Contents

Introduction

A considerable interest in understanding intra-individual variability is a distinct feature of recent psychological research (Hamaker, Dolan, & Molenaar, 2005; McArdle & Prescott, 2010; Molenaar, 2004; Werner, 2005). As a result, process oriented methodologies like time series analysis (TSA) have become increasingly popular among psychologists. Numerous empirical studies (Günter, Winker, Böttcher, & Brosig, 2013; Hoeppner, Goodwin, Velicer, & Helshe, 2007; McArdle & Plassman, 2009; Schiepek, 2003; Stadnitski, 2012a; Tschacher & Ramseyer, 2009) and methodological articles (Browne & Nesselroade, 2005; Hamaker, Zhang, & Van der Maas, 2009; Huitema & McKean, 2007; McArdle, Grimm, Hamagami, Bowles, & Meredith, 2009; Rovine & Molenaar, 2005; Stadnitski, 2012b; Stadnytska & Werner, 2006; Stadnytska, Werner, & Braun, 2008a, 2010a; Velicer & Fava, 2003) from the last decade reflect this tendency. Particularly, multivariate methods that treat variables as an interacting dynamic system are relevant tools for modeling behavior or other psychological phenomena.

Generally, there are two different longitudinal approaches within this domain. First, multiple measurements can be collected from a large number of individuals belonging to different groups over several discrete occasions. The appropriate methods for this kind of research situation from repeated measures MANOVA and cross-lagged regression to structural equation modeling procedures like latent growth curves or latent change score models are described and compared by McArdle (2008). Multiple time series analyses that model at least 50 observations from one or two individuals represent another type of longitudinal design. Dynamic factor analysis (Molenaar, 1985; Zhang, Hamaker, & Nesselroade, 2008) is currently the most well-known method of this class among psychologies. DFA is a generalization of the P-technique factor analysis (Cattell, Cattell, & Rhymer, 1947; Molenaar & Nesselroade, 2009) which permits modeling multivariate time series with latent variables incorporating lagged effects. This paper deals with multivariate procedures for analyzing dynamic interdependencies between manifest variables such as VAR, SVAR, VECM, SVECM, and cointegration.

The primary objective of the paper is to demonstrate the application of the multivariate time series analyses to practitioners by focusing on empirical examples which show the implementation of the discussed methods with psychological data employing the open source statistical software *JMulTi* (Lütkepohl & Krätzig, 2004) and *R* (http://www.r-project.org/).

The paper starts with a review of the research questions that can be adequately addressed by the described methods and proceeds with outlining some basics of time series analysis necessary for understanding of subsequent contents. Then, vector autoregressive models (VAR) and their structural advancements (SVAR), capturing instantaneous dependencies and allowing theory-based inference, are presented. Further, methods for nonstationary time series such as SVAR of differenced data with long-run restrictions, vector error correction models (VECM), their structural variants (SVECM), and cointegration are considered. Impulse response analyses (IRA) and forecast error variance decompositions (FEVD) are used to illustrate dynamic interrelations between elements of the analyzed systems. Finally, the Johansen procedure is introduced as a reliable diagnostic tool to distinguish between different types of time series relationships: stationary systems, cointegrated systems, and independent integrated variables. Each topic ends with elaborate empirical demonstrations. A detailed documentation of the analyses conducted with *JMulTi* and *R,* which can be found in Appendix, aims at enabling researchers to implement the discussed multivariate strategies in applied settings.

The following reasons justify the use of the free software. First of all, implementations of longitudinal methods in psychology remain limited because applied scientists are usually not familiar with standard time series statistical packages like *EViews* or *RATS* or have no interest in complex programming. Therefore, one of the goals of this paper is to show that the described multivariate techniques can be easily utilized employing freely available routings from *JMulTi* and *R*. *JMulTi* is interactive software specifically designed for univariate and multivariate time series analysis. Because of its easy handling, *JMulTi* is especially suitable for researchers who are used to work with statistical packages like *SPSS*. *R* is a free software environment increasingly used in the social and behavioral sciences. Compared with other software tools, *R* has many advantages: It provides a variety of statistical and graphical techniques and is highly extensible allowing users to develop new computational routines by combining the existing functions. The various packages that are available for *R* are under constant development and cover a wide range of modern statistics.

The paper contains six empirical examples. The first one demonstrates all essential steps of a VAR analysis such as searching for a proper model of the data generation process, parameter estimation, checking the adequacy of the estimated model, and dynamic analyses on the time series of the *heart rate* and the *amount of talk* of a speaker in a conversation data that are freely available in the textbook of Warner (1998). The availability of the data allows reproducing the described calculations and can facilitate understanding of the multivariate techniques. Examples 2 to 6 employ empirical time series data comprising of somatic symptoms and mental states of a married couple over a period of 144 days from the clinical study by Kupfer, Brosig, and Brähler (2005).

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