Inferences With Longitudinal Data

Christopher R. Dishop[1], Michael T. Braun[2], Goran Kuljanin[3], & Richard P. DeShon[1]

[1] Michigan State University

[2] University of South Florida

[3] DePaul University

Author Note

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Correspondence concerning this article should be addressed to Christopher R. Dishop, 316 Physics Road, Psychology Building, Room 348, East Lansing, MI, 48823. E-mail: dishopch@msu.edu

Abstract

Organizational scientists recognize that psychological phenomena and processes unfold over time. To better understand psychological phenomena over time, organizational researchers increasingly work with longitudinal data and explore inferences within those data structures. Longitudinal inferences may focus on any number of fundamental patterns, including construct trajectories, relationships between constructs, or dynamics. Although the diversity of longitudinal inferences provides a wide foundation for garnering knowledge in any given area, it also makes it difficult for researchers to know the set of inferences they may explore with longitudinal data, which statistical models to use given their question, and how to locate their specific study within the broader set of longitudinal inferences. In this paper, we develop a framework to describe the variety of between-unit research questions and inferences researchers may explore with longitudinal data and link those inferences to statistical models so researchers know where to turn to given their particular interests.

Keywords: longitudinal inferences, growth trends, dynamics, relationships over time, processes

Word count: 151

Inferences With Longitudinal Data

Organizational scientists recognize that psychological phenomena and processes unfold over time (Beal, 2015; Pitariu & Ployhart, 2010). Individuals in the workplace, over time, strive to accomplish work goals, team members collaborate so the whole eventually becomes greater than the sum of its parts, and managers repeatedly promote values to build vibrant, innovative work cultures. To better understand psychological phenomena, such as motivation, teamwork, and organizaitonal culture, researchers must attent not to static snapshots of behavior (Ilgen & Hulin, 2000; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013, 2016) but to variables and relationships as they move through time. They must observe or obtain longitudinal data capturing the unfolding set of events, interactions, behaviors, cognitions, or affective reactions responsible for psychological phenomena.

Researchers may explore a variety of inferences when they analyze longitudinal data. For example, researchers may examine the shape of trajectories on psychological constructs (e.g., did job satisfaction generally increase or decrease over six months after a merger?), how two or more constructs relate to each other (e.g., did team communications and cohesion positively correlate over time?), or whether changes in one variable relate to changes in another (e.g., did changes in goal-setting lead to changes in employee performance?; Dunford, Shipp, Boss, Angermeier, & Boss, 2012; Hardy, Day, & Steele, 2018; Jones et al., 2016; Judge, Simon, Hurst, & Kelley, 2014; Lanaj, Johnson, & Wang, 2016; Rosen, Koopman, Gabriel, & Johnson, 2016; Scott & Barnes, 2011). Given the variety of inferences researchers may explore with longitudinal data, an organizing framework would elucidate their subtle differences, enhance theoretical insight, guide data collection, and facilitate sound analytical work.

We developed a framework to capture these inferences, a way to organize the fundamental patterns researchers explore with longitudinal data despite focusing on different content areas or using different statistical models. Researchers often focus on one famililiar inference despite having the data to explore many more fundamental patterns. We bring attention to the span of questions available so that researchers can fully appreciate and take advantage of their data. Moreover, there are many complex statistical models lingering in our literature and it is not always clear for which questions they are appropriate. We provide readers with potential models for each inference so that they can be sure that the model they evoke is appropriate for the reseearch question that they are interested in. In summary, this paper exposes researchers to the span of inferences they may investigate when they collect longitudinal data, links those inferences to statistical models, and explains differences between various longitudinal inferences.

Longitudinal Research in Psychology

This paper is devoted to inferences with repeated measures, so we begin with a few labels and definitions. Authors typically identify a "longitudinal" study by contrasting either (a) research designs or (b) data structures. Longitudinal *research* is different from cross-sectional research because longitudinal designs entail three or more repeated observations (Ployhart & Vandenberg, 2010). We therefore emphasize differences on the number of observations when we distinguish longitudinal from other types of research. Longitudinal or panel *data* are repeated observations on several units (i.e., N or $i > 1$), whereas time-series data are observations of one unit over time – a distinction that focuses on the amount of people in the study (given repeated measures). Most organizational studies collect data on more than one unit, therefore our discussion below focuses on longitudinal research with panel data, or designs with $N > 1$, $t \geq 3$, and the same construct(s) measured on each i at each t. That is, we focus on designs with repeated measures across many people (units) where every variable is measured at each time point.

Longitudinal applies to both short and long-term research. An experiment with ten trials is longitudinal, as is a study spanning 10 years that assesses its measures once every year. Longitudinal is not reserved for "long-term" studies that last more than one year irrespective of the frequency of their observations. Rather, certain processes unfold over short time horizons (e.g., decision-making on simple tasks) whereas other psychological phenomena unfold over long time horizons (e.g., the development of a shared organizational culture; Mitchell & James, 2001), so the informativeness of a particular study depends on its rationale, research design, analytical work, and effective interpretation of results – as with any study. Short and long time horizons both offer valuable insights.

Framework for Longitudinal Inferences

We use three inference categories to partition our discussion, including trends, relationships, and dynamics. Briefly, longitudinal inferences focusing on trends assess whether trajectories follow a linear or curvilinear pattern or whether trends differ between-units; longitudinal inferences focusing on relationships between constructs assess the between-unit relationship among one or more constructs; longitudinal inferences focusing on dynamics in constructs assess how one or more constructs evolve as functions of themselves and each other. Each category comes with box-and-arrow model heuristics[1] that represent the broad inferences, research questions to orient the reader as to what the sub-inferences capture (i.e., inferences are the answers to the research questions that we present), and a discussion of statistical models.

