Inferences With Longitudinal Data

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Abstract

Our field is increasingly interested in how things that happen over time, in within-person phenomena, dynamics, growth, person-oriented frameworks, and fundamental patterns in longitudinal data structures. Longitudinal data lend themselves to many different inferences and there are a variety of statistical models available for anyone armed with repeated measures. Although the diversity of inferences and models provides a wide foundation for exploring a content area, it also makes it difficult for researchers to know all of the inferences available to them, which models to evoke given their question, and how to locate their specific study within the broader set of "over time" inferences. We developed a framework that situates these inferences into a core set that exposes researchers to the variety of questions and inferences that can explore with longitudinal data. In this paper we unpack that framework and link every inference to a set of models so that researchers know where to turn given their specific interest.

Keywords: Inferences, dynamics, growth, longitudinal, process, over time, tvc, hlm, sem, models

Word count: 95

Inferences With Longitudinal Data

Organizational phenomena unfold over time. They are processes that develop, change, and evolve (Pitariu & Ployhart, 2010) that create a sequence of events within a person's stream of experience (Beal, 2015). Moreover, organizations are systems with many connected parts that are inherently dynamic. Studying these systems and processes, therefore, requires that we attend not to static snapshots of behavior (Ilgen & Hulin, 2000), but to variables and relationships as they move through time; doing so puts us in a better position to capture the sequence, understand it, and can lead to new and interesting insights (Kozlowski & Bell, 2003).

Researchers explore a variety of inferences when they apply models to longitudinal data. Some focus on whether trajectories increase or decrease, others highlight relationships, and many are increasingly interested in dynamics (e.g., 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). How are these common ways of asking questions about patterns in longitudinal data different?

We developed a framework to capture these inferences; a way to organize the fundemental patterns researchers explore with longitudinal data despite focusing on different content areas or using different statistical models. Researchers often focus on one familiar inference despite having the data to explore many more fundamental patterns. There are also a number of complex statistical models lingering in our literature and it is not always obvious for which questions they are appropriate. We bring attention to the span of questions available so that researchers can fully appreciate and take advantage of their data. Although the inferences all concern trajectories over time, their small differences have large implications for what we take away from them – what we ultimately conclude. We provide readers with potential models for each inference so that they can be sure that the model they evoke is appropriate for the research 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 models, and parses some of the modeling literature that may be difficult to consume for researchers with only graduate level training in statistics.

Longitudinal Definitions

This paper is exclusively devoted to inferences with respect to data sets containing repeated observations, so we begin by identifying 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 *data* are repeated observations on several units (i.e., N or $i > 1$), whereas panel data are observations of one unit over time – a distinction that focuses on the amount of people in our study (given repeated measures). Most organizational studies collect data on more than one unit, therefore our discussion below focuses on longitudinal research with longitudinal data, or designs with $N > 1$, $t >= 3$, and the same construct(s) measured on each i at each t. That is, we focus on designs that measure their variables repeatedly across many people – and every variable is measured at each time point.

Note that 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. Assessing variables and relationships within a 60 minute study can be as informative as a study that spans multiple years given adequate sampling frequency.

Framework

We use three inference categories to partition our discussion, including trend, relationships, and dynamics, and each has its own sub-inferences and models. Our writing style is the same throughout each section, where we first discuss the category itself and then sequentially walk through the inferences. During that sequence, we pose questions to orient the reader as to what the inference captures, unpack graphs and figures, and provide inference statements that can be used to guide hypothesis development. We use box-and-arrow diagrams throughout to represent the broad inferences, but we also graph a few of the more challenging inferences with mock data – we feel that some of the inferences in the trend and relationships section 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 – although it is certainly possible. We are using these "data plots" to clearly convey what the inferences mean, but please be aware that field data will always be messy.

Finally, we end each inference section by pointing researchers to respective statistical models. Although we direct researchers to models, our paper is not about statistical modeling only – it is about inferences – and researchers therefore need to be sure that they appreciate all of the nuance before applying a recommended model. There are many complex statistical issues that arise with longitudinal modeling – like stationarity – and the models differ in how they handle these issues, the assumptions they make, and the data format they require. There are plenty of great references on each model, we are simply guiding researchers to those references based on the underlying inferences that interest them.

Trend

The first inference category is 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 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 go up or down across time, or is its trajectory relatively flat? Does trainee skill 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 global shape of the 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, 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 inference, therefore, concerns the shape of the trajectory. What is the average trend?

