Is Timing Everything? Measurement Timing and the Ability to Accurately Model Longitudinal Data

by

Sebastian L.V. Sciarra

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ABSTRACT

IS TIMING EVERYTHING? MEASUREMENT TIMING AND THE ABILITY TO ACCURATELY MODEL LONGITUDINAL DATA

Sebastian L.V. Sciarra
University of Guelph, 2022

Advisor(s):
David Stanley

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DEDICATION

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1 Introduction

> "Neither the behavior of human beings nor the activities of organizations can be defined without reference to time, and temporal aspects are critical for understanding them" (Navarro et al., 2015, p. 136).

The topic of time has received considerable attention in organizational psychology over the past 20 years. Examples of well-received articles published around the beginning of the 21st century discuss how investigating time is important for understanding patterns of change and boundary conditions of theory (Zaheer et al., 1999), how longitudinal research is necessary for disentangling different types of causality (Mitchell & James, 2001), and explicate a pattern of organizational change (or institutionalization; Lawrence et al., 2001). Since then, articles have emphasized the need to address time in specific areas such as performance (Dalal et al., 2014; Fisher, 2008), teams (Roe et al., 2012), and goal setting (Fried & Slowik, 2004) and, more generally, throughout organizational research (Aguinis & Bakker, 2021; George & Jones, 2000; Kunisch et al., 2017; Navarro et al., 2015; Ployhart & Vandenberg, 2010; Roe, 2008; Shipp & Cole, 2015; Sonnentag, 2012; Vantilborgh et al., 2018).

The importance of time has also been recognized in organizational theory. In defining a theoretical contribution, Whetten (1989) discussed that time must be discussed in regard to setting boundary conditions (i.e., under what circumstances does the theory apply) and in specifying relations between variables over time (George & Jones, 2000; Mitchell & James, 2001). Even if a considerable number of organizational theories do not adhere to the definition of Whetten (1989), theoretical models in organizational psychology consist of path diagrams that delineate the causal underpinnings of a process. Given that temporal precedence is a necessary condition for establishing causality (Mill, 2011), time has a role, whether implicitly or explicitly, in organizational theory.

Despite the considerable attention given towards investigating processes over time and its ubiquity in organizational theory, the prevalence of longitudinal research has historically remained low. One study examined the prevalence of longitudinal research from 1970–2006 across five organizational psychology journals and found that 4% of articles used longitudinal designs (Roe, 2014). Another survey of two applied psychology journals in 2005 found that approximately 10% (10 of 105 studies) of studies used longitudinal designs (Roe, 2008). Similarly, two surveys of studies employing longitudinal designs with mediation analysis found that, across five journals, only about 10% (7 of 72 studies) did so in 2005 (Maxwell & Cole, 2007) and approximately 16% (15 of 92 studies) did so in 2006 (Mitchell & Maxwell, 2013).[1] Thus, the prevalence of longitudinal research has remained low.

In the seven sections that follow, I will explain why longitudinal research is necessary and the factors that must be considered when conducting such research. In the first section, I will explain why conducting longitudinal research is essential for understanding the dynamics of psychological processes. In the second section, I will overview patterns of change that are likely to emerge over time. In the third and fourth sections, I will, respectively, discuss some methods for modelling nonlinear change and the frameworks in which they can be used. In the fifth section, I will overview design and analytical issues involved in designing longitudinal studies. In the sixth section, I will explain how design

[1]Note that the definition of a longitudinal design in Maxwell & Cole (2007) and Mitchell & Maxwell (2013) required that measurements be taken over at least three time points so that measurements of the predictor, mediator, and outcome variables were separated over time.

and analytical issues encountered in conducting longitudinal research can be investigated. Finally, in the seventh section, I will provide a systematic review of the research that has investigated design and analytical issues involved in conducting longitudinal research. A summary of the three simulation experiments that I conducted in my dissertation will then be provided.

1.1 The Need to Conduct Longitudinal Research

Longitudinal research provides substantial advantages over cross-sectional research. Unfortunately, researchers commonly discuss the results of cross-sectional analyses as if they have been obtained with a longitudinal design. However, cross-sectional and longitudinal analyses often produce different results. One example of the assumption that cross-sectional findings are equivalent to longitudinal findings comes from the large number of studies employing mediation analysis. Given that mediation is used to understand chains of causality in psychological processes (Baron & Kenny, 1986), it would thus make sense to pair mediation analysis with a longitudinal design because understanding causality, after all, requires temporal precedence. Unfortunately, the majority of studies that have used mediation analysis have done so using cross-sectional designs—with estimates of approximately 90% (Maxwell & Cole, 2007) and 84% (Mitchell & Maxwell, 2013)—and have often discussed the results as if they were longitudinal. Investigations into whether mediation results remain equivalent across cross-sectional and longitudinal designs have repeatedly concluded that using mediation analysis on cross-sectional data can return different, and sometimes completely opposite, results from using it on longitudinal data (Cole & Maxwell, 2003; Maxwell et al., 2011; Maxwell & Cole, 2007; Mitchell & Maxwell, 2013; O'Laughlin et al., 2018). Therefore, mediation analyses based on cross-sectional analyses may be misleading.

