as a psychiatrist, psychologist, psychiatric nurse, or clinical social worker during the past 12 months (1 = yes, 0 = no). Note that treatment and psychological distress are measured according to different time frames, which is a limitation of the measures in the data. Because causal order could not be determined, neither outcome measure was used to predict the other. For additional analyses with different dependent variables, including SMI and medication use, see Appendix A in the online version of the article.

Independent Variables

The key independent variables were age, age-squared, period, and birth cohort. I measured period using survey year and birth cohort using five-year groupings of birth year, following existing APC research (Yang and Land 2008). There were 17 birth cohorts included in the analysis, with birth years ranging from 1913 to 1998.[2] I also included demographic controls for race-ethnicity, gender, marital status, education, and poverty status. Race-ethnicity was included as one binary indicator for white/non-white and another binary indicator for Hispanic/non-Hispanic. Gender was measured as a binary (1 = woman). Marital status was a binary indicator (1 = married). Education was included as a binary indicator for college attainment (1 = 4+ years of college or a BA). Poverty was measured as a binary indicator (1 = below the poverty line, 0 = at or above the poverty line). I also included controls for self-reported general health (measured on a scale of 1 to 5 from poor to excellent and then standardized) and, for the treatment model, a control for health insurance (1 = has health insurance). Model results were robust to the inclusion of controls.

Methods

I began with descriptive analyses. I first graphed each outcome by period, cohort, and age to show overall patterns in each of the three APC effects. Although visualizations are not sufficient to fully demonstrate the relationships between age, period, and cohort and the outcomes, they provided initial evidence for patterns over time and are less susceptible to modeling decisions. I used them to frame my analytical results.

Model specification of age, period, and cohort effects is difficult because the three effects are collinear, meaning that only two of the three can be included in any quantitative model. However, because one effect must be excluded, each effect is potentially confounded by the others, leading to what is called the "identification problem" (Blalock 1966; Glenn 1977). Analysts have developed many methods to solve the identification problem (for a recent review, see Fosse and Winship 2019).

In this analysis, I utilized the hierarchical age-period-cohort cross-classified random effects models (HAPC-CCREM) introduced by Yang and Land (2006, 2013). These are generalized linear mixed models estimated at two levels of analysis: the individual and the social context. In addition to being one of the most popular APC approaches and tested in several empirical contexts (Masters 2012; Pampel and Hunter 2012; Reither, Hauser, and Yang 2009), mixed models make theoretical and intuitive sense: Although age, period, and cohort are all related, they are social processes that occur at different levels of analysis. The HAPC-CCREM approach treats period and cohort as "random" effects external to the individual, in that people are "nested in, and cross-classified by, the two higher-level social contexts defined by time period and birth cohort" (Yang 2008:211). In addition, by using random effects, this

model accommodates the possible random error correlation between individuals surveyed in the same year or born in the same birth cohort.

The HAPC-CCREM model specification avoids the identification problem by not assuming that age, period, and cohort effects are additive and linear at the same level of analysis (Yang and Land 2006). Rather, at the first level, I regressed the outcome on individual-level covariates, including age, and at the second level, I accounted for social context by including survey year and birth cohort as random effects that vary the Level 1 model intercept.[3] Level 1 covariates are referred to as "fixed effects" because they are fixed across cohorts and periods and can include individual covariates beyond APC variables.[4] The full regression models are represented as:

$$K6_{ijk} = \gamma_0 + \boldsymbol{X}_{ijk}\boldsymbol{\beta} + u_{0j} + v_{0k} + e_{ijk}$$

$$\ln\left(\frac{p\left(TREATMENT_{ijk}\right)}{1-p\left(TREATMENT_{ijk}\right)}\right) = \gamma_0 + \boldsymbol{X}_{ijk}\boldsymbol{\beta} + u_{0j} + v_{0k} + e_{ijk}$$

for individual i in cohort j and period k where $\boldsymbol{\beta}$ is a vector of coefficients for individual-level covariates, γ_0 is the overall model intercept, u_{0j} is the residual random effect of the cohort averaged across all periods, and v_{0k} is the residual random effect of the period averaged across all cohorts.[5] Although descriptive analyses were weighted using NHIS sample person weights (adjusted for pooled survey years), all regression models were unweighted, but substantive results were robust to weighting decisions (see Appendix B in the online version of the article).

Random effects models make the assumption of zero correlation between individual-level covariates such as age, race, and gender and the contextual effects coefficients for cohort and period. Logically, individual characteristics should be unrelated to and distributed randomly throughout birth cohort or historical period.[6] Mixed models also result in "shrinkage," in that predicted random effects are "shrunk" toward the grand mean. Because I used predicted random effects to show period and cohort effects, this resulted in conservative estimates of period and cohort patterns because the models tend to favor similarity across periods and cohorts.

The HAPC-CCREM approach allows for the simultaneous estimation of all three APC effects. Thus, I was not forced to make the decision to drop one effect when there was no theoretical basis to do so (cf. Bell 2014). Nevertheless, the HAPC-CCREM approach is not without controversy. Critiques of the HAPC-CCREM modeling approach have problematized the assumption that these models fully "solve" the identification problem (Luo 2015; O'Brien 2017) and note the potential impact of data structure on the model results (Bell and Jones 2018). To show the robustness of my findings beyond any one modeling approach, I utilized several other APC analysis methods (see Appendix C in the online version of the article), including the dummy variable model (Yang and Land 2008), the APC interaction model (Luo 2015), and the inductive parsimony model (Harding and Jencks 2003). I also ran data structure analyses to demonstrate the robustness of my findings to other data structures (see Appendix C in the online version of the article). The core conclusions regarding age and period trends made in this article were robust to these modeling specifications. Cohort trends were less certain, and I comment on this in the following. Overall, the conclusions I present here were robust to modeling decisions. I return to potential limitations in the discussion.

