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Analyzing Dynamic Process Systems:

Cointegration Methodology as a Tool of Psychological Research

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pentru însoţitorii mei iubiţi

Ioan şi Marian

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Summary

The present paper-based thesis puts forward cointegration methodology as a multivariate tool of psychological research. Aiming at familiarizing psychologists with the toolbox of cointegration techniques, the studies conducted here provide strategies to analyze complex dynamic process systems. Within the framework of these systems, integrated processes display an unpredictable course due to stochastic trends interact over time. If these non-stationary series are co-integrated, their interaction is driven by common stochastic trends with the systems returning to stable equilibrium states in the long run. Vector error-correction (VEC) modeling, a frequently used representation of cointegrated systems, allows insights into these short- and long-term dynamics at a glance.

The objectives of this thesis are (a) to adapt this econometric approach to psychological circumstances based on conceptual considerations; (b) to provide a systematic investigation of the mathematical models behind integrated and cointegrated processes as well as their VEC representation, thus clarifying how their parameters are to be interpreted from a psychological perspective; and (c) to address issues of research practice such as spurious relations or long memory characteristics. By means of simulated as well as empirical data from different domains of psychology, this work is designed as a step-by-step guideline inducing psychological applications.

Considered Publications

This thesis is paper-based considering the following peer-reviewed publications:

- Stroe-Kunold, E., Gruber, A., Stadnytska, T., Werner, J. & Brosig, B. (2010). Cointegration methodology for psychological researchers: An introduction to the analysis of dynamic process systems. Manuscript submitted for publication.

- Stroe-Kunold, E., Stadnytska, T., Werner, J. & Braun, S. (2009). Estimating long-range dependence in time series: An evaluation of estimators implemented in R. *Behavior Research Methods, 41,* 909-923.

- Stroe-Kunold, E. & Werner, J. (2009). A drunk and her dog: A spurious relation? Cointegration tests as instruments to detect spurious correlations between integrated time series. *Quality & Quantity, 43,* 913-940.

- Stroe-Kunold, E. & Werner, J. (2008). Modeling human dynamics by means of cointegration methodology. *Methodology, 4,* 113-131.

- Stroe-Kunold, E. & Werner, J. (2007). Sind psychologische Prozesse kointegriert? Standortbestimmung und Perspektiven der Kointegrationsmethodologie in der psychologischen Forschung. [Are psychological processes cointegrated? Present role and future perspectives of cointegration methodology in psychological research.] *Psychologische Rundschau, 58,* 225-237.

Contents

1 Introduction

The present thesis is based on publications introducing cointegration methodology to psychological research. The purpose of this synopsis ('Mantelteil') is to reveal the scientific motivation behind these studies thus clarifying their coherence.

Adapting cointegration techniques – worth a Nobel Prize in Economic Sciences to Clive W. J. Granger in 2003 – to psychological research requires demonstrating which aspects of human nature might be adequately addressed by this approach. In contrast to other time series procedures, *co-integration* allows modeling dynamic systems cointaining processes with unpredictable temporal course due to stochastic trends called *integrated*. Empirical evidence suggests that various psychological phenomena display such time-variant, non-stationary qualities. Most time series methodologies are confined to the analysis of stationary data, however. Because of common stochastic trends, cointegrated systems exhibit stationary long-term equilibria in spite of short-term instabilities.

Conceptually, this is consistent with recent psychological perspectives subsumed in the three elements of the term *dynamic process system*. The increasing popularity of time series analysis underlines the necessity of tools granting insights into the temporal fluctuation of behavior and performance. Hence, (non-)stationary dynamics are reflected. Finally, the systemic perspective suggests that many long-term phenomena are mutually interconnected forming a dynamic system.

On the basis of well-known psychological notions, the relevance of cointegration methods is discussed employing examples from recent research. After explaining the approach, the findings on cointegration are outlined providing a framework for the results described in detail in the papers considered.

2 Relevant Psychological Concepts and Approaches

> We are now reaching the point in the behavioral sciences at which the data analysis method will be matched to the research problem rather than the research problems being determined by the available methods of data analyis. (Velicer & Fava, 2003, p. 603)

The crucial question is: How may cointegration methods enrich the insight into the functioning of psychological phenomena? The three concepts described here will help understanding what cointegration implies for psychological research. Benefits of time series longitudinal analysis are discussed first. Then the concept of (in-)stability is reflected in its relevance for the temporal characterization of psychological phenomena. Finally, the dynamic systems perspective explaining such phenomena in a systemic framework and not as separate entities is outlined.

2.1 Process Perspective: Time Series Analysis

A technique useful in one situation, may be rather limited in another context. Thus, the researcher needs to evaluate whether the tools available are appropriate to capture what is addressed by the research question (Grayson, 2004). Since a considerable part of psychological research is interested in the distribution of a phenomenon in the population, the focus of this approach is inter-individual. The drawn conclusions are based on the assumption that the phenomena under investigation are randomly distributed in time around a rather stable mean.

At the same time, there is a great psychological interest in describing and understanding psychological processes that unfold within the individual over time. Temporal fluctuations of behavior and performance represent an important topic in psychological research accounting for a substantial proportion of variability (Gilden, 1997). As variables of interest, development, learning, appraisal, habituation, cognitive information processing, perception, feeling, emotion, coping and motor behavior are cases in point (e.g., Molenaar, 2007). Comparing mean and standard deviations, however, is not helpful in understanding the pattern of change over time or evaluating the long-term effects of intervention (Slifkin & Newell, 1998). Obtaining knowledge about intra-individual change requires techniques allowing conclusions about the structure of temporal variability (Hamaker, 2004), no longer relegating these fluctuations 'to a statistical purgatory known as unexplained variance' (Gilden, 2001, Abstract). Time series analysis as the exemplar of longitudinal design allows to explain current behavior on the basis of its past, even enabling the researcher to predict future performance (Velicer & Fava, 2003). The order in which observations are obtained is not neglected but 'provides the data of interest' (Wagenmakers, Farrell, & Ratcliff, 2004, p. 579). A time series represents a variable measured repeatedly at regular intervals over time. Since autocorrelations usually occur, statistical algorithms postulating uncorrelated measurements are no longer appropriate. The use of time series models enables researchers to identify the lawfulness underlying this set of occasions, thus revealing process characteristics of the variables of interest. Conducting panel analyses allows to draw conclusions from aggregated data.

Although introduced to social and behavioral sciences by Glass, Willson, and Gottman (1975), McCleary and Hay (1980), Gottman (1981) as well as Gregson (1983), time series methods have been rarely used in psychology for many years. Recently, however, an increasing interest and discussion on these tools can be observed among psychological researchers (Delignières, Fortes, & Ninot, 2004; Gilden, Thornton, & Mallon, 1995; Molenaar, 2007; Van Orden, Holden, & Turvey, 2003; Wagenmakers, Farrell, & Ratcliff, 2005, inter alia). Wagenmakers et al. (2004, pp. 595-597) give a detailed discussion of recent time series experiments in cognitive psychology. In the meanwhile, the scientific community aggrees that time series analysis represents an adequate tool for analyzing psychological processes (e.g., Molenaar, 2004; Nesselroade, 2004). A thorough introduction to time series analysis combined with empirical psychological examples is provided by Werner (2005).