Although we use box-and-arrow diagrams throughout to represent the broad inferences, we also graph a few of the more challenging inferences with mock data – some of the

[1] Note that statistical models differ from the term, "model heuristic" that we use in the inference sections. A model heuristic is a visual representation only, whereas a statistical model is characterized by a formula explaining the data, assumptions on the errors, and an estimation technique. In this paper, we never use the term, "model" without pairing it either with "statistical" or "heuristic" – the two differ substantially.

inferences in the trend and relationships sections are difficult to grasp without seeing them in data form. Keep in mind, however, that data are always messy. It is rare to find data where the inferences expose themselves simply by plotting – althought it is certainly possilbe. We use these “data plots” to clearly convey what the inferences mean, but be aware that field data are often noisy.

Finally, despite pointing researchers to statistical models, our paper puts a majority of its emphasis on inferences, therefore researchers need to be sure that they appreciate all of the nuance before applying a recommended statistical model. Numerous issues arise when modeling longitudinal data and the statistical models differ in how they handle these issues, the assumptions they make, and the data format they require. We do not speak directly to those issues here, but we refer readers to a number of informative references for each statistical model.

Trend

Made popular in the organizational literature by Bliese and Ployhart (2002) and Chan (1998), trend inferences represent a class of thinking where researchers create an index of time and relate it to their response variable. The first panel of Figure 1 shows a box-and-arrow model heuristic where time is related to an outcome, y, and ultimately the analyst is interested in a variety of questions about trend and its correlates. Trend inferences have two components: trend itself and level. For clarity, we discuss them separately.

Component 1 - Trend. Does affect, in general, go up or down across time, or is its trajectory relatively flat? Does trainee skill generally increase over the training session? These are questions about trend, and these first two are specifically about linear trend. It is also possible to explore how variables bend or curve across time. Do newcomer perceptions of climate increase and then plateau over time? Does the response time of a medical team decrease with each successive case but then remain stable once the team can no longer improve their coordination? These latter questions concern curvilinear trajectories.

Trend has to do with the systematic direction or global shape of a trajectory across time. If we put a variable on the y-axis and plot its values against time on the x-axis, do the values tend to go up or down over time? It can be thought of as the coarse-grained direction of a trajectory. A positive trend indicates that, on average across units, we expect the variable to increase over time and a negative trend indicates that we expect the variable to decrease over time. Our first trend research question, therefore, concerns the shape of the trajectory.

Research Question 1: On average across units, is there a positive/negative/curvilinear trend?

Many research questions and inferences begin with the average pattern (or relationship) and then move to variability, the same applies here. After learning about the average trend across the sample researchers then focus on trend variability. How much consistency is there in the trend pattern? Do all trainees develop greater skill across time? Is there variability in the trend of helping behaviors, or counterproductive work behaviors over time?

Research Question 2: Does trend differ across units?

Research questions one and two concern one variable, but they can also be iterated across all observed variables. For example, we might discover that – on average across unit – affect and performance trends both decrease, but there is greater variability across units in the affect trend. Or we might learn that affect has a negative trend while performance has a positive trend.

Correlating these trends between-units is the next inference. Correlating indicates co-occuring patterns, where a large, positive, between-unit correlation between affect and performance trends would indicate that people with a positive affect trend (usually) have a positive performance trend and people with a negative affect trend (usually) have a negative performance trend.

Figure 2 shows the inuition behind this inference with a set of graphs. In Panel A, we plot affect and performance across time for three individuals. Affect goes up while performance goes down for person one, this pattern is reversed for person two, and person three reports trendless affect and performance (i.e., zero trend). We use different colors to label the trends for each person. The affect and performance trends for person one are labeled with red lines, whereas person two has green lines and person three has blue lines.

Panel B then maps those pairings onto a scatterplot that demonstrates the between-unit relationship among affect and performance trends. For example, person one has a positive affect trend and a negative performance trend, so their value in Panel B goes on the bottom right, whereas person two has the opposite pattern and therefore is placed on the top left (where the performance trend is positive and the affect trend is negative). Producing this bottom scatter plot tells us that the between-unit association among affect and performance trends is negative. That is, people with a positive affect trend are expected to have a negative performance trend, people with a negative affect trend are expected to have a positive performance trend, and people with an affect trend of zero are expected to have a performance trend of zero.

Insert Figure 2 about here

Research Question 3: What is the between-unit trend correlation?

The final trend inference is about identifying covariates or predictors of trend. Does gender predict depletion trends? Does the trend in unit climate covary with between-unit differences in leader quality?

Figure 3 demonstrates the inference in a plot. We graph affect across time for six employees, and these employees differ by job type. The first three individuals work in research and development, whereas the final three work in sales. Affect trajectories tend to decrease over time for employees in research and development, whereas affect trajectories tend to increase for those in sales. An individual's job type, then, gives us a clue to their likely affect trend – said formally, job type covaries with affect trend, such that we expect individuals in sales to have positive affect trends and individuals in research and development to have negative affect trends. The expected trends are plotted as the thick blue lines.

Insert Figure 3 about here

> **Research Question 4:** What is the betweeen-unit correlation among trend and a covariate?

Note the difference between research questions three and four. Both are between unit, but three is about co-occuring trend patterns whereas four is about the relationship between trend and a covariate/predictor. With respect to our examples, inference three (i.e., the answer to research question three) says, on average, if an individual has a positive affect trend then we expect her to have a negative performance trend. Inference four says, on average, if an individual is in research and development then we expect him to have a negative affect trend.

Component 2 - Level. Researchers that explore trend also assess its predicted value at a given time t, and this second component is called level. Level is almost always evaluated at the first or last observed time point – e.g., What is the predicted level of the trainee skill trend, on average across units, at the beginning of a training session? On average across units, what is the expected level of the unit climate trend at the end of a two-week socialization process? – although researchers are free to asssess level at any t.

Research Question 5: On average across units, what is the expected level of the y trend at time t?

After exploring the average (across units) trend level at a certain time we then move to its variability. Trend lines have a beginning (or end) point, how consistent do we expect that point to be across the sample? Is there variability in affect trend starting level? Are there large between-unit differences in the expected level of the performance trend at the last time point?