> **Inference 1:** On average, there is a positive/negative/curvilinear trend.

Regardless of the specific technique or model, most inferences start with the average pattern (or relationship) and then move to variability, the same applies here. After learning about the average trend 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?

Inference 2: Trend differs/does not differ across units.

Inferences one and two concern one variable, but they can also be iterated across all observed variables. For example, we might discover that – on average – 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 is the next inference. Correlating indicates co-occuring patterns, where a large positive 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

Inference 3: Between-unit trends correlate.

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

Inference 4: There are between-unit correlates of trend.

Note the difference between trend inferences three and four. Both are between unit, but inference three is about co-occuring trend patterns whereas inference four is about the relationship between trend and a covariate/predictor. With respect to our examples, inference 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 at the beginning of a training session? On average, 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.

Inference 5: On average, what is the expected level of the y trend at time t?

After exploring the average 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? 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?

Inference 6: On average, there is variability in the expected level of the y trend at time t.

It is also possible to assess between unit correlations among levels and (a) trend itself in the same variable, (b) levels among different variables, or (c) trends in other variables. First consider a relationship among level and trend in the same variable. On average, 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, tend to have negative CWB trends?

Inference 7: There is a 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, do people with a low initial level of performance trend also have low initial levels of depletion trend? Are organizations with high initial turnover also expected, on average, to have high burnout (based on the initial levels predicted by the turnover and burnout trend lines)?

Inference 8: There is a 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 levels of voice (predicted by the voice trend) expected to have negative satisfaction trends?

Inference 9: There is a 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.

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. Again, the mean estimate will tell you about the trend itself and 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" model.

Broad theoretical discussions of growth and change are found in Pitariu and Ployhart (2010) and Ployhart and Vandenberg (2010), whereas Bliese and Ployhart (2002) describe how to go about running an 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. For two straight-forward empirical examples in our own field see Dunford et al. (2012) and Hülsheger (2016).

Relationships

One of the most common inferences in our literature is to explore between-unit relationships over time. The second panel of Figure 1 shows a relationships heuristic. A predictor is concurrently related to a response variable and the relationship is typically constrained to equality or is averaged over time. Essentially, the inference compiles single-moment between-unit correlations where we assess the correlation between, for example, OCBs and depletion at time one, again and times two and three, and then ultimately take the average of each correlation.

Figure 4 shows the inuition of the inference with data. Panel A plots affect and performance trajectories for each person. 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 correlation coefficients for the rest of the time points. Often these correlations are either averaged over time or constrained to be equal. Again, this inference is one of the most common inferences in our literature – 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.

Inference 1: On average, what is the relationship between x and y between-units? (Typically constrained to be equal over time or averaged over time).

The first relationships inference emphasizes the expected average. As with the trend inferences, the next question is to examine variability in that estimated relationship across the sample.

Inference 2: There is variability in the between-unit relationship among x and y.

Models

Time-varying covariates 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 in our literature 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 diagram. 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.

> **Inference 1:** On average, there is self-similarity in y; y relates to itself across time.

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?

Inference 2: There is variability 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 still has self-similarity across time but it is now predicted by concurrent values of x. 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. 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.

Inference 3: On average, concurrent x relates to change in y.

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

Inference 4: There is variability in the expected change relationship between 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.

Figure 5 depicts lag-one change relationships. Does affect predict subsequent performance change? Do prior counterproductive work behaviors relate to current incivility change? Does metacognition predict subsequent exploratory behavior change? Change relationships are also not restricted to lag-one, these are simply the most common.

> **Inference 5:** On average, there is a cross-lag relationship of change, where x relates to the change in y at a different point in time.

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

> **Inference 6:** There is variability 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). They present a sequence of hypotheses including (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

There are a number of recent papers on dynamic modeling that cover the inferences discussed in this section. 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 models available. When a researcher wants to explore dynamic inferences with respect to a single unit over time they will be examining time-series data, and there are a number of models for this application. DeShon (2012) discusses autoregressive distributed lag (ARDL) and vector autoregressive models, and Jebb and collegues (2017; 2015) introduce ARDL and autoregressive distributed moving average (ARIMA) models. Finally, Xu and DeShon (almost) discuss a dynamic model first introduced by Bollen and Brand (2010). This dynamic panel model is appropriate for researchers who want to model dynamics across more than one unit. Moreover, it is better suited than HLM for typical situations in organizational psychology and management (i.e., short t and large N).

