Journal of Research in Personality 59 (2015) 1–14

Contents lists available at ScienceDirect

Journal of Research in Personality

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

Bayesian hierarchical modeling of the temporal dynamics of subjective well-being: A 10 year longitudinal analysis ☆

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A R T I C L E   I N F O

Article history:
Received 11 August 2015
Revised 18 August 2015
Accepted 19 August 2015
Available online 20 August 2015

Keywords:
Subjective well-being
Homeostasis
Longitudinal
Bayesian hierarchical models
Set-point theory

A B S T R A C T

This study demonstrates, for the first time, how Bayesian hierarchical modeling can be applied to yield novel insights into the long-term temporal dynamics of subjective well-being (SWB). Several models were proposed and examined using Bayesian methods. The models were assessed using a sample of Australian adults ($n = 1081$) who provided annual SWB scores on between 5 and 10 occasions. The best fitting models involved a probit transformation, allowed error variance to vary across participants, and did not include a lag parameter. Including a random linear and quadratic effect resulted in only a small improvement over the intercept only model. Examination of individual-level fits suggested that most participants were stable with a small subset exhibiting patterns of systematic change.

1. Introduction

Researchers have long been interested in the long-term stability and change of subjective well-being (SWB). Test–retest correlations from longitudinal data (Schimmack & Oishi, 2005) and twin studies (Lykken & Tellegen, 1996), together with the generally small long-term effect of major life events, all attest to the stability of SWB over time. However, test–retest correlations do decline as test–retest intervals increase (Schimmack & Oishi, 2005), and more recent work suggests that some life events lead to long-term changes in SWB for some people. To explain these temporal dynamics, several theoretical models of SWB have been proposed (e.g., Brickman & Campbell, 1971; Cummins, 2015; Easterlin, 2003; Headey & Wearing, 1989). Underpinning the evidence for these theoretical models are various statistical approaches that have been used to analyze longitudinal datasets (e.g., Charles, Reynolds, & Gatz, 2001; Easterlin, 2003; Ehrhardt, Saris, & Veenhoven, 2000; Headey & Wearing, 1989; Helliwell, 2003; Lucas & Donnellan, 2007; Mroczek & Spiro, 2005; Orth, Trzesniewski, & Robins, 2010). In particular, various hierarchical modeling and latent variable approaches have provided insights into the nature of SWB dynamics.

While these statistical models have provided useful insights, they also have their limitations. In particular, they have tended to rely on standard distributional assumptions and used a limited set of model comparison tools. More recently, researchers in a wide range of fields, including psychology, have begun to explore the potential of the Bayesian approach to model estimation and comparison (e.g., Anglim & Wynton, 2015; Averell & Heathcote, 2011; Elliott, Gallo, Ten Have, Bogner, & Katz, 2005; Lee, 2008; Nikodijevic, Moulding, Anglim, Aardema, & Nedeljkovic, 2015). Software such as BUGS, Jags, and Stan have made flexible Bayesian model specification more accessible to applied quantitative researchers by reducing the need for the user to specify an algorithm for parameter estimation. Furthermore, the Bayesian approach offers a range of powerful model comparison tools which include model recovery, measures of fit with advanced penalties for model complexity, and checks on whether models recover theoretically important features of the data (Gelman et al., 2013). However, despite their increased accessibility, such models have not yet been applied to longitudinal SWB research.

Thus, the purpose of this paper is to apply the Bayesian approach in order to parsimoniously model the features of long-term change in SWB. We propose several alternative models and show how a Bayesian approach to estimation and model comparison provides novel insights into the temporal dynamics of SWB.

☆ Data and code for presented analyses are available on Figshare ("Data and code for Bayesian Hierarchical Modeling of the Temporal Dynamics of Wellbeing" http://dx.doi.org/10.6084/m9.figshare.1373525).

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http://dx.doi.org/10.1016/j.jrp.2015.08.003
0092-6566/

We estimate models and apply this approach to 10 years of SWB data from a large representative sample of Australian adults.

1.1. Subjective well-being (SWB): An overview

Subjective well-being (SWB) commonly refers to a broad range of emotional reactions and cognitive evaluations that represent an individual's assessment of their overall life quality (Diener, Suh, Lucas, & Smith, 1999). When measured either by a single global life satisfaction item or by a composite scale based on satisfaction with multiple domains of life (e.g., the Personal Wellbeing Index, International Wellbeing Group, 2013), several robust findings have particular relevance to the current investigation. First, most people report feeling positive about their lives most of the time (Cummins, 1998, 2003, 2013). Second, positive mood provides an explanation for this stability with the combination of happiness, contentment, and alertness accounting for up to 80% of SWB variance (Blore, Stokes, Mellor, Firth, & Cummins, 2011). Third, from the perspective of homeostatic theory, individual differences in this positive affect forms the basis of an affective set-point (Tomyn & Cummins, 2011), and when emotions create a level of SWB different from set-point, a homeostatic system is activated with responsibility for returning SWB to set-point (Cummins, Li, Wooden, & Stokes, 2014).