Research Question 6: Is there variability across units in the expected level of the y trend at time t?

It is also possible to assess between-unit correlations among level and (a) trend in the same variable or (b) level or (c) trend in a different variable. First, consider a relationship among level and trend in the same variable. On average across units, do people with low initial skill show positive skill trends whereas people with high initial skill show negative skill trends? Do organizations with high initial CWBs, on average across units, tend to have negative CWB trends?

Research Question 7: What is the between-unit correlation between trend and level in y?

Second, consider a between-unit correlation between level in one variable and level in another. On average across units, do people with a low initial performance also have low initial depletion (based on the initial levels predicted by the performance and depletion trends)? Are organizations with high initial turnover also expected, on average across units, to have high burnout (based on the initial levels predicted by the turnover and burnout trends)?

> **Research Question 8:** What is the between-unit correlation between level of the x trend and level of the y trend at t?

Finally, researchers are free to mix the inferences above and assess whether levels in one variable covary with trend in another. Are people with high initial voice (predicted by the voice trend) expected to have negative satisfaction trends?

> **Research Question 9:** What is the between-unit correlation between the level of the x trend at time t and the trend in y?

A note on phrasing. The inferences we explored in this section have to do with correlating levels and trends, where a statement like "affect and performance trends covary between-units, such that people with a negative affect trend have a positive performance trend" is appropriate. There is a less precise phrase that is easy to fall into – and we have seen it used in our literature. Sometimes, researchers will correlate trends and then state, "when affect decreases performance goes up." We urge researchers to avoid this second statement because it is not clear if it refers to a static relationship about trends or a dynamic statement about how trajectories move across time. That is, the phrase "when affect decreases performance goes up" could refer to between-unit correlated trends, but it could also mean something like, "when affect decreases performance immediately or subsequently goes up." This second statement is far different and it should not be used when an analysis only correlates trends or evokes predictors of trend. Again, we urge researchers to phrase their inferences as we have shown here.

Statistical Models

Trend is called the slope in the statistical modeling literature. That is, when a researcher estimates a model to explore whether a variable goes up or down over time she is estimating the trend coefficient. The mean estimate refers to trend itself, whereas the variance estimate refers to the trend variability across units. In the statistical modeling literature these models are called growth-models or growth-curves. Keep in mind, however, that researchers use the word "change" informally to mean growth as well, so when you read a theoretical discussion you may see words like "change" and "increase" despite the researcher using a "growth" statistical model.

Broad theoretical discussions of growth are in Pitariu and Ployhart (2010) and Ployhart and Vandenberg (2010) (keep in mind that they call growth "change"), whereas Bliese and Ployhart (2002) describe actual growth-curve analysis. Growth curves are a core topic in developmental psychology, so there are many great articles and textbooks to read from their field. See Grimm, Ram, and Estabrook (2016) and Singer, Willett, and Willett (2003) for two great textbooks on growth curve modeling, and McArdle and Epstein (1987) for an empirical discussion. Two straight-forward empirical examples in our own field are in Dunford et al. (2012) and Hülsheger (2016).

Relationships

A relationships inference explores between-unit relationships over time, the second panel of Figure 1 shows a model heuristic. A predictor is concurrently related to a response variable at each time point and the relationship is typically constrained to equality or is averaged over time. Essentially, the inference compiles single-moment between-unit correlations. For example, we assess the between-unit correlation between, say, OCBs and depletion at time one, again and times two and three, and then ultimately take the average of each individual correlation.

Questions about static relationships over time take the following forms. What is the relationship between helping behaviors and incivility? Does burnout predict turnover intention? Is unethical behavior related to self-control?

Figure 4 shows the inuition of the inference with data. Panel A plots affect and performance trajectories for three people. The red circles in Panel A highlight each individual's affect and performance values at time point six. Given that we have three people at time point six, we can calculate a correlation between affect and performance at that moment (granted, it is a small sample). The calculated coefficient is then graphed in Panel B with another red circle. At time point six, the correlation between affect and performance across people is large and positive.

Insert Figure 4 about here

Panel B also shows between-unit correlation coefficients for the rest of the time points. Often these (between-unit) correlations are either averaged over time or constrained to be equal. Note that when a researcher uses a time-varying covariates, hierarchical linear, random-coefficient, or multi-level model on longitudinal data to explore concurrent relationships among one or more variables (and they are not analyzing trend) they are making this inference.

> **Research Question 1:** What is the average between-unit relationship of x and y? (Typically constrained to be equal over time or averaged over time).

The first relationships inference emphasizes the between-unit expected average. As with the trend inferences, the next question is to examine variability in that estimated relationship across the sample. How consistent across the sample is the relationship between distractions and fatigue? Is there variability in the relationship between emotions and volunteering behaviors?

> **Research Question 2:** What is the variability across units in the between-unit relationship among x and y?

Statistical Models

Time-varying covariates (tvc) analysis is the workhorse behind relationship inferences. A discussion of tvc models is in Schonfeld and Rindskopf (2007) and Finch, Bolin, and Kelley (2016). Relatively straight-forward empirical examples are in Barnes, Schaubroeck, Huth, and Ghumman (2011) and Chi, Chang, and Huang (2015).

Dynamics

Dynamics refers to a specific branch of mathematics, but the term is used in different ways throughout our literature. It is used informally to mean "change", "fluctuating," "volatile," "longitudinal," or "over time" (among others), whereas formal definitions are presented within certain contexts. Wang (2016) defines a dynamic *model* as a "representation of a system that evolves over time. In particular it describes how the system evolves from a given state at time t to another state at time $t + 1$ as governed by the transition rules and potential external inputs" (p. 242). Vancouver, Wang, and Li (2018) state that dynamic *variables* "behave as if they have memory; that is, their value at any one time depends somewhat on their previous value" (p. 604). Finally, Monge (1990) suggests that in dynamic *analyses*, "it is essential to know how variables depend upon their own past history" (p. 409). In this section we discuss a number of inferences couched in the idea that the past constrains future behavior.