Discussion

There are many different patterns to explore with longitudinal data structures. What does performance look like over time? Does it fluctuate? Is the trajectory consistent across people? What is its initial or ending level? Does it show a growth pattern? Does that growth pattern covary with another trend? Does it move across time in relation to another variable? Does it show self-similarity or memory? Does it show lagged relationships with other variables? Is it part of a reciprocal system? In this paper we presented a framework that organizes these inferences into a fundamental set. We discussed what the inferences mean, how to pose questions and hypotheses about them, and linked the inferences to appropriate statistical models. As our field dives into within-person, dynamic, and process-oriented methods we hope this paper helps researchers understand the spectrum of inferences that they can explore with rich longitudinal data.

within person stuff

References

Barnes, C. M., Schaubroeck, J., Huth, M., & Ghumman, S. (2011). Lack of sleep and unethical conduct. *Organizational Behavior and Human Decision Processes*, *115*(2), 169–180.

Beal, D. J. (2015). ESM 2.0: State of the art and future potential of experience sampling methods in organizational research. *Annu. Rev. Organ. Psychol. Organ. Behav.*, *2*(1), 383–407.

Bliese, P. D., & Ployhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustrations. *Organizational Research Methods*, *5*(4), 362–387.

Bollen, K. A., & Brand, J. E. (2010). A general panel model with random and fixed effects: A structural equations approach. *Social Forces*, *89*(1), 1–34.

Chan, D. (1998). The conceptualization and analysis of change over time: An integrative approach incorporating longitudinal mean and covariance structures analysis (lmacs) and multiple indicator latent growth modeling (mlgm). *Organizational Research Methods*, *1*(4), 421–483.

Chi, N.-W., Chang, H.-T., & Huang, H.-L. (2015). Can personality traits and daily positive mood buffer the harmful effects of daily negative mood on task performance and service sabotage? A self-control perspective. *Organizational Behavior and Human Decision Processes*, *131*, 1–15.

DeShon, R. P. (2012). Multivariate dynamics in organizational science. *The Oxford Handbook of Organizational Psychology*, *1*, 117–142.

Dunford, B. B., Shipp, A. J., Boss, R. W., Angermeier, I., & Boss, A. D. (2012). Is burnout static or dynamic? A career transition perspective of employee burnout trajectories. *Journal of Applied Psychology*, *97*(3), 637–650. doi:http://dx.doi.org.proxy2.cl.msu.edu/10.1037/a0027060

Finch, W. H., Bolin, J. E., & Kelley, K. (2016). *Multilevel modeling using r*. Crc Press.

Grimm, K. J., Ram, N., & Estabrook, R. (2016). *Growth modeling: Structural equation and multilevel modeling approaches*. Guilford Publications.

Hardy, J. H., Day, E. A., & Steele, L. M. (2018). Interrelationships Among Self-Regulated Learning Processes: Toward a Dynamic Process-Based Model of Self-Regulated Learning. *Journal of Management*, 0149206318780440. doi:10.1177/0149206318780440

Hardy III, J. H., Day, E. A., & Steele, L. M. (2018). Interrelationships among self-regulated learning processes: Toward a dynamic process-based model of self-regulated learning. *Journal of Management*, 0149206318780440.

Hülsheger, U. R. (2016). From dawn till dusk: Shedding light on the recovery process by investigating daily change patterns in fatigue. *Journal of Applied Psychology*, *101*(6), 905–914. doi:http://dx.doi.org.proxy2.cl.msu.edu/10.1037/apl0000104

Ilgen, D. R., & Hulin, C. L. (2000). *Computational modeling of behavior in organizations: The third scientific discipline.* American Psychological Association.

Jebb, A. T., & Tay, L. (2017). Introduction to time series analysis for organizational research: Methods for longitudinal analyses. *Organizational Research Methods*, *20*(1), 61–94.

Jebb, A. T., Tay, L., Wang, W., & Huang, Q. (2015). Time series analysis for psychological research: Examining and forecasting change. *Frontiers in Psychology*, *6*, 727.

Jones, K. P., King, E. B., Gilrane, V. L., McCausland, T. C., Cortina, J. M., & Grimm, K. J. (2016). The baby bump: Managing a dynamic stigma over time. *Journal of*

Management, *42*(6), 1530–1556.