An essential feature of SWB that can be understood as a consequence of the above is that it tends to be fairly stable over time. Hartmann (1934) provided initial evidence of this, reporting a one-month test–retest correlation of .70 in self-reported general happiness among college students. By the 1970s it was clear that considerable levels of stability in SWB extend over several years (Andrews & Withey, 1976; Palmore & Kivett, 1977). A meta-analysis by Schimmack and Oishi (2005) obtained average test–retest correlations for multi-item scales at 1 year of around $r = .60$, and at 10 years of around $r = .35$, but estimates based on more than 5 years were based on small sample sizes. Supporting a partial genetic basis for this stability, Lykken and Tellegen (1996) found much larger SWB intraclass correlations for monozygotic twins ($r = .44$) than for dizygotic twins ($r = .08$). Finally, many major life events appear to have only a temporary effect on SWB (Headey & Wearing, 1989; Suh, Diener, & Fujita, 1996).

Adding to the understanding of these trends, several strands of evidence suggest that SWB measurement for a given individual is more than just sampling from a stationary distribution. Test–retest correlations do tend to decline somewhat over time and even over one-year intervals such correlations are typically less than internal consistency measures of reliability. Furthermore, covariance models that seek to partial out trait and auto-regressive variance have estimated that auto-regressive factors explain almost as much variance as traits (Lucas & Donnellan, 2007). Additional auto-regressive variance may be explained by extreme life events, like approaching death (Gerstorf et al., 2008), marital transition (Lucas, Clark, Georgellis, & Diener, 2003), and acquiring a disability (Lucas, 2007). Finally, studies of overall age effects do suggest that small but meaningful changes in SWB occur over the life course (e.g. Mastekaasa & Moum, 1984).

Despite the demonstration of such small changes, it is the overall stability of SWB over time that has led researchers to propose various stabilizing mechanisms (Cummins, 1995; Cummins, Eckersley, Pallant, Van Vugt, & Misajon, 2003). For example, Brickman and Campbell (1971) proposed that people adjust expectations to changing circumstances while Headey and Wearing (1989, 1992) proposed that stable personality traits systematically influence the experience and perception of life events which, in turn, influences SWB. Finally, Cummins (2015) proposed that homeostatically protected mood (HPMood) set-points are the key to SWB stability, where systematic change in SWB is caused by homeostatic failure, when an individual's resources are insufficient to effectively counter the level of experienced challenge. Such failure, however, is usually an acute event, with SWB normally recovering to the level of its set point.

1.2. Longitudinal statistical models of SWB

Researchers have applied a range of statistical models to study the long-term temporal dynamics of SWB (for a review, see Eid & Kutscher, 2014). Such models have almost always included a random intercept and generally adopt either a latent growth curve (e.g., Helson, Jones, & Kwan, 2002; Orth et al., 2010) or a hierarchical modeling approach (e.g., Lucas & Donnellan, 2011; Mroczek & Spiro, 2005). Stochastic change is typically modeled using a lag parameter, whereas systematic change is commonly modeled using random linear and quadratic effects, although discrete change and growth-mixture models have also been employed (Mancini, Bonanno, & Clark, 2011; Wang, 2007). In particular, trait-state-error models (Kenny & Zautra, 2001) include parameters representing stable and lag components, as well as a state component which includes both occasion specific variance and measurement error (for a review, see Cole, Martin, & Steiger, 2005).

In contrast to latent growth curve models, hierarchical models have the benefit of easily incorporating unequal numbers of observations per participant, as well as placing the emphasis on predicting the criterion variable. A range of other approaches include iterative procedures to explore set points (Cummins et al., 2014), models designed to capture changes in test–retest structure over time (Fraley & Roberts, 2005), and models of momentary measurement error and short to medium-term response biases (Ehrhardt et al., 2000).

Despite the popularity and insights gained from traditional hierarchical and latent growth curve approaches, they both have several limitations. First, many such models are incorporated into software which makes assumptions that are both difficult to modify and inappropriate for SWB data. For example, individuals differ in within-person variability, but standard models assume that variability is constant over individuals. Second, the data generating process implied by such models is rarely evaluated in terms of whether it captures theoretically relevant features of longitudinal SWB data, as described earlier. Such features include degree of change, distributions of individual scores, and distribution of person-level means. Third, models are only sometimes compared, which in turn raises a number of challenges related to evaluating model complexity. To overcome these limitations, a Bayesian data analytic approach provides a promising framework for refining longitudinal models of SWB.

1.3. Bayesian hierarchical modeling

Bayesian hierarchical methods are increasingly applied in psychology to model repeated measures data (e.g., Anglim & Wynton, 2015; Averell & Heathcote, 2011; Lee, 2008; Nikodijevic et al., 2015). Adoption of Bayesian methods has been aided by increased computational power, refinement of algorithms, accessible software (e.g., WingBugs, JAGS, and Stan) and textbooks relevant to a general applied quantitative audience (e.g., Gelman & Hill, 2007; Gelman et al., 2013; Kruschke, 2010). While Elliott et al. (2005) performed a Bayesian analysis of short term mood data, we are not aware of any attempt to apply Bayesian hierarchical methods to the study of long-term temporal dynamics of SWB.

The Bayesian hierarchical approach incorporates all the advantages of standard hierarchical modeling, but also offers several additional benefits. First, it allows substantial flexibility in defining the probability model proposed to underlie the data generating process. For example, the distribution of residuals is not required