Does performance relate to itself over time? Do current helping behaviors depend on prior helping behaviors? Does unit climate demonstrate self-similarity across time? Does income now predict income in the future? These are questions about the relationship of a single variable with itself over time – does it predict itself at each subsequent moment? Is it constrained by where it was in the past?

Panel A of Figure 5 shows the concept with a box-and-arrow model heuristic. y predicts itself across every moment – it has self-similarity and its value now is constrained by where it was a moment ago. In our diagram, we show that y at time t is related to y at time $t+1$. In other words, we posit that y shows a lag-one relationship, where y is related to its future value one time-step away. Researchers are of course free to suggest any lag amount that they believe captures the actual relationship. Note that the statistical term to capture self-similarity or memory is called autoregression.

> **Research Question 1:** On average across units, what is the relationship of y to itself over time? (Autoregression)

Insert Figure 5 about here

As before, after exploring the expected average we turn to variability. How consistent are the self-similarity relationships? Are there between-unit differences in autoregression in, for example, employee voice? Do we expect a large variance in the autoregression of helping behaviors?

Research Question 2: What is the variability across units in the expected autoregression of y?

The next inference is about relating a predictor to our response variable while it still retains memory. Panel B of Figure 5 shows a box-and-arrow diagram: y is predicted by concurrent values of x but it also retains self-similarity. This model is therefore said to partial prior y: it examines the concurrent relationship between x and y while statistically partialling values of y at $t - 1$, or statistically accounting for y at the prior moment.

Our literature has converged on calling this kind of relationship "change" because it emphasizes the difference between y now and where it was in the past (e.g., Lanaj et al., 2016; Rosen et al., 2016). The association asks how current x relates to the difference between y now and its immediately prior value. How does affect relate to change in performance? Does depletion covary with change in OCBs? Note that change can be construed from any prior time point (baseline, the prior time point, $t - 3$); our literature commonly emphasizes lag-one change.

Research Question 3: On average across units, what is the relationship betweeen concurrent x and change in y?

The analyst is also free to assess variability in the expected change relationship.

Research Question 4: What is the variability across units in the expected change relationship between concurrent x and y?

Change relationships do not have to be concurrent. Panel C of Figure 5 shows concurrent relationships as we saw above but it also includes lags from the predictor to the outcome. y retains memory, but it is predicted by both concurrent and prior values of x. Typically, we call these cross-lag relationships.

Questions about lag-one change relationships take the following forms. Does affect predict subsequent performance change? Do prior counterproductive work behaviors relate to current incivility change? Does metacognition predict subsequent exploratory behavior change? Of course, researchers can also explore longer lags by relating predictors to more distal outcomes.

> **Research Question 5:** On average across units, what is the cross-lag relationship between x and change in y at a different point in time?

Again, typically researchers explore variability after assessing the average estimate.

> **Research Question 6:** What is the variability over units in the expected cross-lag relationship of change?

Extensions

We described a simple set of inferences above, but the ideas generalize to more complex dynamics as well. Often researchers are interested in reciprocal relationships, where x influences subsequent y, which then goes back to influence x at the next time point. Said formally, x_t influences y_{t+1}, which then influences x_{t+2}. Said informally, current performance influences subsequent self-efficacy, which then influences performance on the next trial. These inferences are no different than what we saw above – they are cross-lag predictions – all we did was add more of them. Panel D of Figure 5 shows reciprocal dynamics, where both x and y show self-similarity and cross-lag relationships with one another.

Researchers typically posit a sequence of single cross-lag predictions when they are interested in reciprocal dynamics. For example, Hardy III, Day, and Steele (2018) explored reciprocal relationships among performance and motivation (self-efficacy, metacognition, and exploratory behavior). Their hypotheses include, (1) prior self-efficacy negatively relates to subsequent exploratory behavior and (2) prior exploratory behavior positively relates to subsequent self-efficacy (among others). These single inferences are used in aggregate to make conclusions about reciprocal influence.

The dynamic inferences shown here also generalize to systems of variables where a researcher posits self-similarity and cross-lag predictions across many variables. There could be reciprocal dynamics between a set of variables like performance, self-efficacy, and affect, or a sequence of influence between dyadic exchanges, performance, and team perceptions: perhaps initial dyadic exchanges influence subsequent team perceptions, which later influence performance. Following the performance change, the structure of the task updates and this initiates new dyadic exchanges. Once a researcher grasps the foundational ideas presented here he or she is free to explore any number of complex relationships.

Also notice that complex dynamics subsume the concept of mediation. It is of course an important idea, but when we focus on systems of variables and reciprocal dynamics we place our emphasis elsewhere. If readers are interested in mediation we urge them to read one of the many great papers on it (Maxwell & Cole, 2007; Maxwell, Cole, & Mitchell, 2011; Stone-Romero & Rosopa, 2008).

Models

Wang et al. (2016) reviews many different types of dynamic models and, although his paper will not provide readers will specific code it is an excellent starting paper to observe the variety of dynamic models.

Discussion

There are many different patterns to explore with longitudinal data structures. This paper, by unpacking between-unit patterns, mirrors the common questions and inferences currently emphasized by organizational scientists. What is the between-unit relationship (averaged over time)? What is the between-unit expected trend? Are there between-unit differences in trend (also phrased as, "between-unit differences in within-unit change")? We organized these questions and inferences into a fundamental set, discussed what they mean, and linked the inferences to appropriate statistical models. Ultimately, researchers should now be able to understand the spectrum of between-unit inferences that they can explore with rich, longitudinal data.