RESULTS

Descriptive Results

Beginning descriptively, Figures 1 and 2 show a clearer time trend in treatment seeking than in psychological distress. Note that these figures do not disentangle APC effects. Figure 1 plots each outcome by period (averaged across age and cohort) and cohort (averaged across period and age). Looking first at time trends in mental health (Figure 1a), there is no clear increase in K6 scores over survey years. Figure 1b, on the other hand, provides evidence that the proportion of individuals seeking mental health treatment has increased by more than 50%, from 5.9% in 1997 to 9% in 2017 with a small dip in 2012 to 2014. Turning to trends by birth year, Figure 1c indicates subtle cohort trends in mental health, with the earliest, middle, and most recent cohorts experiencing greater psychological distress. Cohort trends in treatment (Figure 1d) match trends in mental health for cohorts born in the 1940s and later. The 1940s, 1950s, and 1990s cohorts have the highest rates of mental health treatment, which parallels their greater psychological distress. The earliest cohorts (those born in the 1910s and 1920s) have the lowest rates of mental health treatment, but age effects may also be at play here because they are not

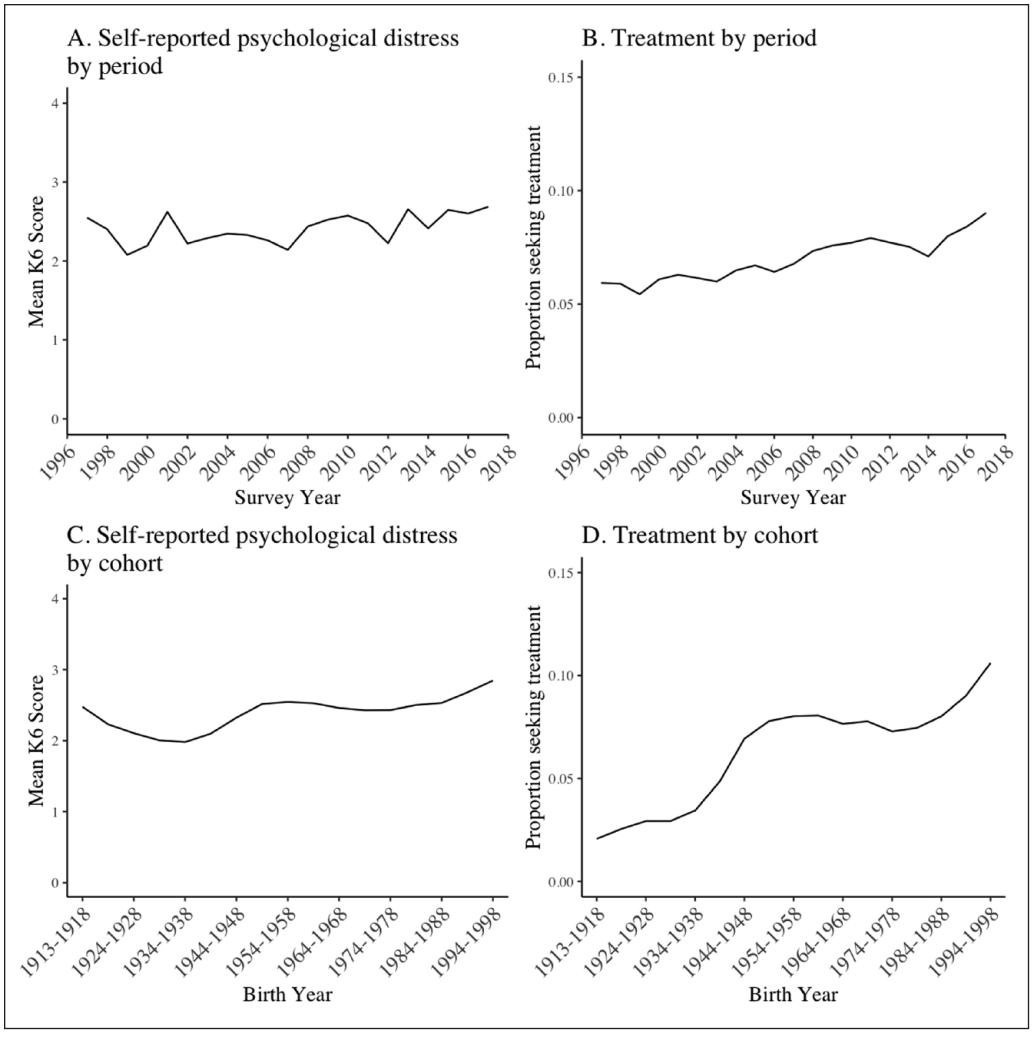

Figure 1. Mental Health Outcomes by Period and Cohort with Data from the National Health Interview Survey, 1997–2017

Note: Data are weighted using National Health Interview Survey Sample Person weights adjusted for pooled survey years. The Kessler 6 index (K6) is measured on a scale of 0 to 24, with higher scores indicating greater psychological distress. Numbers are averaged across ages. $N = 628{,}218$.

controlled for. Given that earlier cohorts are only observed at older ages, we do not know if their low treatment rates are due to their birth cohort or their age (and in Figure 2, we can see that older ages correspond with lower treatment rates).

Figure 2 plots both outcomes by age and period.[7] Looking at treatment, the 2013 to 2017 period has clearly higher treatment rates than the 1997 to 2001 period across all ages. Young adults aged 18 to 30 show a particularly substantive increase in treatment rates over time, suggesting a potential cohort effect and matching Figure 1d. Comparing across periods and looking at adults under 70, the 2013 to 2017 period shows higher K6 scores (i.e., greater psychological distress) than the 1997 to 2001 period. This pattern, however, reverses for adults over 70, weakening evidence for a period trend in psychological distress.[8] Figure 2 also shows similar age patterns to previous research (Bell 2014; Blanchflower and Oswald 2008). K6 scores are highest during early adulthood and middle age. Mental health improves after age 50 and then worsens again after age 70. The age patterns in treatment are similar, with young and middle-aged adults