The non-equivalence of cross-sectional and longitudinal results that occurs with mediation analysis is, unfortunately, not due to a specific set of circumstances that only arise with mediation analysis, but a consequence of a broader systematic cause that affects the results of many analyses. The concept of ergodicity explains why cross-sectional and longitudinal analyses seldom yield similar results. To understand ergodicity, it is first important to realize that variance is central to many statistical analyses—correlation, regression, factor analysis, and mediation are some examples. Thus, if variance remains unchanged across cross-sectional and longitudinal data sets, then analyses of either data set would return the same results. Importantly, variance only remains equal across cross-sectional and longitudinal data sets if two conditions put forth by ergodic theory are satisfied (homogeneity and stationarity; Molenaar, 2004; Molenaar & Campbell, 2009). If these two conditions are met, then a process is said to be ergodic. Unfortunately, the two conditions required for ergodicity are highly unlikely to be satisfied and so cross-sectional findings will frequently deviate from longitudinal findings (for a detailed discussion, see Appendix **??**).

Given that cross-sectional and longitudinal analyses are, in general, unlikely to return equivalent findings, it is unsurprising that several investigations in organizational research—and psychology as a whole—have found these analyses to return different results. Beginning with an example from Curran & Bauer (2011), heart attacks are less likely to occur in people who exercise regularly (longitudinal finding), but more likely to happen when exercising (cross-sectional finding). Correlational studies find differences in correlation magnitudes between cross-sectional and longitudinal data sets Fisher et al.

(2018).[2] Moving on to perhaps the most commonly employed analysis in organizational research of mediation, several articles have highlighted cross-sectional data can return different, and sometimes completely opposite, results to longitudinal data (Cole & Maxwell, 2003; Maxwell et al., 2011; Maxwell & Cole, 2007; O'Laughlin et al., 2018). Factor analysis is perhaps the most interesting example: The well-documented five-factor model of personality seldom arises when analyzing person-level data that was obtained by measuring personality on 90 consecutive days (Hamaker et al., 2005). Therefore, cross-sectional analyses are rarely equivalent to longitudinal analyses.

Fortunately, technological advancements have allowed researchers to more easily conduct longitudinal research in two ways. First, the use of the experience sampling method (Beal, 2015) in conjunction with modern information transmission technologies—whether through phone applications or short message services—allows data to sometimes be sampled over time with relative ease. Second, the development of analyses for longitudinal data (along with their integration in commonly used software) that enable person-level data to be modelled such as multilevel models (Raudenbush & Bryk, 2002), growth mixture models (Mo Wang & Bodner, 2007), and dynamic factor analysis (Ram et al., 2013) provide researchers with avenues to explore the temporal dynamics of psychological processes. With one recent survey estimating that 43.3% of mediation studies (26 of 60 studies) used a longitudinal design (O'Laughlin et al., 2018), it appears that the prevalence of longitudinal research has increased from the 9.5% (Roe, 2008) and 16.3%

[2] Note that Fisher et al. (2018) also found the variability of longitudinal correlations to be considerably larger than the variability of cross-sectional correlations.

(Mitchell & Maxwell, 2013) values estimated at the beginning of the 21st century. Although the frequency of longitudinal research appears to have increased over the past 20 years, several avenues exist where the quality of longitudinal research can be improved, and in my dissertation, I focus on investigating these avenues.

1.2 Understanding Patterns of Change That Emerge Over Time

Change can occur in many ways over time. One pattern of change commonly assumed to occur over time is that of linear change. When change follows a linear pattern, the rate of change over time remains constant. Unfortunately, a linear pattern places demanding restrictions on the possible trajectories of change. If change were to follow a linear pattern, then any pauses in change (or plateaus) or changes in direction could not occur: Change would simply grow over time. Unfortunately, effect sizes have been shown to diminish over time (for meta-analytic examples, see Cohen, 1993; Griffeth et al., 2000; Hom et al., 1992; Riketta, 2008; Steel et al., 1990; Steel & Ovalle, 1984). Moreover, many variables display cyclic patterns of change over time, with mood (Larsen & Kasimatis, 1990), daily stress (Bodenmann et al., 2010), and daily drinking behaviour (Huh et al., 2015) as some examples. Therefore, change over is unlikely to follow a linear pattern.

A more realistic pattern of change to occur over time is a nonlinear pattern (for a review, see Cudeck & Harring, 2007). Nonlinear change allows the rate of change to be nonconstant; that is, change may occur more rapidly during certain periods of time, stop altogether, or reverse direction. When looking at patterns of change observed across psychology, several examples of nonlinear change have been found in the declining rate of speech errors throughout child development (Burchinal & Appelbaum, 1991), rates of forgetting (Murre & Dros, 2015), development of habits (Fournier et al., 2017), and the formation of opinions (Xia et al., 2020). Given that nonlinear change appears more likely than linear change, my dissertation will assume change over time to be nonlinear.

1.3 Methods of Modelling Nonlinear Patterns of Change Over Time

Given that, unlike modelling linear change, several methods exist for modelling nonlinear change, it is important to discuss these methods. On this note, I will provide an overview of two commonly employed methods for modelling nonlinear change: 1) the polynomial approach and 2) the nonlinear function approach.[3,4] Importantly, the simulation experiments in my dissertation will use the nonlinear function approach to model nonlinear change.

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[3]It should be noted that nonlinear change can be modelled in a variety of ways, with latent change score models (e.g., O'Rourke et al., 2021) and spline models (e.g., Fine & Grimm, 2020) offering some examples.

[4]The definition of a nonlinear function is mathematical in nature. Specifically, a nonlinear function contains at least one parameter that exists in the corresponding partial derivative. For example, in the logistic function $\theta + \frac{\alpha-\theta}{1+exp(\frac{\beta-t}{\gamma})}$ is nonlinear because β exists in $\frac{\partial y}{\partial \beta}$ (in addition to γ existing in its corresponding partial derivative). The n^{th} order polynomial function of $y = a + bx + cx^2 + ... + nx^n$ is linear because the partial derivatives with respect to the parameters (i.e., $1, x^2, ..., x^n$) do not contain the associated parameter.

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