By mere visual inspection of the two time series graphs in Figure 1, the differences of the temporal characteristics between the processes is evident. For a period of one year, Gottschalk, Bauer, and Whybrow (1995) aimed at understanding the longitudinal course of bipolar disorder by collecting daily mood records of a patient with bipolar disorder (top) in comparison to a control subject (bottom, on the same scale). Apart from the differences in mood intensity, the longitudinal approach proves empirically that the mood of bipolar patients really fluctuates between two poles. The authors even identified that their temporal mood pattern originates from a periodic source, especially obvious in the bracketed portion of the series.

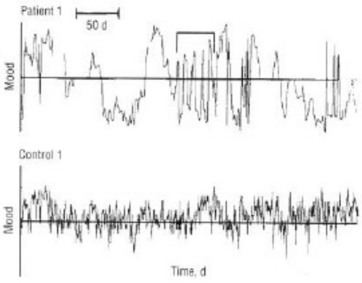

Figure 1: Mood time series of a patient with bipolar disorder (top) and a control subject (bottom; taken from Gottschalk et al., 1995, Figure 1).

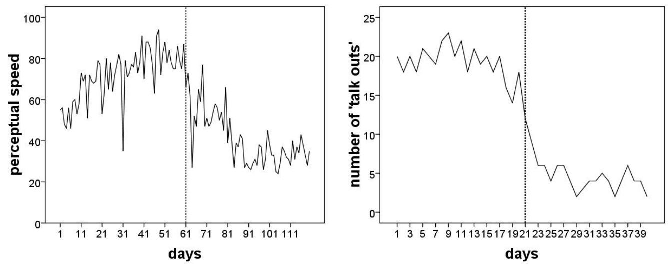

Figure 2: Perceptual speed of a schizophrenic patient, treated with a tranquilizer after 60 days and talking behavior of a school class, taught with modified pedagogic approach after 20 days.

According to Glass et al. (1975, p. 4) time series experiments offer 'a unique perspective on the evaluation of intervention (or 'treatment') effects'. To give two examples[1], Figure 2 (left) plots the perceptual speed of a schizophrenic patient over 120 days. The baseline condition (i.e., without treatment) was followed by a period in which the patient received a tranquilizer. The intervention effects are obvious. This is also true for the graph plotting the disruptive talking behavior of a second-grade class observed over 40 days, with the baseline condition of 20 days followed by 20 days of a modified pedagogic approach. Velicer and Fava (2003, p. 594), for instance, describe different patterns of intervention effects. Undoubtedly, both the insight into the temporal structure of psychological phenomena and the empirical evidence of long-term intervention effects are merits of the longitudinal perspective with time series analysis providing statistical methods going far beyond mere visual impression. *Autoregressive integrated moving average (ARIMA) models* (Box & Jenkins, 1976), a frequently used method of time series analysis, represent processes in terms of the current value's dependence on past values. A detailed introduction to these methods is given at the beginning of the publications considered in this paper-based thesis.

[1]The data are freely available in Glass et al. (1975), based on the original studies of Holtzmann (1963, perceptual speed) and Hall et al. (1971, talking behavior).

2.2 Process Dynamics: (Non-)Stationarity

From a psychological perspective, it is interesting to reveal the temporal dynamics characterizing human behavior. These differ for stable and time-variant processes, for instance. As cointegration methodology is concerned with unstable series due to stochastic trending, it is useful to define what these terms imply.

Stationarity As mentioned above, a considerable number of psychological studies is conducted assuming that the phenomena under investigation are stable over time implying that they have a time-invariant mean and that deviations from this mean are rather small and random. In time series terminology, such processes are called stationary, displaying constant mean and variance. Random deviations in a series are due to numerous unknown influences that are levelled out in the long run, thus normally distributed with zero mean. Hence, the process itself is normally distributed with constant mean, and we expect the same value for each measurement with random fluctuations due to measurement error.

In fact, it is legitimate to assume stationarity for numerous psychological phenomena. Personality traits, as a prominent example, are defined as stable individual dispositions differentiating individuals across time and situations, e.g., by characterizing a person as neurotic, extraverted, open, agreeable or conscientious (Five Factor Model by Costa & McCrae, 1992). Concerning Cattell's concept of fluid and crystallized intelligence (Cattell, 1987), the latter type is assumed to stay relatively stable across most of adulthood. Obviously, some phenomena show stability over a lifetime while others display continuity in shorter lapses of time. In the baseline condition of a temporal estimation task[2], for example, asking participants to repeatedly estimate a time interval of 1000 milliseconds after stimulus onset, a (correct) feedback about the estimated time interval appeared on a screen after subjects had pressed a key. As expected, the estimated time is stationary, randomly fluctuating around 1000 milliseconds. Figure 3 plots this process for 200 observations as a prototypical example of stationarity.

[2]This experiment is described in detail in Stroe-Kunold et al. (2010), one of the publications considered in this thesis.

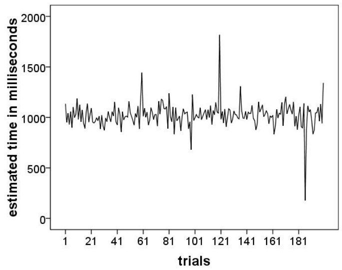

Figure 3: Stationary process: Estimated time in a temporal estimation task with correct feedback (described in Stroe-Kunold et al., 2010).

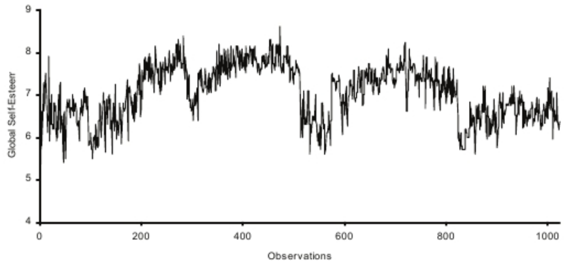

Figure 4: Non-stationary dynamics of global self-esteem [y] over 1024 observations [x] (taken from Delignières et al., 2004, Figure 2).