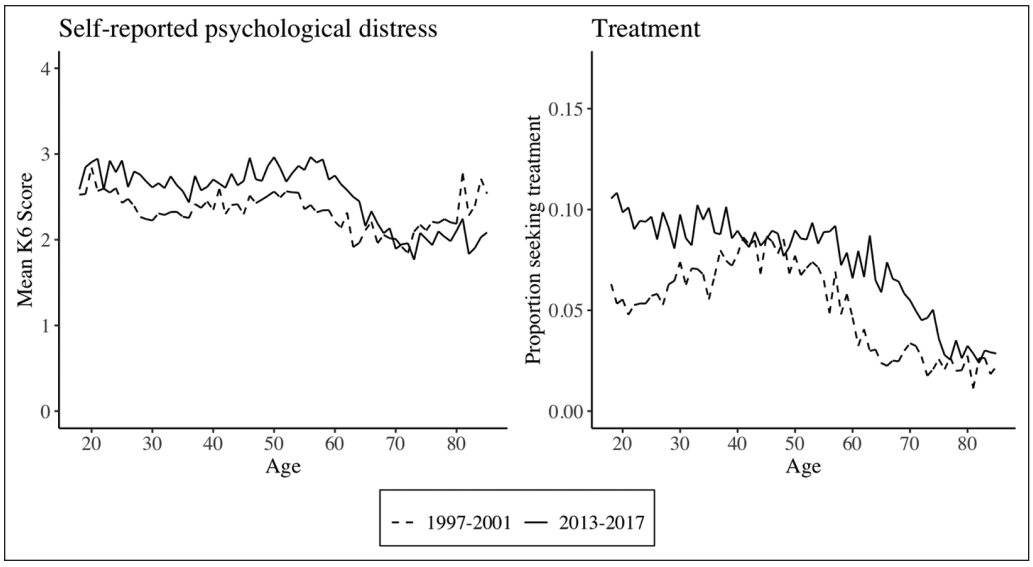

Figure 2. Mental Health Outcomes by Age and Period with Data from the National Health Interview Survey, 1997–2017

Note: Data are weighted using National Health Interview Survey Sample Person weights adjusted for pooled survey years. The Kessler 6 index (K6) is measured on a scale of 0 to 24, with higher scores indicating greater psychological distress. N = 319,435 (for the two periods shown).

more likely to seek mental health treatment, although there is no increase in the likelihood of seeking treatment at older ages.

Most noteworthy about the descriptive results is the decoupling between K6 scores and treatment. Although period and cohort may influence psychological distress, the time trends in treatment are much clearer. Averaging across all ages and birth cohorts, Figure 1b shows that treatment rates have increased over time; this trend, as indicated by Figures 1d and 2, may be at least partially driven by the high treatment rates among the youngest cohorts. Subjective mental health and mental health treatment measure very different things: while the K6 index shows psychological distress, the treatment measure shows how (and whether) people respond to their psychological distress. The fact that there are temporal patterns in treatment unaccompanied by patterns in mental health underscores the extent to which social context may be influencing how people respond to their mental health. Despite no overall change in psychological distress, people have become more likely over the past two decades to seek professional mental health treatment, offering initial evidence that social and cultural changes have shaped health behaviors. Overall, the descriptive results do not support the prediction based on earlier literature that mental health is worsening over time and throw into question whether increasing treatment rates are responding to worsening mental health. Nevertheless, age, period, and cohort effects are conflated in the descriptive results, and statistical analyses are necessary to separate which is driving trends over time.

Model Results

Results from the HAPC-CCREM models are included in Table 1. Overall, the random effects indicate that period and cohort explain trends in both psychological distress and treatment above and beyond individual factors. Bayesian information criterion comparisons between the full HAPC-CCREM models (Models 2 and 4) and individual-level only models without the random effects (Models 1 and 3) show that the CCREM models fit significantly better ($p < .001$). In addition, individual-level parameter estimates are virtually identical across individual-level and mixed models. Although individual-level factors still provide the most explanatory power, variance components indicate that historical context does explain a small amount of the variance in mental health and treatment. A partition of variance on models for each outcome including only age, age-squared, period, and cohort as predictors indicated that period and cohort, combined, explain 0.5% of

Table 1. Linear and Mixed Models Predicting Mental Health and Treatment with Data from the National Health Interview Survey, 1997–2017.

	Self-Reported Psychological Distress		Treatment	
	OLS	Mixed Effects	Logistic	Mixed Effects
	(1)	(2)	(3)	(4)
Age	–.024***	–.024***	–.021***	–.023***
	(.000)	(.001)	(.000)	(.001)
Age-squared	–.001***	–.001***	–.001***	–.001***
	(.000)	(.000)	(.000)	(.000)
Female	.528***	.530***	.302***	.311***
	(.009)	(.009)	(.010)	(.010)
White	.538***	.533***	.608***	.607***
	(.012)	(.012)	(.013)	(.013)
Hispanic	–.424***	–.418***	–.489***	–.490***
	(.013)	(.013)	(.016)	(.016)
General health	–1.341***	–1.340***	–.554***	–.552***
	(.005)	(.005)	(.005)	(.005)
Married	–.646***	–.639***	–.690***	–.676***
	(.010)	(.010)	(.011)	(.011)
College educated	–.096***	–.115***	.477***	.449***
	(.010)	(.010)	(.011)	(.011)
Below poverty line	1.113***	1.104***	.457***	.431***
	(.014)	(.014)	(.013)	(.013)
Health insurance			.717***	.708***
			(.016)	(.016)
Constant	2.322***	2.288***	–3.663***	–3.737***
	(.015)	(.056)	(.022)	(.044)
Variance components				
Cohort		.017		.010
Period		.037		.014
Individual		13.300		
Observations	627,058	627,058	627,058	627,058
BIC	3,405,384	3,403,621***	300,862	300,282***

Note: Standard errors in parentheses. Self-reported psychological distress is measured using the Kessler 6 index, which ranges from 0 to 24. Models 2 and 4 contain random effects for five-year birth cohort and survey year (period). Coefficients in Models 3 and 4 are in log odds. Age and age-squared are grand mean-centered. General health is standardized. BIC comparisons indicate that the mixed effects models fit statistically significantly better ($p < .001$).
OLS = ordinary least squares; BIC = Bayesian information criterion.
***$p < .001$.

the variance in K6 scores and 1.3% of the variance in treatment. These variance components are small in magnitude due to the high level of between-individual variation, which is often the case in time-series cross-sectional analyses. Nevertheless, variance components do not capture the temporal relationships between either period or cohort and the outcomes, only to what extent either periods or cohorts (when taken all together) contribute to reducing variance in the outcome. Thus, further attention to period and cohort patterns offers better insight into the contextual trends.

