Social Science & Medicine 120 (2014) 21–30

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Life-course and cohort trajectories of mental health in the UK, 1991–2008 – A multilevel age–period–cohort analysis

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ARTICLE INFO

Article history:
Received 22 April 2014
Received in revised form
1 September 2014
Accepted 3 September 2014
Available online 6 September 2014

Keywords:
General Health Questionnaire (GHQ)
Mental health
Age–period–cohort models
Life-course analysis
British Household Panel Survey
Multilevel models
UK

ABSTRACT

There is ongoing debate regarding the shape of life-course trajectories in mental health. Many argue the relationship is U-shaped, with mental health declining with age to mid-life, then improving. However, I argue that these models are beset by the age–period–cohort (APC) identification problem, whereby age, cohort and year of measurement are exactly collinear and their effects cannot be meaningfully separated. This means an apparent life-course effect could be explained by cohorts. This paper critiques two sets of literature: the substantive literature regarding life-course trajectories in mental health, and the methodological literature that claims erroneously to have 'solved' the APC identification problem statistically (e.g. using Yang and Land's Hierarchical APC–HAPC-model). I then use a variant of the HAPC model, making strong but justified assumptions that allow the modelling of life-course trajectories in mental health (measured by the General Health Questionnaire) net of any cohort effects, using data from the British Household Panel Survey, 1991–2008. The model additionally employs a complex multilevel structure that allows the relative importance of spatial (households, local authority districts) and temporal (periods, cohorts) levels to be assessed. Mental health is found to increase throughout the life-course; this slows at mid-life before worsening again into old age, but there is no evidence of a U-shape – I argue that such findings result from confounding with cohort processes (whereby more recent cohorts have generally worse mental health). Other covariates were also evaluated; income, smoking, education, social class, urbanity, ethnicity, gender and marriage were all related to mental health, with the latter two in particular affecting life-course and cohort trajectories. The paper shows the importance of understanding APC in life-course research generally, and mental health research in particular.

This paper considers longitudinal and life-course effects on mental health. How mental health varies, between social groups, as individuals age, and over time, is of interest to researchers examining the causes of psychiatric illness and mental distress more generally, and their public health implications.

This poses methodological challenges that are central to this paper. As a result of the age–period–cohort (APC) identification problem, it is impossible to predict APC trajectories accurately without making assumptions regarding at least one of APC (Bell and Jones, 2013; Glenn, 2005). Other sources of dependency, particularly spatial dependency, should also be considered. Given these challenges, a multilevel model is presented which develops the Hierarchical APC (HAPC) model (Yang and Land, 2006, 2013), overcoming its recently exposed flaws (Bell and Jones, 2014b,c; Luo and Hodges, submitted for publication) to model APC effects on mental health robustly. The HAPC model treats periods and cohorts as contexts in which individuals reside, and is here extended to incorporate other contexts, including spatial contexts such as households and geographical areas.

This paper challenges the view that, over the life-course, the trajectory of mental health is U-shaped (Blanchflower and Oswald, 2008; Lang et al., 2011) – worsening through young adulthood until mid-life, then improving into old age. In the analysis presented here – using British Household Panel Survey (BHPS) data – no such U-shape is found, suggesting potential health benefits of old age, including retirement, are overwhelmed by problems like dementia and loneliness. It is argued the U-shape finding resulted from a failure to control for cohort effects appropriately. The paper also explores how longitudinal and life-course trajectories may vary across individuals with different characteristics, e.g. income, education, ethnicity and marital status, and thereby contributes to the wider substantive literature on mental health.

The paper starts with a general overview of the literature on mental health, before considering the APC identification problem and, subsequently, how this relates to the literature on mental

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http://dx.doi.org/10.1016/j.socscimed.2014.09.008
0277-9536/

health over the life-course. This is followed by an explanation of the methods used and the results found.

1. Mental health

Mental health can be defined as "a state of well-being in which an individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community" (WHO, 2014). It is more than simply an absence of symptoms and diagnoses (depression, anxiety, stress, insomnia, etc.), including more subjective, non-clinical criteria, and a "full spectrum of mental health states", from positive (wellbeing) to negative (illness) (Weich et al., 2011:23). It is influenced by socio-economic, spatial and dynamic factors, which interact in complex ways.

In a review, Fryers et al. (2003) found socio-economic status, unemployment, education, income, and material living standards were all predictors of mental health, particularly of persistent depression (see also Lorant et al., 2003). Many of these associations are complex, only occurring within certain groups. For example, urbanity (Verheij, 1996) and socio-economic status (Weich and Lewis, 1998a) has been found to predict mental health particularly for women and the elderly.