Non-Stationarity A considerable amount of psychological processes displays time-evolutionary properties, thus being non-stationary. Here, it makes a difference which section of the process is analyzed. Developmental processes, for instance, are 'almost always non-stationary' as development 'generally implies that some kind of growth or decline occurs' (Molenaar, Sinclair, Rovine, Ram, & Corneal, 2009, p. 261). Classically, self-esteem is regarded as a continuous personality trait not greatly affected by daily events (Mischel, 1969). Delignières et al. (2004) suggest, however, that the combination of two opposite processes (preservation vs. adaptation) underlies the dynamics of self-esteem, following a non-stationary course where local increasing or decreasing trends can be observed. A representative time series of that study[3] is plotted in Figure 4. These instabilities are often explained by some specific life events such as professional success or failure causing meaningful short-term instabilities in self-esteem (Rosenberg, 1995). Childrens' permanently increasing vocabulary is another example of processes whose properties are a function of the time at which they are obtained. In general, the development of childrens' cognitive skills in their first years displays permanent progress. Apart from their psychic development, this is also true for their physiological functioning. With increasing age, trends seem to be rather inverse for many cognitive functions. The ongoing Seattle Longitudinal Study (conducted since 1956; for an overview consult Schaie, 1996) reports that personality remains relatively stable over the adult lifespan while cognitive abilities rather change if untrained. The identification of such trends in neuropsychological data

[3] Note that participants completed questionnaires using specific software twice a day for 512 consecutive days (for details see Delignières et al., 2004).

may be relevant to the detection and treatment of dementia. Concerning the development of coping (i.e., the ability of dealing with stressors), Skinner and Zimmer-Gembeck (2007) investigated age differences or changes in coping from infancy through adolescence. Apart from lifespan psychology, symptoms of disease may change in short order. Note that time series analysis was introduced to social and behavioral sciences to evaluate psychotherapy (Glass et al., 1975). Obviously, the purpose of therapeutic interventions would need to be questioned if the client's symptoms constantly fluctuated around the same value. Time series analysis in psychotherapy research is applied with the goal of studying mechanisms of change in psychotherapy process (e.g., Tschacher & Ramseyer, 2009). As mentioned above, research in social and behavioral sciences is interested in treatment effects. Self-evidently, the development of these psychological variables is not stationary (i.e., fluctuating around a constant mean) but trends can be clearly identified. Such trends are indicators of development and change and thus especially interesting from a dynamic perspective.

Mathematically, trends are either deterministic or stochastic. In case of a deterministic trend, the development of the process follows a predictable course. Linear deterministic trends, for instance, imply that the process moves on a straight line. Due to measurement errors or random deviations from this route, the process fluctuates around this line. It has a stable variance and a changing mean. If we subtract this mean from the measured value at each point of time and this difference is stationary, the resulting series is called *trend stationary*. The procedure is known as polynomial detrending. Psychological interventions are expected to lead to deterministic trends. In lifespan psychology, the development of cognitive skills, as one example, is supposed to be predictable. Van Geert and Van Dijk (2002) investigated the early language development of a small girl for one year. The development of her mean length of utterance in words (MLU-w) is plotted in Figure 5 increasing linearly with a constant slope over time. Obviously, such trends are easy to predict and to interpret.

In contrast to this, variables following a stochastic trend do not display such a straight development. Here, mean and variance change over time. The process is called *differ-*

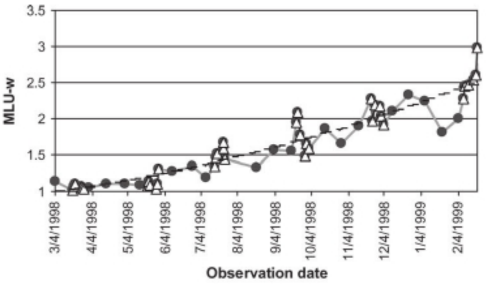

Figure 5: Linear trend in the development of a child's mean length of utterance in words (MLU-w) (taken from Van Geert & Van Dijk, 2002, Figure 2).

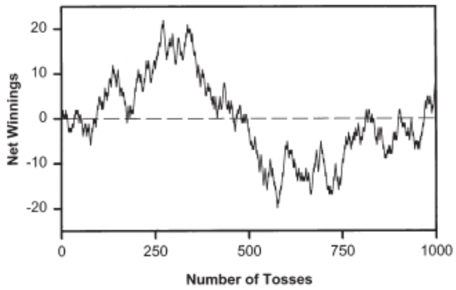

Figure 6: Stochastic trends in the gambler's run (taken from Peterson & Leckman, 1998, Figure 1).

ence stationary as it is stationary after transformation into a series of period-to-period differences. This is possible because the change (i.e., difference) between periods is stationary. Such difference stationary processes are also called integrated implying that the impact of the random component on the series does not dissipate over time, leading to large-amplitude excursions of the process. A prototypical example of an integrated time series is the so-called 'gambler's run'[4] plotted in Figure 6.

As described before, time series analysis in psychology usually aims at identifying and interpreting trends. It is especially challenging if the trends are stochastic as they are not predictable at all. The phenomenon cannot be neglected, however, as a great number of psychological processes exhibits stochastic trends. Glass et al. (1975) found, for instance, that 44 of 95 (i.e., approx. 46%) of psychological time series were integrated. Fortes, Delignières, and Ninot (2004) conclude that time series analysis enables researchers to discern the possible dependence between subsequent values thus introducing *historicity* as an important innovation in the domain of self-esteem. Peterson and Leckman (1998), as another example, found in a panel study with 22 participants that the time series for tics in the Gilles de la Tourette syndrome display burstlike behavior and are thus non-stationary with similar dynamics of the tic interval (TI) processes regardless of the length of the series. They are plotted in Figure 7 for 50, 250 and 500 observations.

[4]This example is taken from Peterson and Leckman (1998): With each toss of a coin winning or losing a dollar, the average winnings through time will equal zero. Still, the incremental change in net winnings from one toss of the coin to another will summate through time producing a quick and remarkable drift of the net winnings from the baseline mean. The variance around the baseline increases in direct proportion to the duration of observation.

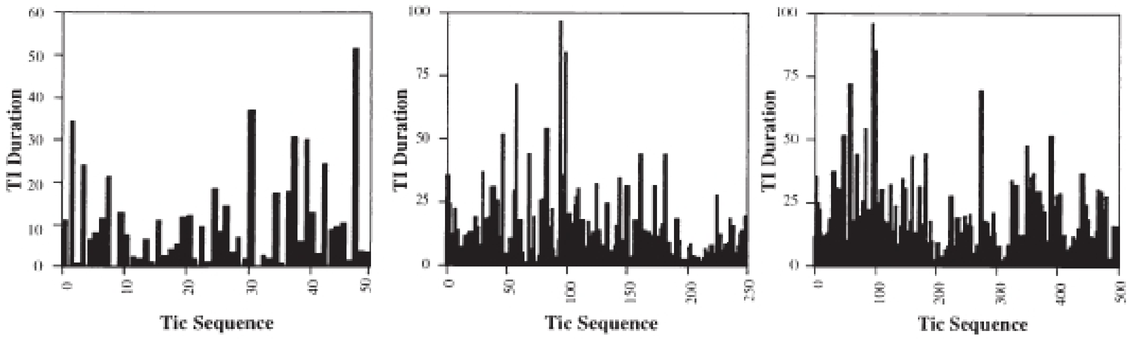

Figure 7: Non-stationary dynamics of tic intervals (TI) in the Gilles de la Tourette syndrome over 50, 250 and 500 observations (taken from Peterson & Leckman, 1998, Figure 9).

Note, however, that most time series methodologies are restricted to stationary data thus failing to capture some crucial aspects of psychological dynamics. Considering that a priori stabilizing transformations may distort interesting characteristics of time series, methods accommodating non-stationary features of the data are required.