Evidence for period patterns. Plotting the random intercepts for each period (averaged across cohorts) and cohort (averaged across periods) compared to the overall model intercept illustrates any period or cohort-specific patterns. These random intercepts

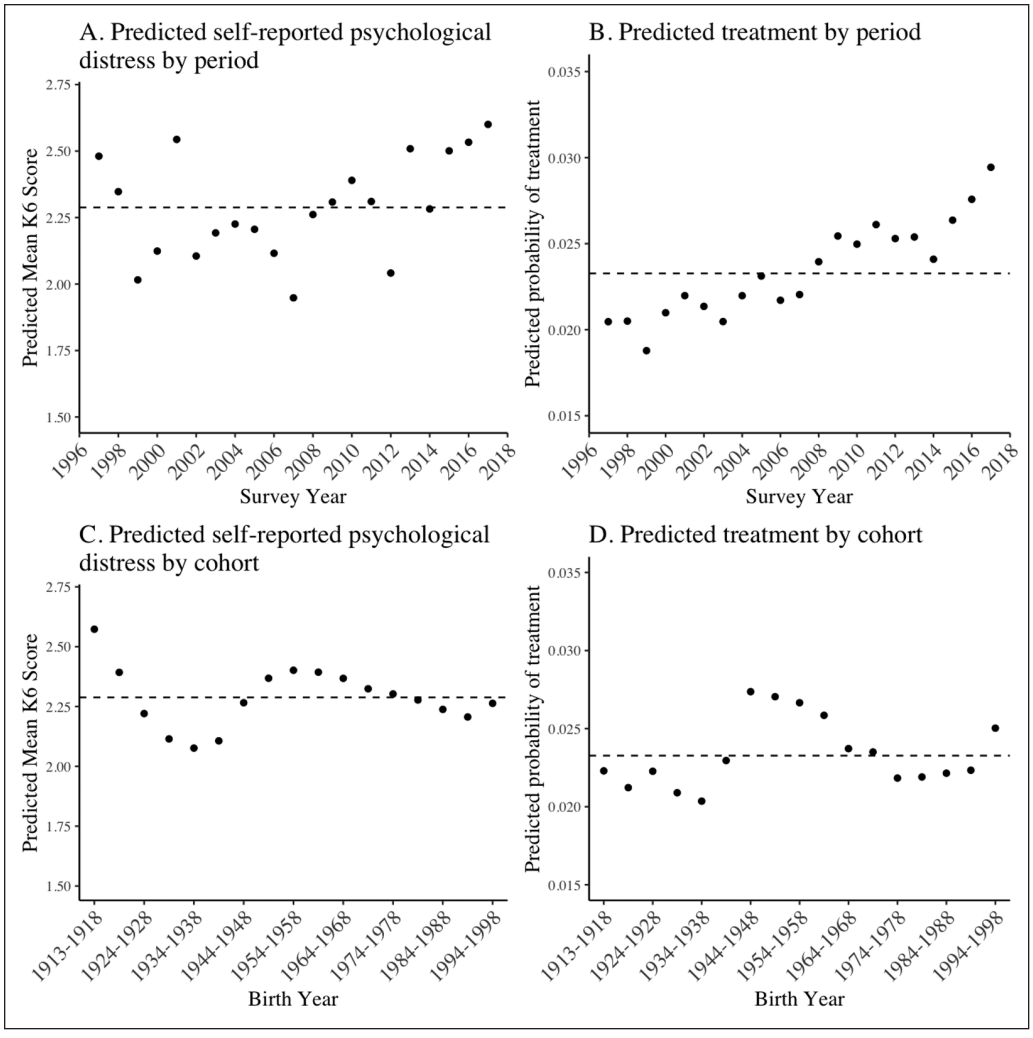

Figure 3. Predicted Period and Cohort Trends in Mental Health Outcomes with Data from the National Health Interview Survey, 1997–2017.

Note: Predicted values in graphs a and c are random intercepts from Table 1, Model 2, which controls for age, age-squared, gender, race, general health, marital status, college education, and poverty. Predicted values in graphs b and d are random intercepts from Table 1, Model 4, which controls for age, age-squared, gender, race, general health, marital status, college education, poverty, and health insurance. A horizontal line is included at each overall model intercept.

are graphed in Figure 3. Compared to the descriptive results in Figure 1, the random effects are "shrunken" toward the grand mean, and patterns look less extreme. Note that these predicted probabilities, like the intercept in all regression models, apply only to the group specified by values of 0 on all other covariates; nevertheless, they are useful for showing patterns over time in the outcomes.

Looking first at period effects (Figures 3a and 3b) demonstrates the key role of historical context in shaping decisions regarding mental health treatment, lending support to the descriptive results. The predicted probability of seeking treatment has increased significantly and almost linearly between 1997 and 2017 for all ages and birth cohorts, controlling for individual-level characteristics. As suggested descriptively, there is no similar period pattern in reported psychological distress. The lack of consistent period trends in K6 scores indicates that there are not uniform period effects on subjective mental

health. This is consistent with prior descriptive research that shows subjective mental health has not worsened over time (Kessler et al. 2005; Mojtabai and Jorm 2015). On the other hand, there seems to be a clear relationship between mental health treatment and period, indicating that treatment may be highly related to contextual factors such as historical period.

Evidence for cohort patterns. Attending to cohort effects (Figures 3c and 3d), both outcomes show similar patterns. The oldest and middle cohorts have the highest K6 scores, indicating the poorest mental health. Cohorts born in the 1940s, 1950s, and 1990s are more likely than the average to seek mental health treatment, with Baby Boomers being the most likely. The similarity of cohort patterns between each outcome indicates that cohort trends in treatment seeking follow cohort trends in overall mental health. Although the CCREM models show cohort-based variation in both outcomes, other model specifications do not (see Appendices in the online version of the article), indicating that evidence for cohort trends is still inconclusive. Thus, I focus on the period trends, which are replicated across model specifications. Whereas descriptive results and past literature suggested the potential for cohort trends, once all three APC effects are accounted for, the descriptive time trend in mental health treatment across birth years (Figure 1d) is not a cohort trend but rather a period trend confounded with age.

Individual-level controls. Individual-level factors are included as controls consistent across periods and cohorts. Looking at Model 2 predicting K6 scores, one can see, consistent with prior research, that women and white Americans have higher K6 scores, whereas Hispanic Americans have lower K6 scores. Being married or college educated is associated with lower K6 scores, whereas living below the poverty line is associated with higher K6 scores. General health has a strong negative relationship with K6 scores, indicating that better health is associated with better mental health. Model 4 predicts the log odds of seeking mental health treatment and shows similar patterns to both the K6 model and prior research. Women and white Americans are more likely to seek treatment, whereas Hispanic Americans are less likely. Married individuals are less likely to seek treatment. Although being college educated is associated with lower K6 scores, it is positively associated with treatment seeking. Living below the poverty line is positively associated with treatment seeking as well. Better health is associated with a lower likelihood of seeking treatment, and having health insurance is positively and strongly correlated with seeking treatment. For a discussion of temporal patterns among demographic subgroups, see Appendix E in the online version of the article.