Between-unit questions are common and useful, but an alternative lens to asking questions and making inferences with repeated measures is to focus on within-unit patterns. Within-unit inferences emphasize fluctuations over time rather than across units. For example, Beal (2015) notes that many of the psychological phenomenon in which we are interested are "sequences of events and event reactions that happen within each person's stream of experience" (p. 5). This is a within-unit statement: it assesses how a construct moves through time within a single individual.

Organizational scientists have become increasingly interested in within-unit perspectives over the past decade. Dalal, Bhave, and Fiset (2014) review theory and research on within-person job performance, Grandey and Gabriel (2015) review emotional labor and differentiate a variety of within-person perspectives, Park, Spitzmuller, and DeShon (2013) present a team motivation model describing within-individual resource allocation and within-team feedback, Vancouver, Weinhardt, and Schmidt (2010) present a within-person model of multiple-goal pursuit, Barnes (2012) describes recent within-person approaches to sleep and organizational behavior, and Methot, Lepak, Shipp, and Boswell (2017) present a within-person perspective of organizational citizenship behaviors.

Taking a within-persons perspective requires greater T – researchers must collect observations over more time points. To collect more observations (over time), researchers can extend their sampling periods (e.g., collect once-a-week observations for 50 weeks rather than 10) or increase the frequency of their observations (e.g., sample three, rather than two, times per day). Adding additional observations of course increases the power of the analysis, but it also allows researchers to assess important statistical properties that must receive attention – although they are currently absent in our literature – during within-unit modeling: stationarity and ergodicity.

Processes give rise to observed data, and those observed data are characterized by distributions and their moments. Stationarity is about whether or not the statistical characteristics of a process remain stable over time. When they do, the analyst has permission to use a variety of regression-based techniques like those described in this paper without additional concerns of faulty inferences. When trajectories are non-stationary, however, then the inferences drawn from regression-based techniques are often misguided (Granger & Newbold, 1974). Growth-models assume non-stationarity, whereas the other statistical models discussed in this paper assume stationarity. Full explanations of stationarity are in Kuljanin, Braun, and DeShon (2011), Braun, Kuljanin, and DeShon (2013), Jebb, Tay, Wang, and Huang (2015), and Metcalfe and Cowpertwait (2009), we draw attention to it here to emphasize that studies with greater T have the ability to assess stationarity and understand which statistical models are appropriate. Moreover, finding evidence of (non)stationary is useful theoretical knowledge and needs to take the foreground of studies that collect longitudinal data.

Ergodicity is another statistical characteristic of a process, and it is important because it determines whether or not researchers can generalize inferences about inter-individual variability from tests of between-unit differences to inferences of within-unit variability. To see the dilemma, consider the following. First, the standard statistical models in psychology and management, such as growth curves, multi-level models, mixture modeling, ANOVA, and factor analysis all focus on between-unit variation (Molenaar, 2004). Second, researchers using these techniques run their computations on a sample drawn from a population and then generalize their results back to the population, so (a) the results live at the level of the population and (b) researchers assume that the population (or sub population in mixture modeling) is homogenous (Molenaar & Campbell, 2009). These notions are fine on their own, but researchers tend to make an additional assumption that is unlikely to hold: because resuls live at the level of the population and because researchers assume that the population is homogenous they often also assume that the results apply to the individuals making up the population (Molenaar, 2008b). In other words, they assume that the results from a test of between-unit variation hold at the level of within-individual variation.

When processes are ergodic, this implicit assumption holds: the results of an analysis of between-unit differences generalize to within-unit patterns and vice versa (Molenaar, 2007, 2008a). Researchers can generalize with ergodic processes, they can use a multi-level model to assess between-unit patterns and then make statements about within-person relationships. But this generalization is rarely appropriate. A Gaussian process is non-ergodic if it is non-stationarity (e.g., it has time-varying trends) and/or heterogeneous across subjects (subject-specific dynamics). Stated simply, a Gaussian process is non-ergodic if it has trend and/or Susie's trajectory is different from Bob's. If either is violated, which is often the case, then standard analyses of between-subject differences (growth models, multi-level or random-coefficient models, mixture models, ANOVA, factor analysis) cannot be used to make within-person statements. In general, within-person inferences need to come from unpooled, subject-specific time-series data structures (Molenaar, 2009).

Collecting large samples across many time points allows researchers to assess stationarity and ergodicity. We urge researchers to start focusing on both so that our field can begin to understand the similarities and differences among between-unit and within-unit relationships. Again, researchers must collect data across many time points to do so.

Often, though, researchers have finite resources and must decide whether to emphasize between-unit or within-unit patterns. Your data collection should align with the inference that you are interested in. If you care about between-unit patterns (as shown in this paper), focus on N – collect data on many participants. If you care about within-unit patterns, focus on T – collect data across many time points. Large samples across many time points of course gives researchers the ability to explore both frameworks, but our field will need to recognize that a small samples (e.g., five or fewer participants) measured across many time points does allow a researcher to make within-person inferences. Given the resource constraints that come with conducting research, we cannot shy away from few participants measured across many time points as viable techniques to assessing within-person relationships.