2.3 Dynamic Process Systems: Multivariate Modeling

Undoubtedly, it would be interesting to find out whether the dynamics of tic intervals in Figure 7 interact with additional variables over time, such as instabilities in the patient's mental state. Concerning the temporal variability of self-esteem described above (Figure 4), Fortes et al. (2004, p. 748) conclude that self can be conceived 'as a complex system composed of many interacting components'. Referring to the mood changes in patients with bipolar disorder (see Figure 1), Bauer et al. (2006) investigated the temporal relation between mood variation and sleep while Rasgon, Bauer, Glenn, Elman, and Whybrow (2003) studied how this interacts with the menstrual cycle of women with bipolar disorder. Figure 8 shows a 180 day mood chart from a woman with bipolar disorder, simultaneously plotting variations in her sleep and her medication (Bauer et al., 2004).

Obviously, the insight into the functioning of psychological variables can be improved if several processes are modeled and analyzed in the context of their common relational structure. This is consistent, for instance, with the holistic concepts of *Gestalt psychology* refreshing Aristotle's conclusion in the Metaphysics that 'the whole is greater than the sum of its parts' (e.g., Guastello, Koopmans, & Pincus, 2009). The dynamic systems

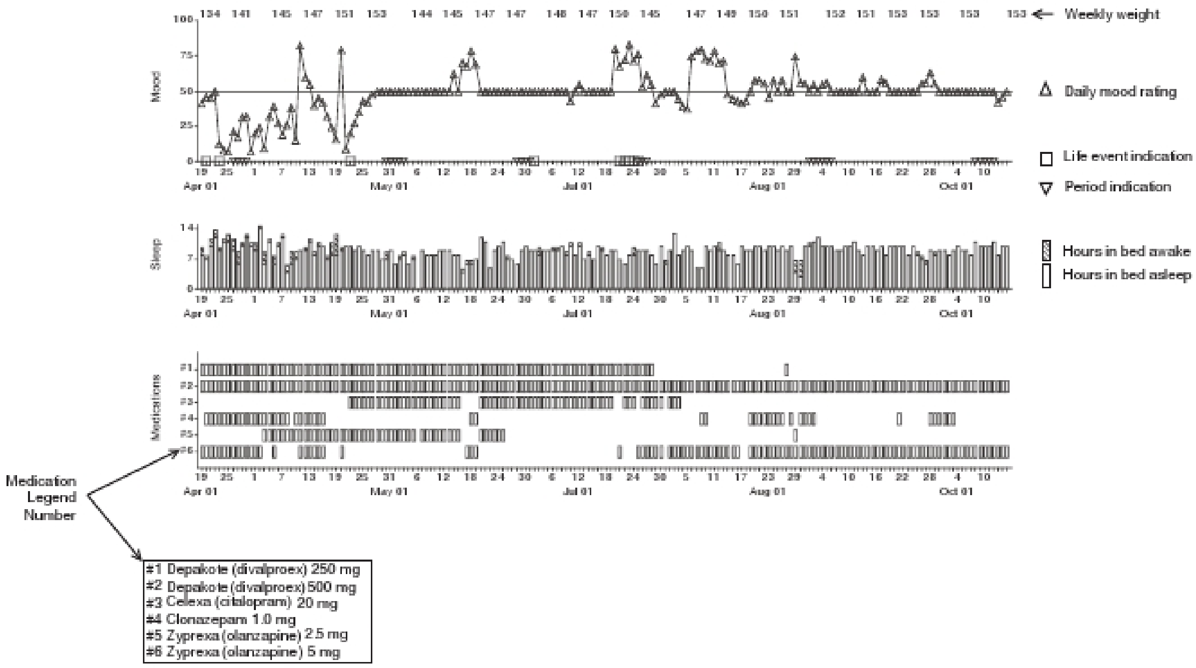

Figure 8: Systemic perspective: 180 day mood (top), sleep (center) and medication (bottom) chart of a patient with bipolar disorder (taken from Bauer et al., 2004, Figure 3).

perspective is increasingly popular. Systemic approaches have a long applied tradition in psychology: systemic therapy addresses the individual as a member of a system identifying interactional patterns and dynamics. In fact, this notion of dynamic systems has led to a new movement of *nonlinear systems science* in psychology (for an overview Guastello et al., 2009). Van der Maas and Molenaar (1992) refer to dynamic systems from the viewpoint of catastrophe theory. In a commentary on Vallacher and Nowak (1997), Carver (1997) outlines how this notion can be fitted to well-known philosophical ideas. Evidently, a complex philosophical field is concerned. In the following, the description is refined to the concepts relevant to understanding cointegration methodology.

Nowak and Vallacher (1998) define a dynamic system as a set of interacting elements undergoing changes in time (see also Gernigon, d'Arripe-Longueville, Delignières, & Ninot, 2004). Thus, the system's development is determined by the mutual relations between its elements (Olthof, Kunnen, & Boom, 2000). Defining a system's current state contributes to the prediction of its future state (Vallacher & Nowak, 1994). Dynamic systems consist of temporally evolving variables characterizing the relevant properties of the system's state (Bisconti, Bergeman, & Boker, 2004). Mathematically, a dynamic system is a set of equations expressing how the system's state changes as a function of its previous state (Hamaker, Zhang, & Van der Maas, 2009). This is consistent with the *Developmental Systems Theory* describing each individual as a complex dynamic system which consists of subsystems (e.g., perception, emotion, cognition, physiology) as well as their dynamic interrelationships. The complete set of variables can be represented as the coordinates of a high-dimensional space called *behavior space*. The individual systems are again part in a larger conglomeration including the systems of a population of human beings (Molenaar et al., 2009). The ability to evolve in time is the important characteristic of a dynamic (process) system (Vallacher & Nowak, 1997). Thus, researchers are supposed to describe the connections among its elements and the resulting changes in the system's behavior. Figure 9 illustrates how a dyadic system or group consisting of two persons can be perceived from this perspective.

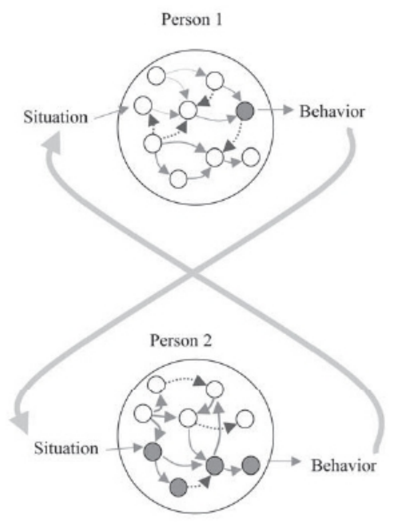

Figure 9: Dyadic dynamic system and its subsystems (taken from Shoda et al., 2002, Figure 3).