DISCUSSION

Overall, both descriptive and model results provide evidence for a time trend in mental health treatment that is unaccompanied by any time trend in subjective mental health. Period effects indicate that all birth cohorts show a similar historical trend of increasing treatment seeking despite no clear pattern of worsening psychological distress. This suggests that changes in the social context have contributed to increased treatment over the past two decades, following a period trend, but have not changed underlying psychological distress.

To address the ongoing discussion around APC methodology, I have provided several different means of verifying the results presented here by acknowledging the role of random effects (Appendix B in the online version of the article) and the structure of cross-sectional survey data (Appendix C in the online version of the article) as well as by replicating my findings with several other model specifications (Appendix C in the online version of the article). Importantly, all analyses show very little time trend in psychological distress, although there may be some cohort differences, and a clear time trend in treatment seeking. That these trends exist in the data descriptively also lends support to my conclusions. The results of most models indicate that the time trend in treatment is primarily a period trend and provide only limited evidence for cohort trends. Nevertheless, I cannot completely rule out cohort trends in mental health treatment. Additionally, a limitation of using cross-sectional data, particularly given the different timings of the two dependent variables, is the possibility that increases in treatment rates are masking what would be worsening psychological distress in the absence of treatment. Although there is no evidence that mental health treatment lowers psychological distress at such a broad scale (Jorm et al. 2017), this is plausible and should be investigated using panel data.

In summary, psychological distress is not worsening over time, either through period or cohort trends, but rates of mental health treatment have increased over the past two decades for all ages and birth cohorts. This suggests that individuals' mental health behaviors are responding to changing context over time even if their subjective mental health is not. My findings strengthen and add theoretical

clarity to existing evidence for increasing treatment rates (Kessler et al. 2005; Mojtabai and Jorm 2015; Olfson et al. 2014) by controlling for confounding APC effects and individual characteristics and complicate the existing assumption in the literature that mental health is worsening due to cohort effects. By using an APC approach, I show that social context can be modeled as a period effect and call attention to how cultural changes over the past 20 years have influenced health behaviors across cohorts.

This work has several implications for future research on mental health. Primarily, I demonstrate that researchers must attend to historical period when studying mental health behaviors. Although much existing literature focuses on cohorts as the key unit of analysis, I demonstrate that cultural context is influencing treatment-seeking behaviors through a period trend. By using cohort groups as the center of analysis, researchers may be missing or misattributing important period trends that are occurring for all cohorts. Furthermore, researchers must be cautious about the time frame of their data. Given the centrality of historical period, health behaviors reported in data collected in the 1990s were influenced by entirely different cultural conditions than in the 2010s, and conclusions made about treatment seeking or other mental health behaviors in the 1990s may not apply to more contemporary periods. In studying historical trends, one must remember that the historical moment is a deeply important underlying context that affects everyone.

A second implication is that patterns in treatment seeking should not be conflated with patterns in subjective mental health. Social and cultural context, over time, has shaped treatment decisions but not subjective mental health. As I demonstrate, although there is some cohort variation, there has not been an overall increase in psychological distress. Thus, explanations for increased treatment that do not center on worsening mental health must be sought out. Additionally, other mental health outcomes—such as diagnosis—are likely influenced by context through different patterns, and temporal patterns in one outcome should not be applied to any other outcome without empirical evidence.

Focusing on period trends, I propose three interlocking mechanisms through which context may have influenced treatment seeking over the past two decades. First, medicalization has likely shaped interpretation of subjective experience. As mental health becomes increasingly medicalized in the health care industry, individuals' understandings of mental health may have also become medicalized. Although historically people may have discussed their emotional problems with a religious leader or even kept them to themselves for fear of being stigmatized, people may now be more likely to discuss mental and emotional health issues with medical professionals (Brinkmann 2016). Future research should look more closely at how medicalization rhetoric has factored into people's decision-making around their subjective mental health experience.

Second, it is likely that mental health treatment has become increasingly destigmatized over the past 20 years. Stigma contributes to general ignorance about mental health issues (Jorm 2000) and leads individuals to be unwilling to seek mental health treatment for fear of being stigmatized and the accompanying status loss or discrimination (Corrigan, Druss, and Perlick 2014; Holland 2016). Stigma is also linked to cultural context: Levels of stigma vary across demographic groups, professions, and other subcultures. For example, men stigmatize mental health issues more than women do and have lower rates of treatment seeking (Clement et al. 2015). It follows that other forms of context, such as contextual changes over time, may be linked to change in stigma. Because the fear of being stigmatized is a known barrier to mental health treatment (Clement et al. 2015), increasing rates of treatment may signal that the overall social stigma has lessened. However, presently, there is only mixed evidence for the destigmatization of mental health. Treatment seems to have been destigmatized, in that Americans increasingly think it is a reasonable response to mental health issues. Using General Social Survey data, Pescosolido (2013) found a 10 to 20 percentage point increase between 1996 and 2006 in the proportion of respondents who said they would recommend seeing a doctor or psychiatrist or taking medication for depression. Yet mental illnesses themselves continue to be stigmatized. My findings suggest that stigma around treatment may have lessened over time, but further research is needed to explore the complex relationship between change in mental health behaviors and stigma. Although prior literature has shown a relationship between age and stigma around mental health treatment (Clement et al. 2015), my findings suggest that destigmatization may be happening across age groups. Future research should explore period-based changes in stigma rather than age- or cohort-based changes.

Finally, policy changes—most notably the ACA in 2010 and the expansion of Medicaid in 2014—required health insurance providers to cover mental health services. In doing so, these policies may have made mental health treatment more accessible,

particularly for disadvantaged Americans, and may have shaped behavior regarding mental health treatment for people of all ages (Beronio, Glied, and Frank 2014; Mark et al. 2015). Descriptive results (see Figure 1b) do show a slight increase in treatment rates after 2014, when Medicaid was expanded. Policy change alone, however, may not explain all variation in mental health treatment given that treatment rates did increase prior to implementation of the ACA. Future work must isolate and determine the effect of the ACA on mental health treatment rates.