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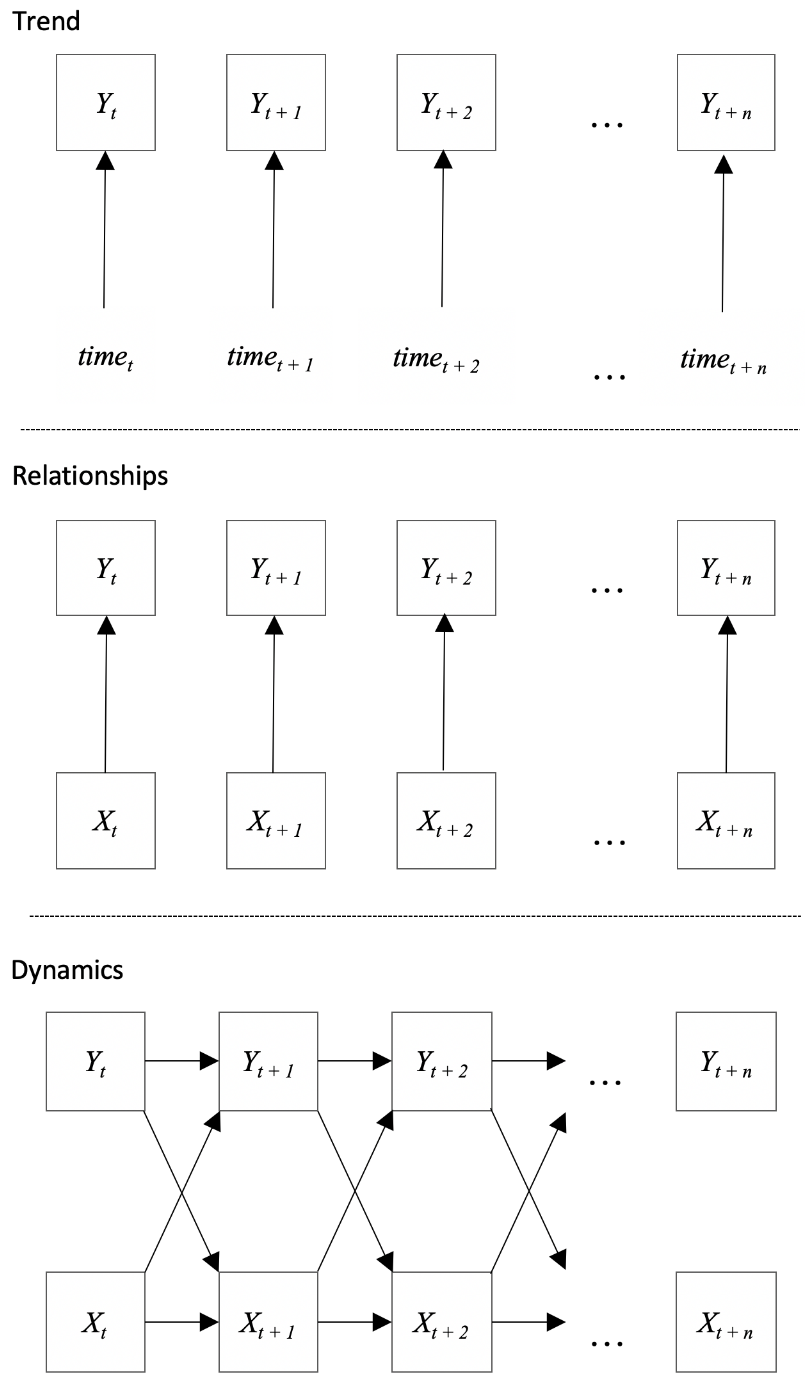

Figure 1. Common inference categories with models applied to longitudinal data.

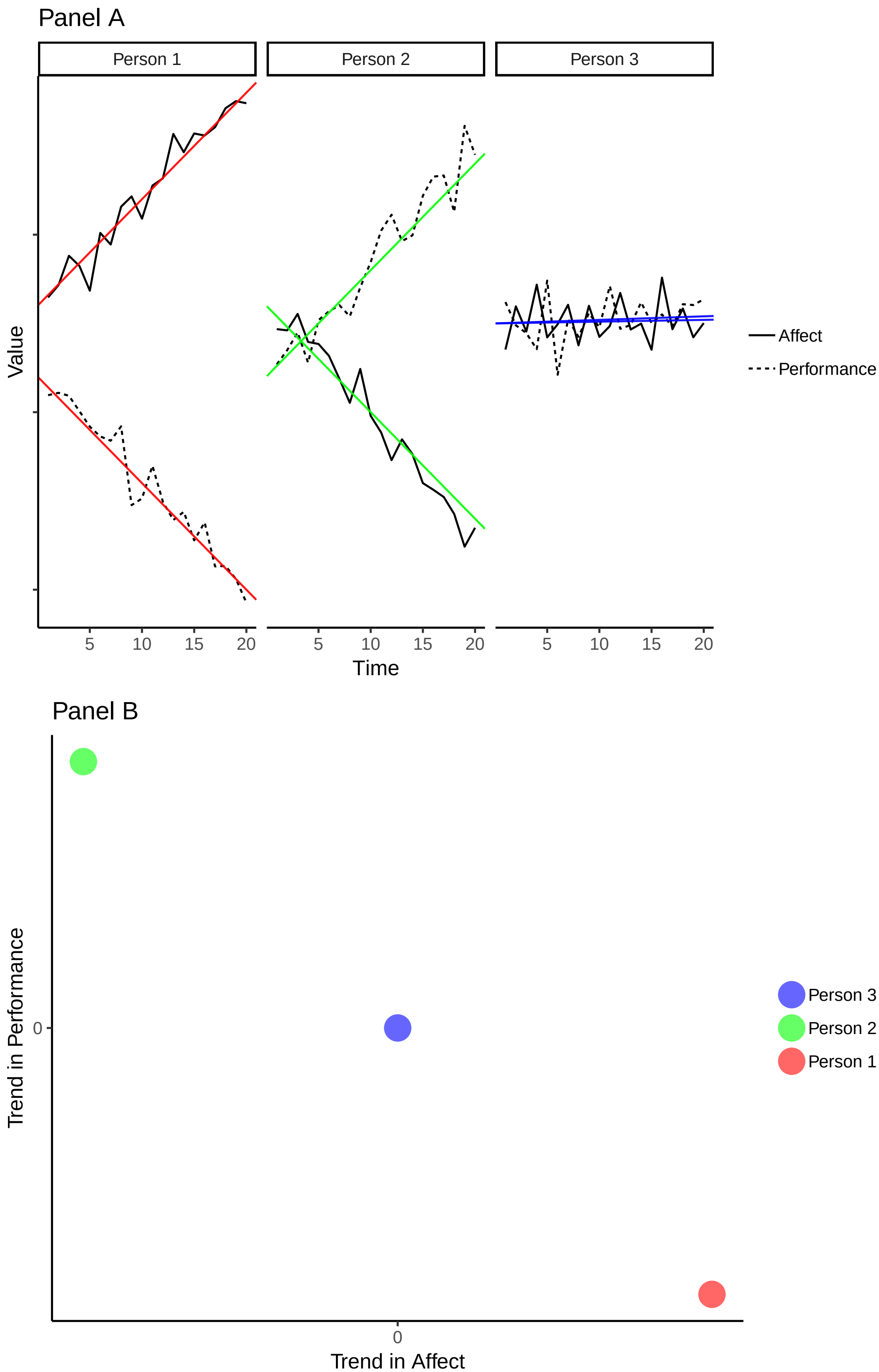

Figure 2. Between-unit correlation of trend in affect and performance.