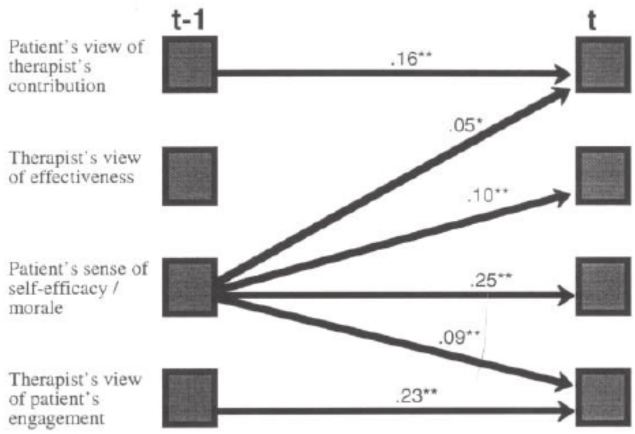

Figure 10: Significant time-lagged associations in the dynamic system of psychotherapy: sample means of the respective VAR parameters ($n = 91$), probabilities of a t-test that the means are zero ($*p < .05; **p < .01$; taken from Tschacher et al., 2000, Figure 2).

Some characteristics of (nonlinear) dynamic systems described in Guastello et al. (2009), Tschacher and Haken (2007) or Vallacher and Nowak (1997), for instance, may be helpful for understanding cointegration and are thus mentioned here. In such systems, a *bifurcation* is a pattern of instability or abrupt change in which a system attains greater complexity by accessing new types of dynamic states. In a mother-child interaction, bifurcations might imply strong fluctuations with the child being highly sensitive to perturbations (Van der Maas & Raijmakers, 2000). *Self-organization* implies that a system not being in equilibrium takes on a structure that allows the system to operate in a more energy-efficient manner. A complex system organizes itself by means of *pattern formation* (i.e., *complexity reduction*) thus optimizing its functionality. In this terminology, *attractors* describe a behavior of systems characterized by stability and dynamic equilibrium. Although systems change dynamically over time, their attractors subsume time-invariant asymptotically stable states. In the dynamic system of personality analyzed by Shoda et al. (2002), for instance, the attractor states represent a person's characteristic states of mind (e.g., a set of beliefs, affective states etc.). In spite of the fact that external influences may cause fluctuations, this person returns to his stable affective state. Thus, the dynamic approach aims at identifying stable temporal patterns of these systems (i.e., attractors; Tschacher et al., 2000). Note that *synergetics* as an interdisciplinary field of research deals with systems composed of several components focusing on the *emergence* of new qualities produced by means of the system's interactional dynamics. In this concern, the main question is whether there are general principles governing the behavior of complex systems (e.g., Haken, 2000) and thus how attractors in complex systems evolve. Tschacher and Haken (2007) give an overview over experimental studies indicating how hypotheses derived from synergetics can be tested. *Synchronization*, playing an important role in cointegrated systems, is a special case of synergetic dynamics relevant to diverse domains in physics, biology, and psychology (e.g., Ramseyer & Tschacher, 2006).

The dynamic systems approach has implications for many domains of psychological research such as neuropsychology, psychopathology, psychotherapeutic processes as well as group dynamics in social and organizational psychology (for a detailed survey consult Guastello et al., 2009). The study of dyadic interaction, for instance, is a frequently used application of this notion in psychological research allowing to determine whether and how the partners influence each other (e.g., Gottman, Murray, Swanson, Tyson, & Swanson, 2002; Hamaker et al., 2009). As another example, Tschacher et al. (2000) investigated the temporal interconnection of process variables in psychotherapy for a sample of 91 patients. Their results (plotted in Figure 10) identify interactional patterns between the patients'

Table 1: Sample of psychological studies on dynamic systems.

field of research	**study**
addiction	Warren, Hawkins, and Sprott (2003), Witkiewitz, Van der Maas, Hufford, and Marlatt (2007)
cognition	Tschacher and Dauwalder (2003)
collective intelligence	Sulis (1997)
development	Van Geert and Van Dijk (2002), Van der Maas and Molenaar (1992)
grief	Bisconti, Bergeman, and Boker (2004)
marital interaction	Cook, Tyson, White, Gottman, and Murray (1995), Hamaker, Zhang, and Van der Maas (2009)
organization change	Dooley (1997)
personality	Shoda, Tiernan, and Mischel (2002)
psychopathology	Granic and Hollenstein (2003), Tschacher and Kupper (2007)
psychotherapy	Schiepek (2003), Tschacher, Baur, and Grawe (2000)
self-concept	Vallacher, Nowak, Froehlich, and Rockloff (2002)
self-regulation of behavior	Carver and Scheier (1998)
social judgement	Vallacher, Nowak, and Kaufman (1994)
sport	Gernigon, d'Arripe-Longueville, Delignières, and Ninot (2004)

view of the therapist's contribution as well as their sense of self-efficacy, the therapist's view of effectiveness and of the patients' engagement. The interactional patterns are time-lagged illustrating the effect of previous (i.e., at $t-1$) on subsequent sessions (at t)[5]. There is a great need for assessment tools enabling researchers and psychological practicioners 'to represent the essential features of the complex systems they are concerned with, i.e., structure of functioning and dynamics' (Schiepek, 2003, Abstract). Table 1 lists a sample of dynamic systems research in several psychological domains.

[5]Note that these results were gained by means of vector autoregression (VAR) time series models which are described in Stroe-Kunold and Werner (2008, 2009) and Stroe-Kunold et al. (2010), publications considered in this thesis.

3 The Idea behind Cointegration

> ... Granger called this phenomenon cointegration. He developed methods that have become invaluable in systems where short-run dynamics are affected by large random disturbances and long-run dynamics are restricted by (economic) equilibrium relationships. (Royal Swedish Academy of Sciences[6], 2003)

The combination of the three dimensions just described – longitudinal perspective, (non-)stationary dynamics and systemic approach – is what makes cointegration methodology unique compared to conventional techniques. For this reason, the concept, for whose invention Clive W. J. Granger was granted the Nobel Prize in Economic Sciences in 2003, attracts the attention as a promising tool for psychological research.

The basic idea behind cointegration, introduced in detail by Engle and Granger (1987), is actually very simple. Multiple processes – non-stationary due to short-term developmental changes – compose a dynamic process system. In spite of their instabilities, the system can be characterized by a stationary equilibrium state in the long run. This is possible if the series share common stochastic trends implying that they move synchronously in a dyadic system, for instance. Recall that processes with a stochastic trend are *integrated* – fulfilling the conditions just mentioned, they are *co-integrated*. Common trends are the motor of the system's dynamic.

Looking back at the characterization of dynamic systems in psychology, the great degree of fit between method and real-life data is evident. The cointegration approach responds to the scientific need to simultaneously model both short-term patterns of instability (bifurcations) and stable temporal patterns (attractors) in these systems. The methods provided herewith open insights into the system's patterns of self-organization (synergetics; with synchronization as an ubiquitous characteristic) and are thus predestined to take part in the toolbox of psychological research. As mentioned above, the need for techniques accommodating non-stationary process features in psychology is evident (e.g., Delignières et al., 2004). Also, the fact that 'developmental processes are a combination of both immediate and long-term processes', thus displaying 'trait and state of development' is well-known (Molenaar et al., 2009, p. 261).