Period effects demonstrate how historical context affects people of all ages and birth cohorts, yet period trends can vary across other demographic categories. Health scholars have long described the "worried well," or people who are healthy but seek medical treatment regardless. This phenomenon likely applies to mental health as well, and there is a concern that people are being "overtreated" for mental health issues (Batstra and Frances 2012). On the other hand, there is evidence that many people who may have serious mental health issues are still deprived of treatment (Kohn et al. 2004). This "treatment gap" in which some individuals are overtreated and others are undertreated represents inequality in mental health treatment, which may be increasing over time. For example, analyses by educational status (see Appendix E in the online version of the article) show that despite no education-based difference in K6 scores, predicted treatment intercepts for the college educated are higher than for the non–college educated. In contrast, gender and racial differences in treatment followed differences in psychological distress. This phenomenon suggests that the changing social context around mental health treatment may be particularly salient for the more highly educated, especially given that those of higher social class likely have greater access to mental health treatment. Their behaviors may thus be more responsive to changing cultural conditions because they are *able* to respond, whereas the choices of the less privileged are more constrained. Future research must continue to look at how contextual trends differentially impact the treatment decisions of different groups.

Using an APC analysis to disentangle patterns of change, I demonstrate that treatment seeking has increased over the past two decades following a period trend. In contrast, psychological distress has not been influenced over time by either period or cohort effects. Thus, I emphasize the need to consider period trends, specifically historical context, as an important factor shaping Americans' mental health behaviors. Historical period shapes rates of mental health treatment through cultural changes that may encourage or discourage people to seek treatment for reasons above and beyond their level of psychological distress. I propose several potential mechanisms, such as destigmatization and policy change, and encourage future research to pay more attention to the role of historical period. Although APC analyses have their methodological limitations, they provide a unique way to unpack dimensions of temporal change. Researchers must continue to explore how social context has shaped reactions to and understanding of mental health experiences to understand the determinants of change.

ACKNOWLEDGMENTS

I gratefully acknowledge the helpful suggestions of Florencia Torche, Michael Rosenfeld, my graduate school cohort, the Stanford Graduate Family Workshop, and the Stanford Inequality Workshop.

ORCID ID

Amy L. Johnson https://orcid.org/0000-0003-1263-7730

SUPPLEMENTAL MATERIAL

Appendices A through E are available in the online version of the article.

NOTES

1. Importantly, mental health issues have not been entirely destigmatized; rather, there has been a process of destigmatization that may have reduced the stigma around certain types of less severe mental health issues and treatments.
2. For 1997 to 2016, birth year was included as a variable in the data set. For the 29,004 observations missing exact birth year, birth year was calculated by subtracting age from the survey year. For the 2017 survey year, birth year was not measured directly but was calculated by subtracting age from the survey year.
3. For a consideration of potential issues with random effects, see Appendix B in the online version of the article.
4. This is a different interpretation of fixed effects than within-individual change in panel data.
5. Following Yang and Land (2013), the model for the Kessler 6 index (K6) is estimated using restricted maximum likelihood (REML), although results are robust to using a maximum likelihood estimation method. The model for treatment is estimated using maximum likelihood with Laplace approximation.
6. For information about Hausman tests, see Appendix B in the online version of the article.

7. For clarity, Figure 2 shows only the first and last five-year period groupings here. For all period groupings, see Appendix D Figure 1 in the online version of the article. Other data visualizations are included in Appendix C Figure 2 in the online version of the article. Full age-by-period and age-by-cohort tables are available in Appendix D in the online version of the article.
8. Note that there are between 3,000 and 6,000 people 70 or older in each survey year.

REFERENCES

Aneshensel, Carol S., Jo C. Phelan, and Alex Bierman. 2012. "The Sociology of Mental Health: Surveying the Field." Pp. 1–19 in *Handbook of the Sociology of Mental Health*, edited by C. S. Aneshensel, J. C. Phelan, and A. Bierman. Dordrecht: Springer.

Batstra, Laura, and Allen Frances. 2012. "Diagnostic Inflation: Causes and a Suggested Cure." *Journal of Nervous and Mental Disease* 200(6):474–79.

Bell, Andrew. 2014. "Life-Course and Cohort Trajectories of Mental Health in the UK, 1991–2008—A Multilevel Age-Period-Cohort Analysis." *Social Science & Medicine* 120:21–30.

Bell, Andrew, and Kelvyn Jones. 2018. "The Hierarchical Age-Period-Cohort Model: Why Does It Find the Results That It Finds?" *Quality and Quantity* 52(2):783–99.

Beronio, Kirsten, Sherry Glied, and Richard Frank. 2014. "How the Affordable Care Act and Mental Health Parity and Addiction Equity Act Greatly Expand Coverage of Behavioral Health Care." *The Journal of Behavioral Health Services & Research* 41(4):410–28.

Blalock Jr., Hubert M. 1966. "The Identification Problem and Theory Building: The Case of Status Inconsistency." *American Sociological Review* 31(1):52–61.

Blanchflower, David G., and Andrew J. Oswald. 2008. "Is Well-Being U-shaped over the Life Cycle?" *Social Science & Medicine* 66:1733–49.

Brinkmann, Svend. 2016. *Diagnostic Cultures: A Cultural Approach to the Pathologization of Modern Life*. London and New York: Routledge.

Clement, Sarah, Oliver Schauman, Tanya Graham, F. Maggioni, Sara Evans-Lacko, Nikita Bezborodovs, Craig Morgan, Nicolas Rüsch, June S. L. Brown, and Graham Thornicroft. 2015. "What Is the Impact of Mental Health-Related Stigma on Help-Seeking? A Systematic Review of Quantitative and Qualitative Studies." *Psychological Medicine* 45(1):11–27.

Conrad, Peter. 1992. "Medicalization and Social Control." *Annual Review of Sociology* 18(1):209–32.

Conrad, Peter. 2007. *The Medicalization of Society: On the Transformation of Human Conditions into Treatable Disorders*. Baltimore: The Johns Hopkins University Press.

Corrigan, Patrick W., Benjamin G. Druss, and Deborah A. Perlick. 2014. "The Impact of Mental Illness Stigma on Seeking and Participating in Mental Health Care." *Psychological Science in the Public Interest* 15(2):37–70.