Judge, T. A., Simon, L. S., Hurst, C., & Kelley, K. (2014). What I experienced yesterday is who I am today: Relationship of work motivations and behaviors to within-individual variation in the five-factor model of personality. *Journal of Applied Psychology*, *99*(2), 199.

Kozlowski, S. W., & Bell, B. S. (2003). Work groups and teams in organizations. *Handbook of Psychology*, 333–375.

Lanaj, K., Johnson, R. E., & Wang, M. (2016). When lending a hand depletes the will: The daily costs and benefits of helping. *Journal of Applied Psychology; Washington*, *101*(8), 1097. Retrieved from http://search.proquest.com/docview/1813203845?pq-origsite=summon

Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, *12*(1), 23.

Maxwell, S. E., Cole, D. A., & Mitchell, M. A. (2011). Bias in cross-sectional analyses of longitudinal mediation: Partial and complete mediation under an autoregressive model. *Multivariate Behavioral Research*, *46*(5), 816–841.

McArdle, J. J., & Epstein, D. (1987). Latent Growth Curves within Developmental Structural Equation Models. *Child Development*, *58*(1), 110–133. doi:10.2307/1130295

Monge, P. R. (1990). Theoretical and analytical issues in studying organizational processes. *Organization Science*, *1*(4), 406–430.

Pitariu, A. H., & Ployhart, R. E. (2010). Explaining change: Theorizing and testing dynamic mediated longitudinal relationships. *Journal of Management*, *36*(2), 405–429.

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management*, *36*(1), 94–120.

Rosen, C. C., Koopman, J., Gabriel, A. S., & Johnson, R. E. (2016). Who strikes back? A daily investigation of when and why incivility begets incivility. *Journal of Applied Psychology*, *101*(11), 1620.

Schonfeld, I. S., & Rindskopf, D. (2007). Hierarchical linear modeling in organizational research: Longitudinal data outside the context of growth modeling. *Organizational Research Methods*, *10*(3), 417–429.

Scott, B. A., & Barnes, C. M. (2011). A multilevel field investigation of emotional labor, affect, work withdrawal, and gender. *Academy of Management Journal*, *54*(1), 116–136.

Singer, J. D., Willett, J. B., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford university press.

Stone-Romero, E. F., & Rosopa, P. J. (2008). The relative validity of inferences about mediation as a function of research design characteristics. *Organizational Research Methods*, *11*(2), 326–352.

Vancouver, J. B., Wang, M., & Li, X. (2018). Translating Informal Theories Into Formal Theories: The Case of the Dynamic Computational Model of the Integrated Model of Work Motivation. *Organizational Research Methods*, 109442811878030. doi:10.1177/1094428118780308

Wang, M., Zhou, L., & Zhang, Z. (2016). Dynamic modeling. *Annual Review of Organizational Psychology and Organizational Behavior*, *3*(1), 241–266. doi:10.1146/annurev-orgpsych-041015-062553