Statistical techniques used for stationary process data lead to misleading results when

[6] retrieved from http://nobelprize.org/ [press release concerning the Nobel Prize in Economic Sciences]

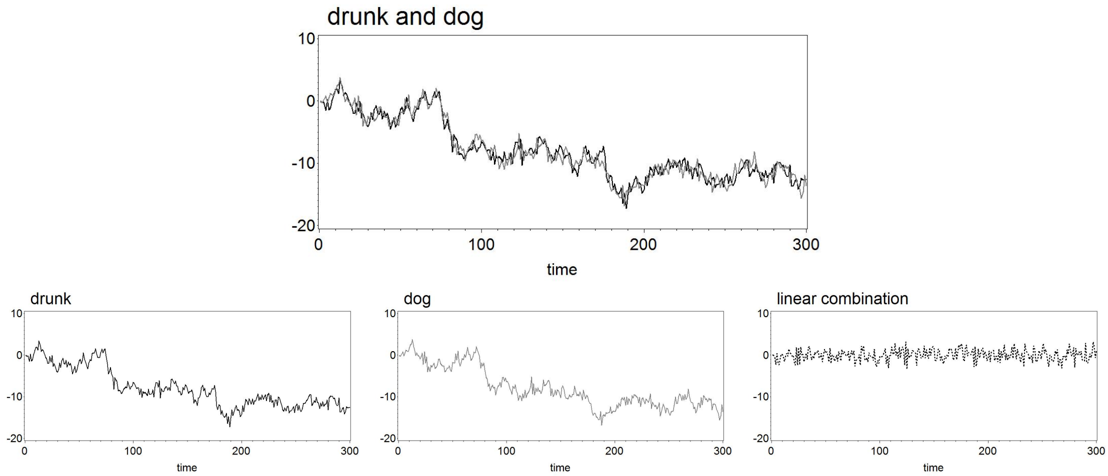

Figure 11: The hypothetical course of a drunk and her dog (top) as well as separate plots of each individual's way and the stationary linear combination (bottom).

applied to non-stationary processes[7]. The landmark finding about cointegration is that specific combinations of non-stationary series may exhibit stationarity, thus allowing for correct statistical inference. Sharing a common stochastic trend implies that two series, for example, can be additionally represented by their stationary linear combination in which the unpredictable trend is eliminated.

Evidently, their common trend is the reason why two series move synchronously as a system in the long run, i.e., why they share a long-run equilibrium relation (which is described by the linear combination). Indeed, this seems suprising because this trend is stochastic implying that the series do not move on a predictable course. The unpredictable walk of a drunkard is a popular metaphor for processes displaying stochastic trends. In section 2.2, the gambler's run was used as another example (plotted in Figure 6). Murray (1994, p. 37) illustrates cointegration with the metaphor of a drunkard and her dog: both for themselves move like processes driven by stochastic trends. In spite of the non-stationarity of each individual's way, one would say: 'if you find her [the drunkard], the dog is unlikely to be very far away'. Figure 11 illustrates how this cointegrated system of drunkard and dog might move. Undoubtedly, the walk of a drunkard is unpredictable while the dog is randomly following impressions stimulating his nose. Note that the dimension of cointegrated systems is not restricted. Imagine that the drunkard and her dog are joined by her also drunk boyfriend, for instance (Smith & Harrison, 1995). Depending on the

[7] This aspect will be further explained in Stroe-Kunold and Werner (2009).

number of identified cointegrating relations in such higher-dimensional systems, numerous common trends are possible. Thus, a system consisting of more than two processes may contain more than one common stochastic trend. In this case, not all series need to display the same combination of trends implying that not all participating processes move synchronously. Still, the three-dimensional process system is driven by two shared trends indicating that its dynamic is not purely random. Thus, the systemic character is only obvious if the variables are appropriately combined. For the example of the drunk, the dog and her boyfriend, these common trends might be the commitment between the dog and his mistress on the one hand and the attraction between the boyfriend and his drunk girlfriend on the other hand. These trends are independent as dog and boyfriend are totally indifferent towards each other[8]. Note that the boyfriend does not hold her hand, just as the dog is not held on a leash.

From a psychological perspective, it is interesting to identify these common trends and to interpret their function for the dynamics of the system. Concerning marital therapy, for example, Willi (1984) defines the unconscious aspects of the complementary defensive patterns in couples as *couple collusion*. They are supposed to stabilize neurotic relationships. If cointegration and thus common trend(s) are identified in couple settings, this psychodynamic concept might serve as an explanation. For the purpose of illustration, the system of a drunk and her dog displays almost perfect synchrony. Note that synchronously functioning psychological processes do not necessarily exhibit such a high degree of congruence.

Cointegrating relations (i.e., stationary linear combinations) define the stable long-run equilibrium inherent in the system. Equilibrium relationships are typical for many psychological variables and represent an interesting subject for researchers interested in conditions maintaining the system. Their identification often means a first step of (e.g., therapeutic) intervention or even prevention. Still, the participating series in such a cointegrated system are unstable as they follow a stochastic trend. It is interesting to find out how the system compensates these instabilities, i.e., how the drunkard and the dog maintain their synchronicity in spite of diverging interests.

[8]Cointegrated systems of higher order are described in detail in Stroe-Kunold et al. (2010).

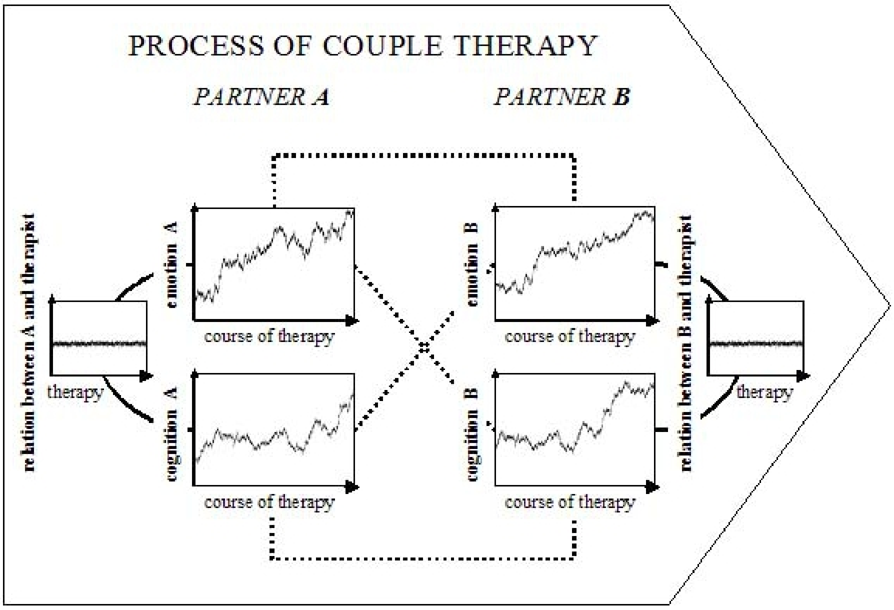

Figure 12: Exemplary options of bivariate cointegration relations in a process of couple therapy (adapted from Stroe-Kunold & Werner, 2007).