Denizet-Lewis, Benoit. 2017. "Why Are More American Teenagers Than Ever Suffering from Severe Anxiety?" *The New York Times Magazine*, October 11. https://www.nytimes.com/2017/10/11/magazine/why-are-more-american-teenagers-than-ever-suffering-from-severe-anxiety.html.

Druss, Benjamin G., Thomas Bornemann, Yvonne W. Fry-Johnson, Harriet G. McCombs, Robert M. Politzer, and George Rust. 2006. "Trends in Mental Health and Substance Abuse Services at the Nation's Community Health Centers: 1998–2003." *American Journal of Public Health* 96(10):1779–84.

Fosse, Ethan, and Christopher Winship. 2019. "Analyzing Age-Period-Cohort Data: A Review and Critique." *Annual Review of Sociology* 45:1–26.

Furukawa, Toshiaki A., Ronald C. Kessler, Tim Slade, and Gavin Andrews. 2003. "The Performance of the K6 and K10 Screening Scales for Psychological Distress in the Australian National Survey of Mental Health and Well-Being." *Psychological Medicine* 33(2):357–62.

Gaydosh, Lauren, Robert A. Hummer, Taylor W. Hargrove, Carolyn T. Halpern, Jon M. Hussey, Eric A. Whitsel, Nancy Dole, and Kathleen Mullan Harris. 2019. "The Depths of Despair among US Adults Entering Midlife." *American Journal of Public Health* 109(5):774–80.

Glenn, Norval D. 1977. *Cohort Analysis*. Beverly Hills, CA: SAGE Publications.

Harding, David J., and Christopher Jencks. 2003. "Changing Attitudes toward Premarital Sex: Cohort, Period, and Aging Effects." *The Public Opinion Quarterly* 67(2):211–26.

Harris, Kathleen Mullan. 2010. "An Integrative Approach to Health." *Demography* 47(1):1–22.

Holland, Donna. 2016. "College Student Stress and Mental Health: Examination of Stigmatic Views on Mental Health Counseling." *Michigan Sociological Review* 30:16–43.

Horwitz, Allan V. 2002a. *Creating Mental Illness*. Chicago: University of Chicago Press.

Horwitz, Allan V. 2002b. "Outcomes in the Sociology of Mental Health and Illness: Where Have We Been and Where Are We Going?" *Journal of Health and Social Behavior* 43(2):143–51.

Horwitz, Allan V., and Jerome C. Wakefield. 2007. *The Loss of Sadness: How Psychiatry Transformed Normal Sorrow into Depressive Disorder*. New York: Oxford University Press.

Hunt, Justin, and Daniel Eisenberg. 2010. "Mental Health Problems and Help-Seeking Behavior among College Students." *Journal of Adolescent Health* 46(1):3–10.

Jorm, Anthony F. 2000. "Mental Health Literacy: Public Knowledge and Beliefs about Mental Disorders." *British Journal of Psychiatry* 177(5):396–401.

Jorm, Anthony F., Scott B. Patten, Traolach S. Brugha, and Ramin Mojtabai. 2017. "Has Increased Provision of Treatment Reduced the Prevalence of Common Mental Disorders? Review of the Evidence from Four Countries." *World Psychiatry* 16(1):90–99.

Kadison, Richard, and Theresa Foy DiGeronimo. 2004. *College of the Overwhelmed: The Campus Mental Health Crisis and What to Do about It*. San Francisco: Jossey-Bass.

Kessler, Ronald C., Matthias Angermeyer, James C. Anthony, Ron de Graaf, Koen Demyttenaere, Isabelle Gasquet, Giovanni de Girolamo, Semyon Gluzman, Oye Gureje, Josep Maria Haro, Norito Kawakami, Aimee Karam, Daphna Levinson, Maria Elena Medina Mora, Mark A. Oakley Browne, José Posada-Villa, Dan J. Stein, Cheuk Him Adley Tsang, Sergio Aguilar-Gaxiola, Jordi Alonso, Sing Lee, Steven Heeringa, Beth-Ellen Pennell, Patricia Bergllund, Michael J. Gruber, Maria Petukhova, Somnath Chatterji, and Bedirhan T. Ustun. 2007. "Lifetime Prevalence and Age-of-Onset Distributions of Mental Disorders in the World Health Organization's World Mental Health Survey Initiative." *World Psychiatry* 6(3):168–76.

Kessler, Ronald C., Peggy R. Barker, Lisa J. Colpe, Joan F. Epstein, Joseph C. Gfroerer, Eva Hiripi, Mary J. Howes, Sharon-Lise T. Normand, Ronald W. Manderscheid, Ellen E. Walters, and Alan M. Zaslavsky. 2003. "Screening for Serious Mental Illness in the General Population." *Archives of General Psychiatry* 60(2):184–89.

Kessler, Ronald C., Olga Demler, Richard G. Frank, Mark Olfson, Harold Alan Pincus, Ellen E. Walters, Philip Wang, Kenneth B. Wells, and Alan M. Zaslavsky. 2005. "Prevalence and Treatment of Mental Disorders, 1990 to 2003." *New England Journal of Medicine* 352(24):2515–23.

King, Marissa, and Peter Bearman. 2009. "Diagnostic Change and the Increased Prevalence of Autism." *International Journal of Epidemiology* 38(5):1224–34.

Kohn, Robert, Shekhar Saxena, Itzhak Levav, and Benedetto Saraceno. 2004. "Policy and Practice: The Treatment Gap in Mental Health Care." *Bulletin of the World Health Organisation* 82(11):858–66.

Kruisselbrink Flatt, Alicia. 2013. "A Suffering Generation: Six Factors Contributing to the Mental Health Crisis in North American Higher Education." *College Quarterly* 16(1).

Luo, Liying. 2015. "Age-Period-Cohort Analysis: Critiques and Innovations." PhD dissertation, Department of Sociology, University of Minnesota.

Mark, Tami L., Lauren M. Wier, Kevin Malone, Michael Penne, and Alexander J. Cowell. 2015. "National Estimates of Behavioral Health Conditions and Their Treatment among Adults Newly Insured under the ACA." *Psychiatric Services* 66(4):426–29.

Masters, Ryan K. 2012. "Uncrossing the U.S. Black-White Mortality Crossover: The Role of Cohort Forces in Life Course Mortality Risk." *Demography* 49(3):773–96.