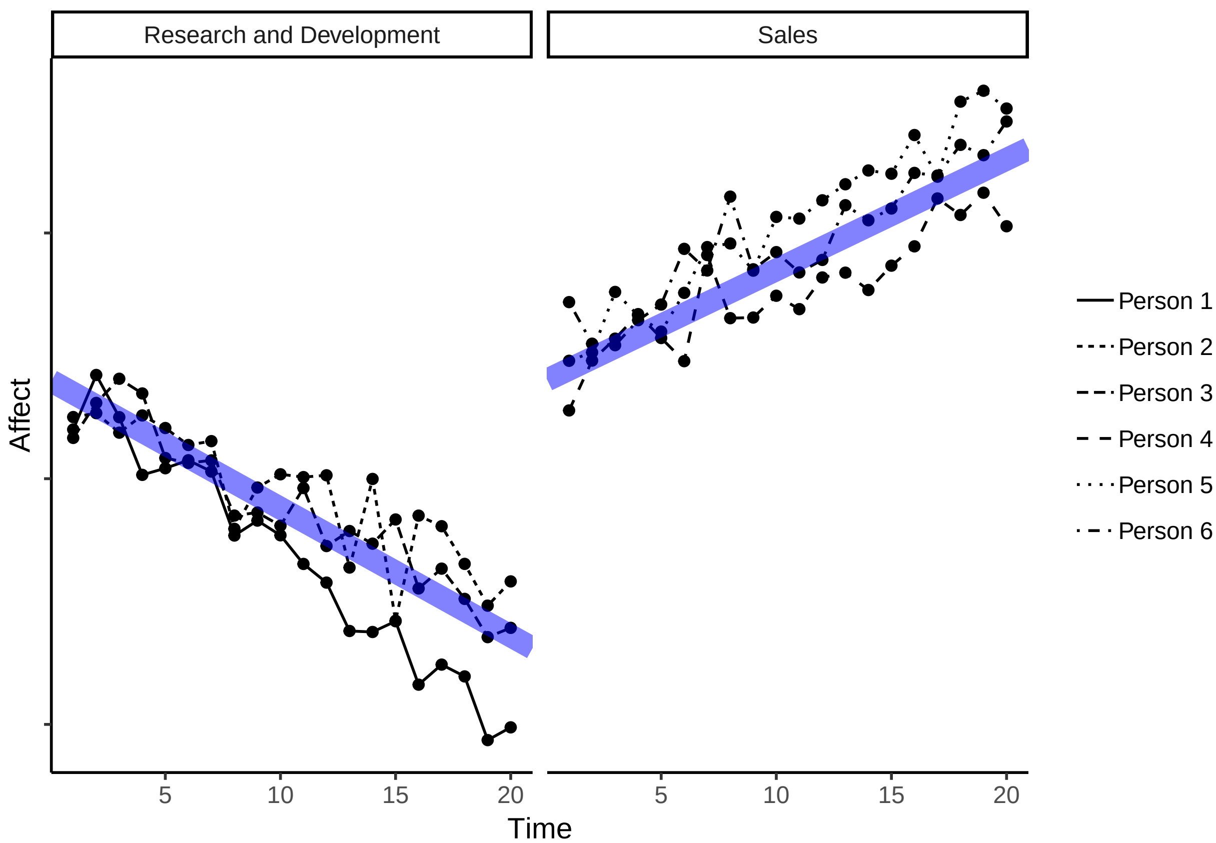

Figure 3. Job type as a covariate of affect trend.