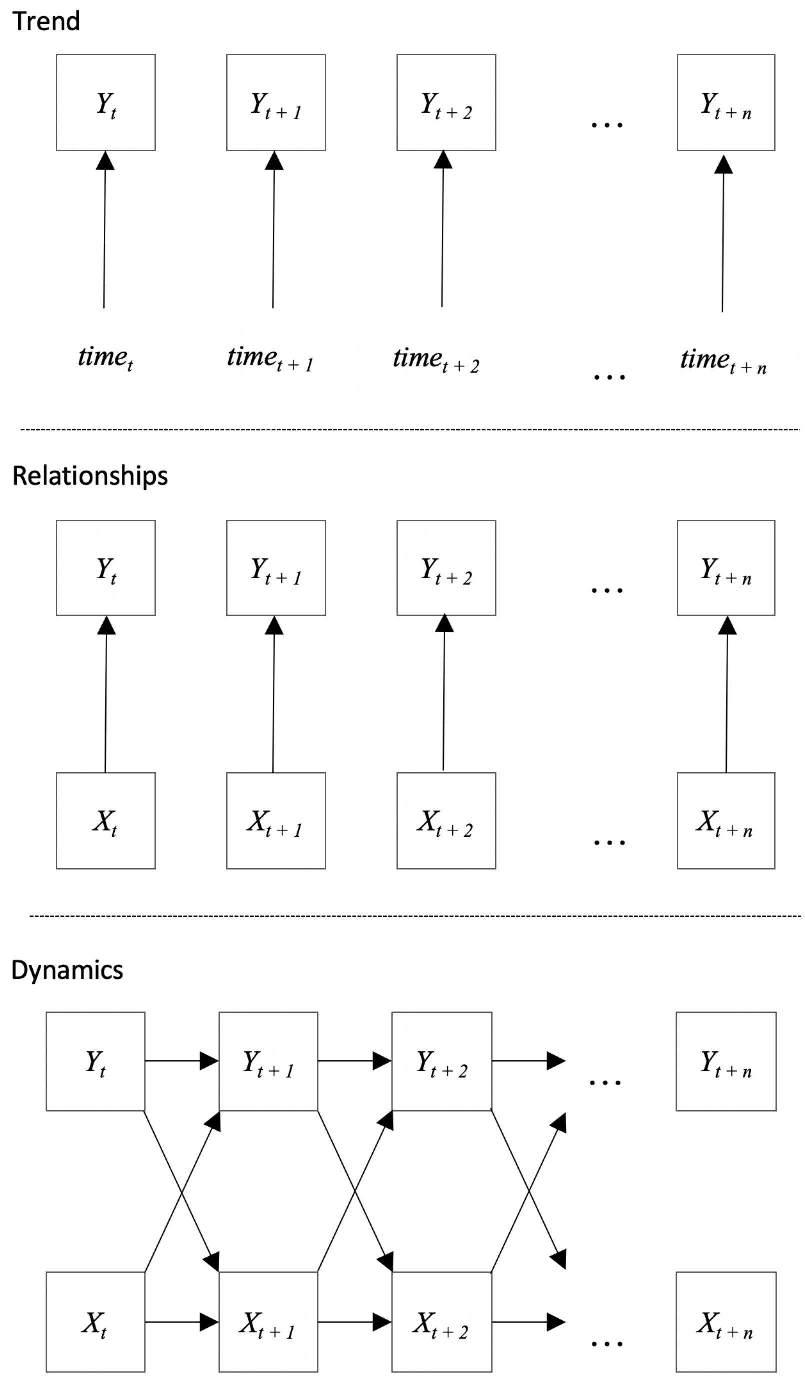

Figure 1. Common inference categories with models applied to longitudinal data.