Vector error-correction (VEC) models allow for insights into these short- as well as long-term system dynamics at a glance. This commonly used representation of cointegrated systems was originally stated by Johansen (1995) with three principal parameters describing the system. First, the long-run equilibrium between the cointegrated component series is characterized, illustrating the relation of the variables necessary to maintain it. Second, the consequences of short-term deviations from the system's equilbrium can be interpreted showing how these system errors (i.e., deviations) are corrected or compensated. Note that this explains the name (vector) error-correction model exclusively enabling this insight. Finally, the adjustment dynamics in the participating series become obvious with a parameter clearly identifying both self- and inter-regulation mechanisms in and between the series if existent. In the publications considered in this thesis, cointegration analysis in three steps is suggested (e.g., Stroe-Kunold & Werner, 2008; Stroe-Kunold et al., 2010): (1) separate analysis of the participating processes by means of stationarity tests, (2) cointegration tests, and (3) VEC modeling[9].

Based on the assumption that synchronous dynamics are characteristic for therapeutic

[9]Note that the vector autoregression (VAR) models mentioned in the previous section (e.g., Figure 10) can be transformed into VEC models if the participating processes are cointegrated. This transformation is described in detail in Stroe-Kunold et al. (2010).

settings (Ramseyer & Tschacher, 2006), Figure 12 hypothesizes possible bivariate cointegrating relations in the course of couple therapy. According to Heatherington, Friedlander, and Greenberg (2005), three intrapersonal processes are essential for the success of couple therapy: emotional experiences, cognitive changes and the development of the relation towards the therapist. Emotional as well as cognitive variables might move randomly due to stochastic trends while the relation between therapist and patients could follow a stable pattern in the course of the therapy. The empirical proof by means of cointegration methods is yet to come.

Apart from their econometric origin, cointegration methods have been increasingly applied to empirical data in the domain of sociology as well as political science. They have been used to clarify the relation between divorce and female labor force participation (Bremmer & Kesselring, 2004), between population and economic growth (Darrat & Al-Yousif, 1999), between age-specific fertility and female labor supply (McNown, 2003), between crime and immigration (Lin & Brannigan, 2003), crime and their economic determinants (Luiz, 2001), between crime arrest rates for males and females (O'Brien, 1999) as well as between crime, prison and female labor supply (Witt & Witte, 2000).

4 Findings on Cointegration

Since cointegration is mostly unknown in psychology, the goal of the publications presented within the framework of this thesis is to popularize this approach by providing a methodological guideline as well as concrete step-by-step applications to empirical data.

The overview of research on cointegration from a psychological perspective starts with describing two articles introducing the concept for the first time to the psychological community in Germany (Stroe-Kunold & Werner, 2007, published in *Psychologische Rundschau*) as well as on an international level (Stroe-Kunold & Werner, 2008, published in *Methodology*). Stroe-Kunold, Gruber, Stadnytska, Werner, and Brosig (2010, submitted for publication in *Multivariate Behavioral Research*) focus on the analysis of dynamic process systems by means of VEC modeling with psychological data from different domains. It is conceptualized as a thorough guideline through the toolbox of cointegration methodology. The study of Stroe-Kunold and Werner (2009, published in *Quality & Quantity*) investigates the sensitivity of cointegration tests to detect spurious correlations between integrated processes, a problem frequently observed. Stroe-Kunold, Stadnytska, Werner, and Braun (2009, published in *Behavior Research Methods*) outline perspectives of future research on cointegrated processes displaying long-range dependence, evaluating estimators implemented in the software R.

4.1 Are Psychological Processes Cointegrated? (Stroe-Kunold & Werner, 2007, 2008)

As the official organ of the German Psychological Society (DGPs), the journal *Psychologische Rundschau* addresses a broad readership. In Stroe-Kunold and Werner (2007), we aimed at attracting their attention to cointegration by stimulating a discussion about the usefulness of the approach. After an introduction to time series analysis and the basic ideas behind cointegration, the review article reflects the present role of these methods in psychological research discussing possible perspectives as a psychological tool in different fields of application.

In Stroe-Kunold and Werner (2008), we introduce cointegration methodology in an international journal, hereby laying particular focus on the implications of the approach for the analysis of human dynamics. The introduction to time series analysis (as a first step) includes explaining Box-Jenkins ARIMA modeling as well as depicting the statistical implications of (non-)stationarity. The univariate perspective is extended to multivariate (i.e., vector) modeling, including the frequently used autoregressive (VAR) models mentioned before. Defining cointegration and vector error-correction (VEC) modeling is followed by a user-friendly step-by-step summary of cointegration analysis. For researchers, it is crucial to disentangle which testing procedures are helpful for applied researchers in indicating (non-)stationarity as well as finding out whether the series are cointegrated. Therefore, these procedures are described. Monte Carlo simulations (overview in Rubinstein, 1981) on short- and long-term cointegration parameters investigate how insights into these micro- and macro-dynamics of a cointegrated system may be gained. The knowledge is directly applied by interpreting the results of cointegration analysis conducted on the basis of a psychological data set indicating the sequence of actions necessary to be taken in a typical research situation (including coding as well as outputs).

Brief Comment The greatest merit of these papers is drawing cointegration methodology into the focus of psychological attention by revealing the basic procedures, illustrating their benefits by means of simulations as well as describing how they may be applied in psychological research by means of empirical examples. Additionally, the article described first reflects the scientific discourse on the topic. In econometric research, this approach has been a part of the methodological standard repertoire for many years. Every scientific domain imposes different requirements on a method as the data display properties particular for each domain. The publications described undertake such an adaptation on the firm basis of econometric research conducted in this concern before, thus serving the purpose of popularizing this method without drowning the reader in mathematical details. Evidently, insights into the methodology have become more elaborate in the course of the doctoral research. The publications depicted hereafter may document this.

4.2 Vector Error-Correction Modeling of Psychological Data (Stroe-Kunold et al., 2010)

In Stroe-Kunold et al. (2010), we present a comprising article about the analysis of dynamic process systems by means of cointegration methodology, focusing on VEC models as a frequently used representation of cointegrated systems. The kernel of this work is a systematic investigation of the mathematical models behind integrated and cointegrated processes as well as their VEC representations. Interpreting their parameters from a psychological perspective represents the greatest challenge. To sum up, the interpretation of VEC models is three-fold (based on three parameters). VEC modeling enables the researcher (1) to characterize the long-run equilibrium relation between cointegrated processes, (2) to identify whether and how a process system compensates or enhances short-term instabilities, and (3) to indicate self- and inter-regulation mechanisms in such systems. In these concerns, possible parameter variations and their interpretation are discussed, including cases with enhancing disequilibrium (i.e., the processes are not cointegrated). The structured findings serve as an interpretation guideline, illustrated by graphs on the basis of simulated series. In a first step, this analysis concentrates on bivariate (i.e., dyadic) systems, applying the insights directly to two psychological datasets from cognitive psychology and psychosomatics in a marital-interaction framework, thus exemplifying that the common stochastic trend as a system's driving force is easily identified in the experimental case while requiring a differentiated theoretical background in the clinical example. In a similar way, VEC models representing cointegrated systems of higher order are described implying an increasing complexity in the interpretation of common trends, in particular. Their usefulness is discussed based on empirical examples. Undoubtedly, the chosen complexity depends on the specific research interest. Our examples show, however, that bivariate VEC modeling provides a great deal of information about causal or interactional patterns. Aiming to find out whether a larger amount of processes functions as a system, a combined strategy is suggested.