Mayes, Rick, and Allan Horwitz. 2005. "DSM-III and the Revolution in the Classification of Mental Illness." *Journal of the History of the Behavioral Sciences* 43(3):249–67.

Miech, Richard Allen, and Michael J. Shanahan. 2000. "Socioeconomic Status and Depression over the Life Course." *Journal of Health and Social Behavior* 41(2):162–76.

Mojtabai, Ramin. 2007. "Americans' Attitudes toward Mental Health Treatment Seeking: 1990–2003." *Psychiatric Services* 58(5):642–51.

Mojtabai, Ramin, and Anthony F. Jorm. 2015. "Trends in Psychological Distress, Depressive Episodes and Mental Health Treatment-Seeking in the United States: 2001–2012." *Journal of Affective Disorders* 174:556–61.

O'Brien, Robert M. 2017. "Mixed Models, Linear Dependency, and Identification in Age-Period-Cohort Models." *Statistics in Medicine* 36(16):2590–600.

Olfson, Mark, Kurt Kroenke, Shuai Wang, and Carlos Blanco. 2014. "Trends in Office-Based Mental Health Care Provided by Psychiatrists and Primary Care Physicians." *The Journal of Clinical Psychiatry* 75(3):247–53.

Pampel, Fred C., and Lori M. Hunter. 2012. "Cohort Change, Diffusion, and Support for Environmental Spending in the United States." *American Journal of Sociology* 118(2):420–48.

Pescosolido, Bernice A. 2013. "The Public Stigma of Mental Illness." *Journal of Health and Social Behavior* 54(1):1–21.

Reither, Eric N., Robert M. Hauser, and Yang Yang. 2009. "Do Birth Cohorts Matter? Age-Period-Cohort Analyses of the Obesity Epidemic in the United States." *Social Science & Medicine* 69(10):1439–48.

Ryder, Norman B. 1965. "The Cohort as a Concept in the Study of Social Change." *American Sociological Review* 30(6):843–61.

Scheff, Thomas S. 1966. *Being Mentally Ill: A Sociological Theory*. Chicago: Aldine.

Scheid, Teresa L., and Tony N. Brown. 2010. "Approaches to Mental Health and Illness: Conflicting Definitions and Emphases." Pp. 1–5 in *A Handbook for the Study of Mental Health: Social Contexts, Theories, and Systems*, edited by T. L. Scheid and T. N. Brown. Cambridge, UK: Cambridge University Press.

Sweet, Paige L., and Claire Laurier Decoteau. 2018. "Contesting Normal: The DSM-5 and Psychiatric Subjectivation." *BioSocieties* 13(1):103–22.

Szasz, Thomas S. 1970. *The Manufacture of Madness: A Comparative Study of the Inquisition and the Mental Health Movement*. New York: Harper & Row, Publishers, Inc.

Szasz, Thomas S. 1974. *The Myth of Mental Illness: Foundations of a Theory of Personal Conduct*. New York: Harper Perennial.

Thomson, Rachel M., and Srinivasa Vittal Katikireddi. 2018. "Mental Health and the Jilted Generation: Using Age-Period-Cohort Analysis to Assess

Differential Trends in Young People's Mental Health Following the Great Recession and Austerity in England." *Social Science & Medicine* 214:133–43.

Twenge, Jean M. 2011. "Generational Differences in Mental Health: Are Children and Adolescents Suffering More, or Less?" *American Journal of Orthopsychiatry* 81(4):469–72.

Twenge, Jean M. 2017a. "Have Smartphones Destroyed a Generation?" *The Atlantic*. https://www.theatlantic.com/magazine/archive/2017/09/has-the-smartphone-destroyed-a-generation/534198/.

Twenge, Jean M. 2017b. *iGen: Why Today's Super-Connected Kids Are Growing up Less Rebellious, More Tolerant, Less Happy and Completely Unprepared for Adulthood*. New York: Atria Books.

Wakefield, Jerome C., and Allan V. Horwitz. 2015. "Psychiatry's Continuing Expansion of Depressive Disorder." Pp. 173–203 in *Sadness or Depression? International Perspectives on the Depression Epidemic and Its Meaning*, edited by J. C. Wakefield and S. Demazeux. Dordrecht, the Netherlands: Springer.

Weinberger, Andrea H., Misato Gbedemah, Adriana M. Martinez, Denis Nash, Sandro Galea, and Renee D. Goodwin. 2018. "Trends in Depression Prevalence in the USA from 2005 to 2015: Widening Disparities in Vulnerable Groups." *Psychological Medicine* 48(8):1308–15.

Wickrama, K. A. S., Conger D. Rand, Frederick O. Lorenz, and Tony Jung. 2008. "Family Antecedents and Consequences of Trajectories of Depressive Symptoms from Adolescence to Young Adulthood: A Life Course Investigation." *Journal of Health and Social Behavior* 49(4):468–83.

World Health Organization. 2004. *Promoting Mental Health*. Geneva: World Health Organization.

Yang, Yang. 2007. "Is Old Age Depressing? Growth Trajectories and Cohort Variations in Late-Life Depression." *Journal of Health and Social Behavior* 48(1):16–32.

Yang, Yang. 2008. "Social Inequalities in Happiness in the United States, 1972 to 2004: An Age-Period-Cohort Analysis." *American Sociological Review* 73:204–26.

Yang, Yang, and Kenneth C. Land. 2006. "A Mixed Models Approach to the Age-Period-Cohort Analysis of Repeated Cross-Section Surveys, with an Application to Data on Trends in Verbal Test Scores." *Sociological Methodology* 36(1):75–97.

Yang, Yang, and Kenneth C. Land. 2008. "Age-Period-Cohort Analysis of Repeated Cross-Section Surveys—Fixed or Random Effects?" *Sociological Methods & Research* 36(3):297–326.

Yang, Yang, and Kenneth C. Land. 2013. *Age-Period-Cohort Analysis: New Models, Methods, and Empirical Applications*. Boca Raton, FL: CRC Press.

Zivin, Kara, Daniel Eisenberg, Sarah E. Gollust, and Ezra Golberstein. 2009. "Persistence of Mental Health Problems and Needs in a College Student Population." *Journal of Affective Disorders* 117(3): 180–85.

AUTHOR BIOGRAPHY

Amy L. Johnson is a PhD candidate in sociology at Stanford University. Her research looks at the subjective consequences of twenty-first-century social and cultural change, with a focus on mental health and well-being.