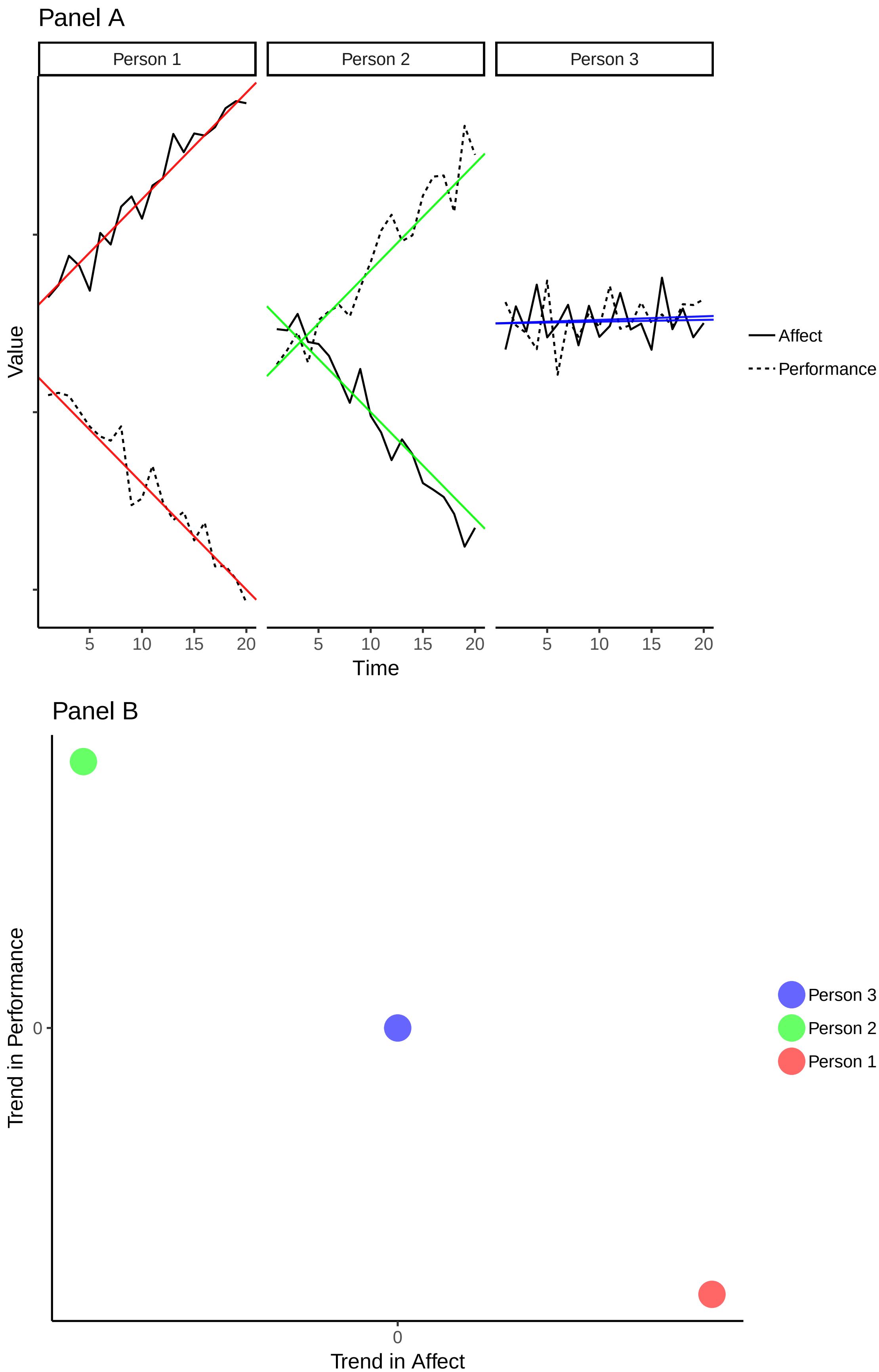

Figure 2. Correlating slopes, or relating the affect to performance trend.