Brief Comment This most recent paper of the doctoral project represents a thorough structure on which researchers can rely when applying cointegration methods to psychological data. The mathematical perspective induces a great deal of clarity on how these models should be interpreted. This may appear technical, especially in the section investigating the parameters of VEC modeling, but illustrative exemplification (e.g., the drunkard and her dog; empirical examples from different psychological domains) is undertaken throughout the paper. Interested readers can find more complex mathematical conclusions in an encompassing appendix. A conceptual discussion points out the relevance of this approach for psychological research.

4.3 Co-Integrated vs. Spuriously Related Integrated Processes (Stroe-Kunold & Werner, 2009)

Due to the characteristics of integrated processes described before, their significant correlation does not necessarily imply a meaningful relation, i.e., spurious interconnections may be indicated. To forestall spurious correlations, integrated series are usually transformed implying a possible loss of information inherent in the process. Obviously, the relation between co-integrated processes is meaningful. In Stroe-Kunold and Werner (2009), we study the implications of spurious relations for psychological research investigating adequate ways of prevention by means of cointegration methods. The paper introduces the problem of spurious correlations frequently addressed in scientific publications aiming at finding out in which way cointegration tools can contribute to their indication. As many of the postulated causal or feedback mechanisms in psychology reside within the organism, this topic has a high relevance. Our extensive study comprises four Monte Carlo simulations, beginning with a replication of the finding in Granger and Newbold (1974) that the probability of accepting the hypothesis of 'no relationship' becomes very small when regressions involve independent integrated processes. Note that these findings were regarded as an error of programming when presented for the first time at the London School of Economics by Clive Granger. Our replication underlines the relevance of this topic. A second simulation experiment shows that the methods of utilizing certain statistics for the identification of spurious relations as recommended by some authors is rather imprecise. A principal finding is that cointegration tests are a much more accurate alternative (third Monte Carlo study). Systematically varying the degree of dependency as well as synchronicity between the system's series, hereby considering causal as well as feedback relations, demonstrates the high sensitivity of cointegration tests. We find that they distinguish between spurious and meaningful relations even if the dependency between the processes is very low pointing out that beyond this usefulness, the researcher may gain interesting insights into the system dynamics if the processes are cointegrated.

Brief Comment The fact that many psychological processes are integrated implies that considerable care has to be taken concerning the problem of spurious correlations. The study contributes to this topic by proving that cointegration tools may serve as sensitive instruments in this concern thus additionally increasing their attractiveness for psychological researchers. Due to the simulated model spectrum, however, these findings neglect integrated processes not sharing a common stochastic trend, thus not cointegrated. Therefore, a combined approach utilizing both cointegration tests as well as the described statistics is advisable.

4.4 Perspectives of Research: Fractional Cointegration (Stroe-Kunold et al., 2009)

Cointegration methodology has been further developed including extensions considering cointegrated systems whose participating processes display long-range dependence. This phenomenon is called *fractional cointegration*. Numerous empirical studies (for an overview consult Wagenmakers et al., 2004) have demonstrated that many psychological time series exhibit a long memory, i.e., statistical dependence between observations separated by a large number of time units implying interesting dynamic features, in particular from a psychological perspective. Therefore aiming at investigating fractionally cointegrated systems in future research, we start with evaluating estimators capturing long-range dependence. Hereby, we focus on estimators implemented in R, a popular and freely available[10] software package frequently used in the applied social and behavioral sciences. After explaining the crucial concepts of fractal processes, reviewing empirical findings in this domain, and describing the available estimators, we undertake their systematic evaluation by means of a Monte Carlo study. The results indicate that the performance of certain estimators is much better than that of some of the others. Two examples combining these results with the procedure proposed by Delignières et al. (2006) illustrate how this evaluation can be used as a guideline in psychological research.

Brief Comment This paper offers a complement to recent studies in the domain of fractionally integrated processes. Considering the conceptual background of this thesis, their dynamic properties of self-similarity and self-organized criticality (SOC) are particularly interesting. Generally speaking, self-similar series possess similar statistical features at different scales (Mandelbrot & Wallis, 1969). The concept of SOC, introduced by Bak, Tang, and Wiesenfeld (1987), is consistent with the definition of self-organization described in section 2.3 of this thesis. This study, confined to fractional Gaussian noise, i.e., stationary series, aims at stimulating follow-up investigations on non-stationary fractional Brownian motion. Dealing with fractionally cointegrated systems in future studies, these findings need to be considered.

[10]This software can be downloaded from http://www.R-project.org.

5 Concluding Remarks

The purpose of this thesis is to introduce cointegration methodology to psychologists. Providing strategies for analyzing complex dynamic process systems, the cointegration approach is reflected as a tool of psychological research. Its application to psychological data is affirmed by well-known conceptual considerations. The process perspective effectuated by time series analysis allows conclusions about the structure of temporal variability in human phenomena. Instead of perceiving them as separate entities, the insight into their functioning can be improved by modeling them in the context of their common relational structure forming a dynamic system. Displaying unpredictable dynamics, processes non-stationary due to stochastic trends are called integrated, thus representing a challenging task in longitudinal analysis. Empirical studies prove, however, that numerous psychological processes exhibit these qualities. Hence, cointegration techniques accommodate such features treating multiple integrated processes as a dynamic system. Due to common stochastic trends, this cointegrated system is in stationary equilibrium in the long run in spite of individual short-term instabilities. Presuming the goal of matching methods with research problems, the findings described reveal the relevance of this approach for psychology. By means of simulations as well as empirical studies, the research provides a guideline on the crucial mathematical models as well as their interpretation from a psychological perspective. In this concern, issues of research practice such as spurious relations or long memory characteristics are addressed.

Based on the present work, future research may be two-fold. Clearly, the appropriateness of related approaches for psychological circumstances needs to be methodologically evaluated. Apart from the fractional cointegration analysis already mentioned, structural VEC models enabling the distinction between lagged and simultaneous influences in dynamic process system (Lütkepohl & Krätzig, 2004) or Bayesian VEC modeling (Congdon, 2003) are cases in point. It would be interesting to find out whether cointegration analysis can be enriched by techniques such as multivariate state-space modeling (see Molenaar et al., 2009). Above all, this thesis is designed to induce further psychological applications improving the understanding of dynamic process systems in psychology.

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Erklärungen

- **Erklärung gemäß § 8 Abs. 1 Buchst. b)**
  der Promotionsordnung der Universität Heidelberg für die Fakultät für Verhaltens- und Empirische Kulturwissenschaften:
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Heidelberg, März 2010

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