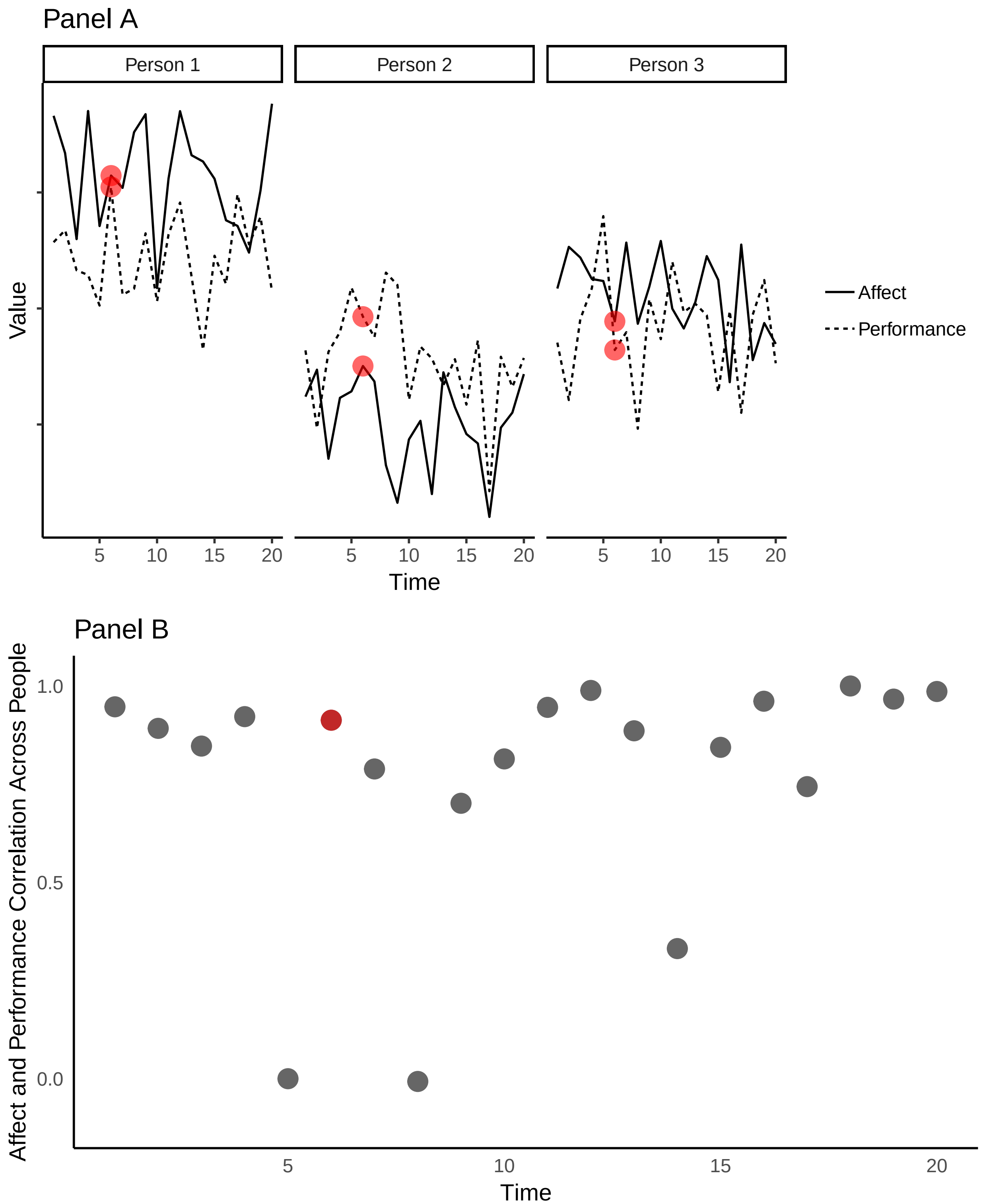

Figure 4. Relating affect to performance across units over time. The red circles demonstrate the between unit correlation at time point six. A typical time-varying covariates model constrains the correlation to be equivalent across time. Here, the relationship is unconstrained at each time point.

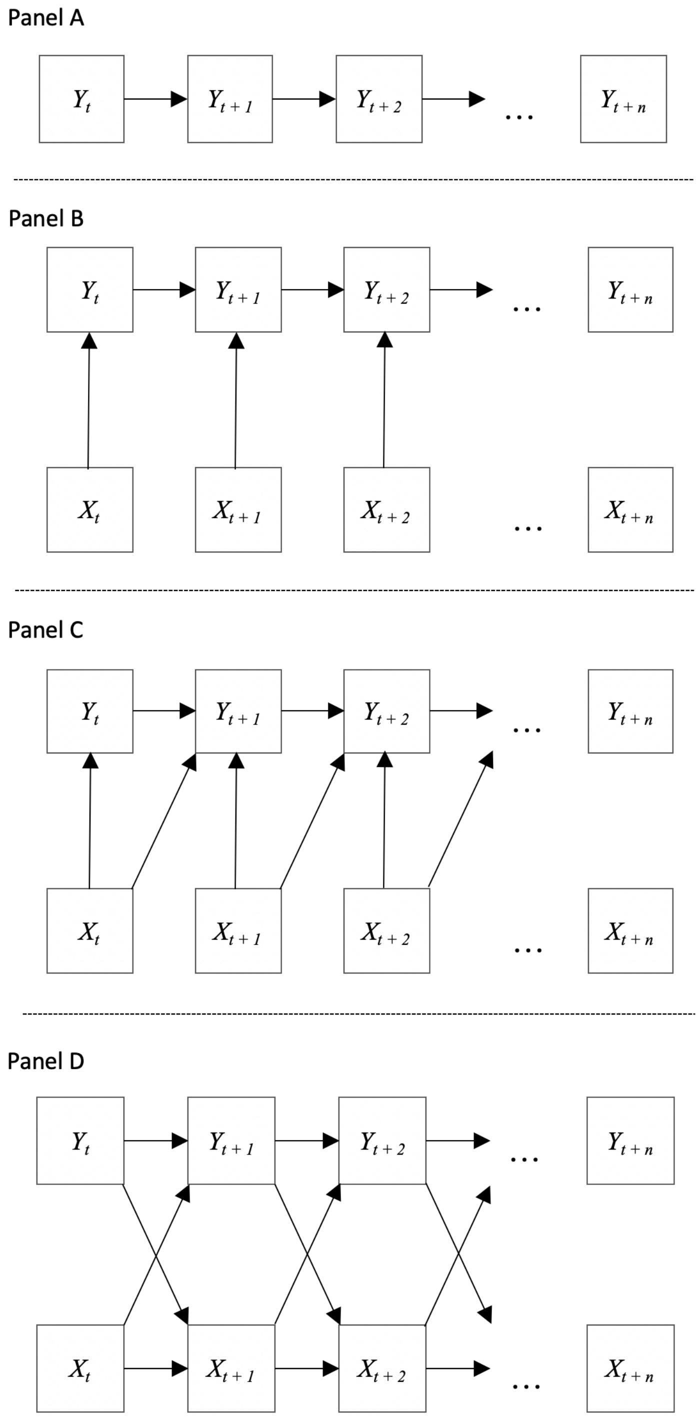

Figure 5. Univariate and bivariate dynamics adapted from DeShon (2012). Panel A shows self-similarity or autoregression in Y across time. Panel B shows concurrent X predicting change in Y. Panel C shows lagged change relationships. Panel D shows reciprocal dynamics between X and Y.