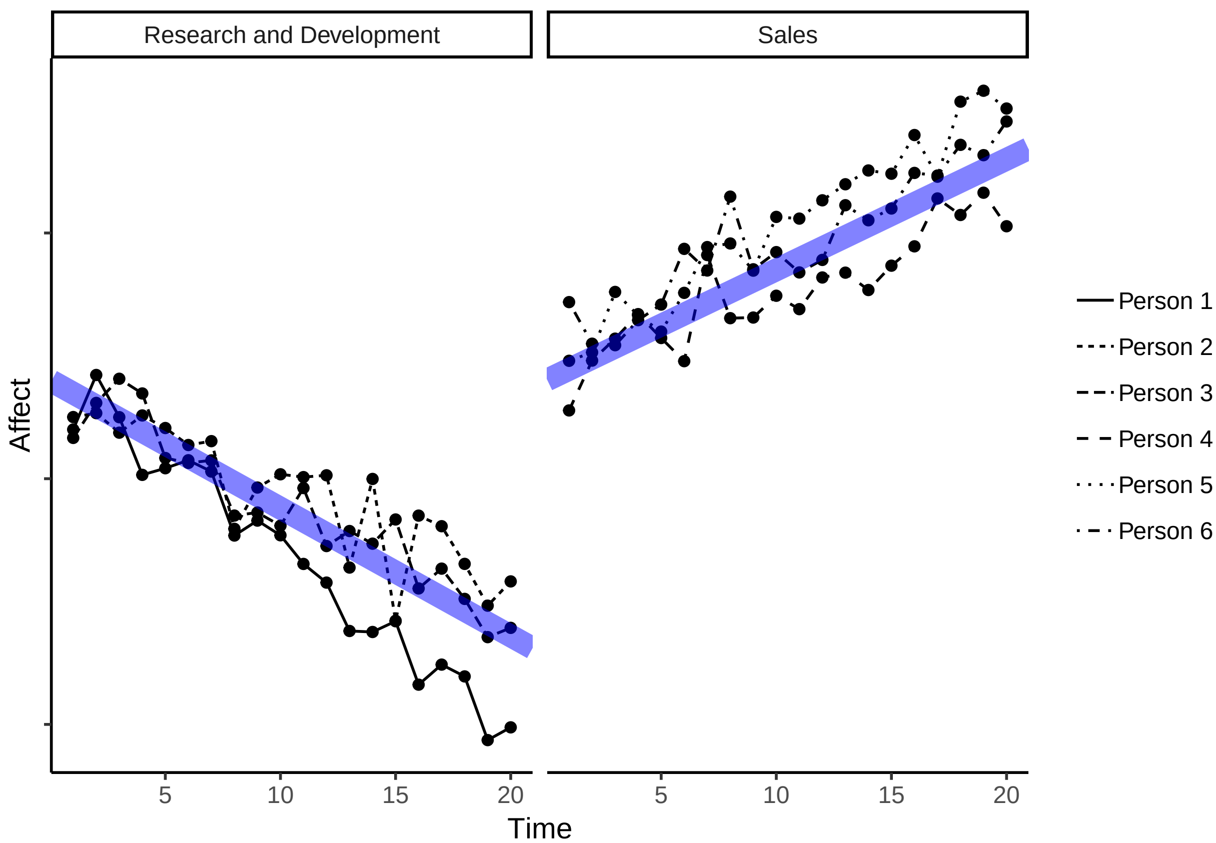

Figure 3. Job type as a covariate of affect trend.