Where you live also affects your mental health. McKenzie et al. (2002) argue that the social network in which you interact (your 'social capital') is important in predicting mental disorders like schizophrenia. Weich et al. (2002) consider the built environment, finding that deck-access and recently built housing are associated with depression. Weich et al. (2005) also examined the importance of the household, finding similar levels of depression among cohabiting individuals. Larger-scale spatial units appear less important, with minimal differences between neighbourhoods in mental health (Propper et al., 2005; Weich et al., 2003). Larger-still geographical scales of analysis may be important; local authority districts (LADs) are units by which public health funding is now distributed in the UK (Department of Health, 2012), which could be an important mechanism by which spatial differences arise. Evidently, geography may matter at some scales more than others.

Mental health is dynamic. Psychiatric disorders have onsets and recoveries and can be chronic or more temporary in nature (Weich and Lewis, 1998a:9), whilst their predictors also vary over time. Thus, Weich and Lewis (1998b) find that poverty and unemployment effect recovery from, but not the onset of, mental disorders. Benzeval and Judge (2001) find that long-term poverty has a bigger effect on mental health than short term poverty. Lindstrom et al. (2014) find that risk factors accumulate through the life-course, with factors in childhood adding to contemporary factors to affect mental health later in life. Regarding changes over the life-course, Musick and Bumpass (2012) find that the positive association of marriage and mental wellbeing dissipates through the life-course, whilst Jorm (1999) finds the association between mental disorders and smoking is smaller in old age.

2. The age–period–cohort identification problem

A key methodological conundrum when considering temporal facets of mental health is the APC identification problem. Whilst this has been part of the literature for decades (Glenn, 1977; Mason et al., 1973; Ryder, 1965), serious misunderstandings remain across the social sciences (Bell and Jones, 2014b). This section clarifies these misunderstandings before considering their relevance to understanding changing mental health.

The differences between age, period, and cohort effects are explicated by this fictional dialogue by Suzuki (2012:452):

A: I can't seem to shake off this tired feeling. Guess I'm just getting old. [Age effect]
B: Do you think it's stress? Business is down this year, and you've let your fatigue build up. [Period effect]
A: Maybe. What about you?
B: Actually, I'm exhausted too! My body feels really heavy.
A: You're kidding. You're still young. I could work all day long when I was your age.
B: Oh, really?
A: Yeah, young people these days are quick to whine. We were not like that. [Cohort effect]

In summary, age effects result from individuals growing older, period effects result from factors specific to the year of measurement, and cohort effects result from similarities between individuals born contemporaneously (e.g. due to common factors affecting them in their formative years).

However, APC are exactly co-linear, such that the value of one can be found if you know the values of the other two:

$$\text{Period} = \text{Age} + \text{Cohort} \tag{1}$$

As shown previously (Bell and Jones, 2014b:336–337), this means an apparent effect of age could fully or in part be the result of combined period and cohort processes. Imagine that mental health is determined solely by cohort and age effects, each of value 2:

$$\text{Mental Health} = (2{*}\text{Age}) + (2{*}\text{Cohort}) \tag{2}$$

Substituting (1) into (2), the following data generating processes produce *identical* dependent variables:

$$\begin{aligned}\text{Mental Health} &= (1{*}\text{Age}) + (1{*}\text{Period}) + (1{*}\text{Cohort})\\ \text{Mental Health} &= 2{*}\text{Period}\end{aligned} \tag{3}$$

Therefore one cannot tell, from a given dataset alone, which of the above processes produced the outcome variable, and thus the true size of (or even presence of) an age effect. A model attempting to differentiate all three linear effects cannot be estimated because of exact collinearity, whilst controlling for only two of APC risks confounding with the third. This problem is "in the population, not just in the sample … [meaning it] cannot simply be solved by manipulating the data or the model" (Bell and Jones, 2014b:338), unlike other problems of (inexact) collinearity, where collecting more data could be a solution.

Regardless, many have attempted to solve the identification problem statistically (Mason et al., 1973; Robertson and Boyle, 1986). Some group one of APC to break the exact collinearity – producing results that arbitrarily depend on the chosen grouping (Glenn, 1976; Osmond and Gardner, 1989). Others use more complex statistical legerdemain. Here I consider the Hierarchical APC (HAPC) model (Yang and Land, 2006, 2013), since it is adapted for use in this paper. This cross-classified multilevel model is designed for repeated-cross-sectional data, and treats periods and cohorts as contexts in which individuals reside (Fig. 1). It can be specified as a

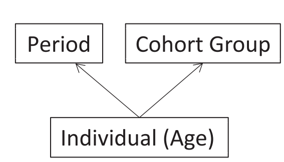

Fig. 1. Multilevel cross-classified structure of the HAPC model, with individuals nested within year of measurement, and cohort group. Note that the data are not structured in a strict hierarchy.