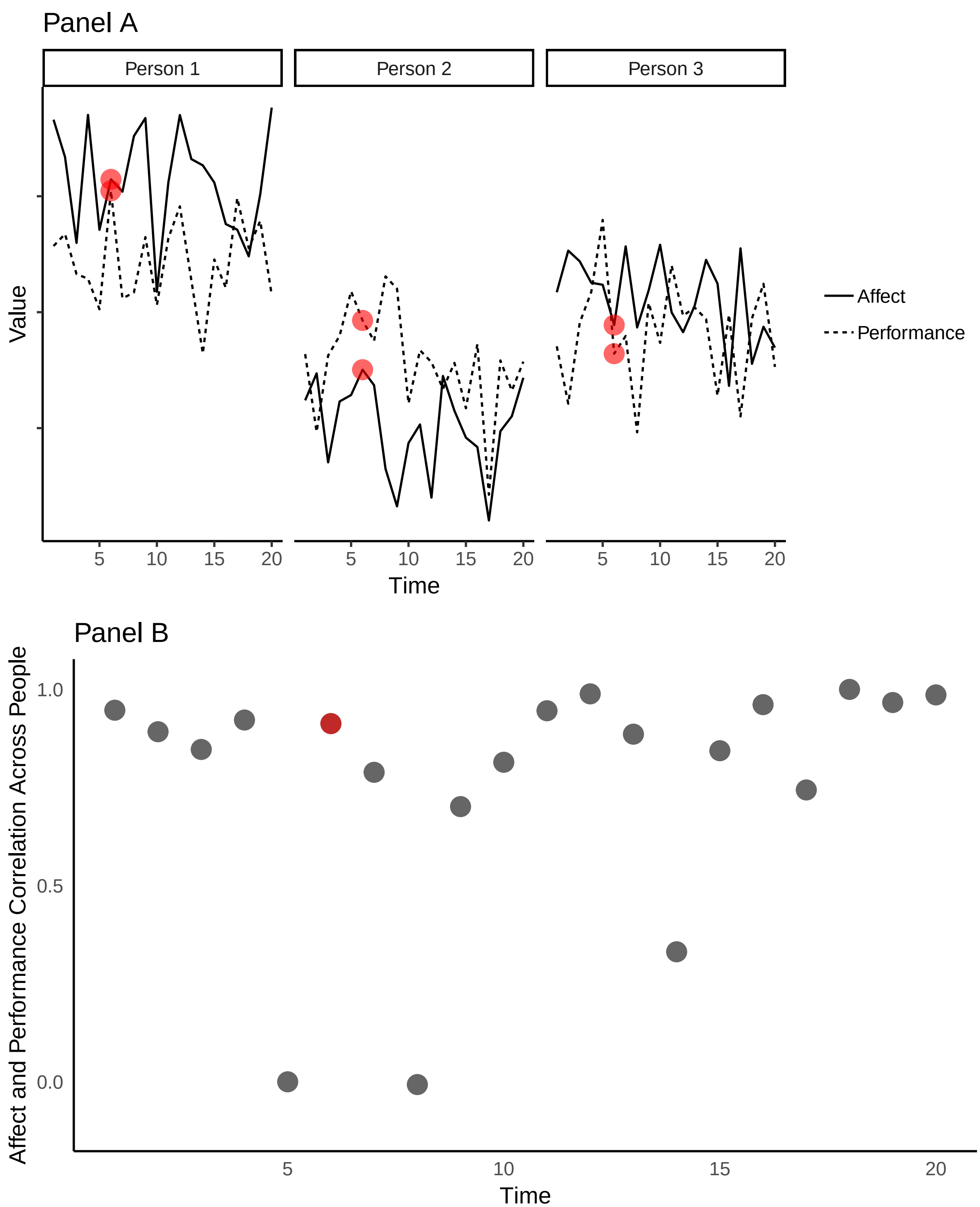

Figure 4. Relating affect to performance across units over time. The red circles demonstrate the between unit correlation at time point six. A typical time-varying covariates model constrains the correlation to be equivalent across time. Here, the relationship is unconstrained at each time point.

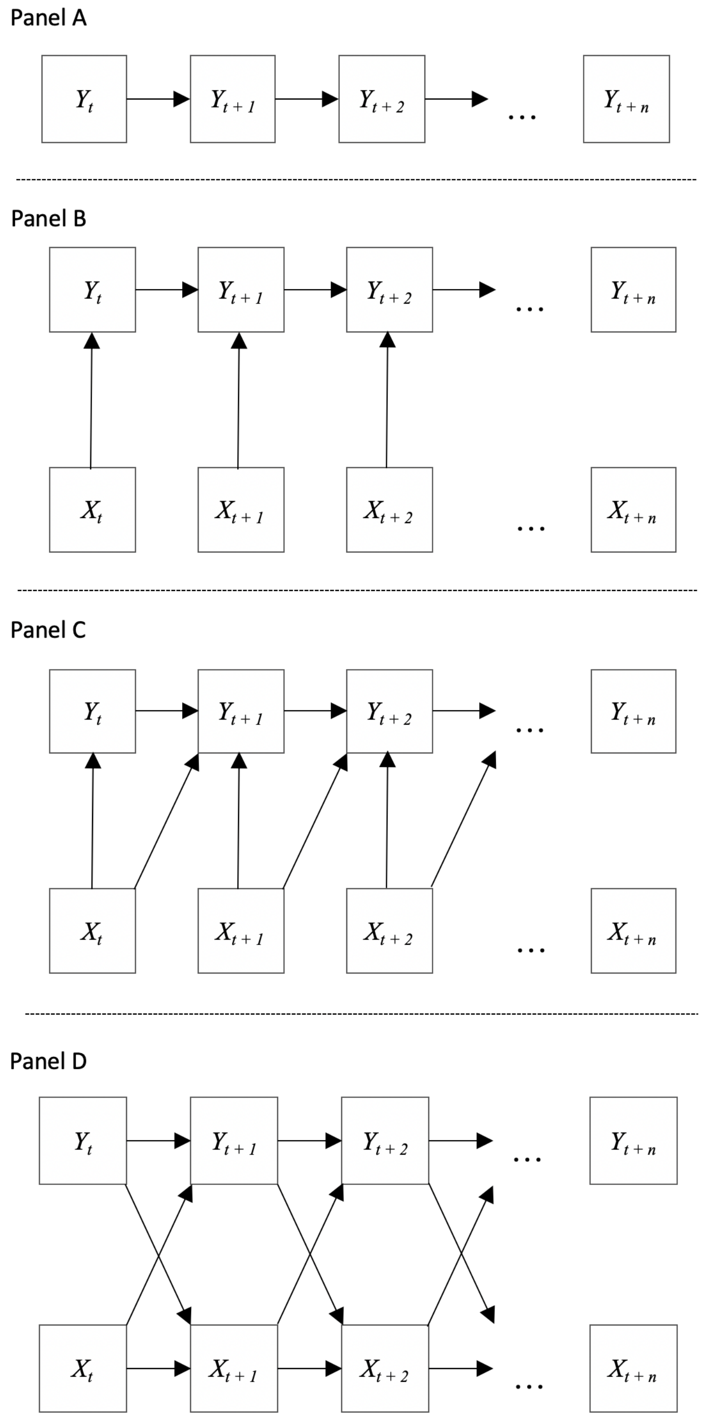

Figure 5. Univariate and bivariate dynamics adapted from DeShon (2012). Panel A shows self-similarity or autoregression in Y across time. Panel B shows concurrent X predicting change in Y. Panel C shows X lagged change relationships. Panel D shows reciprocal dynamics between X and Y.