Inferences With Longitudinal Data

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Abstract

Organizational scientists recognize the need to study psychological phenomena and processes as they unfold over time. To better understand psychological phenomena and processes, organizational researchers must work with longitudinal data and understand longitudinal inferences. Longitudinal inferences may focus on trajectories of constructs, relationships between constructs, or dynamics in constructs. 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 work, we develop a framework to describe the variety of research questions and inferences researchers may explore with longitudinal data, explicate longitudinal inferences with visualizations, and link 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

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Inferences With Longitudinal Data

Organizational scientists readily recognize psychological phenomena and processes unfold over time (Beal, 2015; M. T. Braun et al., 2013a; Kuljanin, Braun, & DeShon, 2011; Pitariu & Ployhart, 2010). Individuals in the workplace strive to accomplish work goals energized by motivational processes (e.g., goal-setting); team members collaborate so the whole becomes greater, instead of less, than the sum of its parts; managers promote values to build vibrant, innovative work cultures. In order to better understand psychological processes and phenomena such as motivation, teamwork, and organizaitonal culture, researchers must go beyond observing and analyzing static snapshots of individual and collective affect, behavior, and cognition (Ilgen & Hulin, 2000; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013, 2016). They must observe or obtain longitudinal data capturing the unfolding set of events, interactions, behaviors, cognitions, or affective reactions responsible for psychological processes and phenomena. Fortunately, available technology (e.g., hand-held devices, online platforms, sensors, computer tracking, text traces, cameras) and data repositories (e.g., organizational databases, open science framework) makes it easier to collect or obtain longitudinal data than previously possible. Obtaining and analyzing longitudinal data illuminates organizational psychological functioning at any or multiple levels of analysis.

Researchers may explore a variety of inferences when they analyze longitudinal data. In particular, researchers may examine whether individual or average trajectories increase or decrease on psychological constructs of interest (e.g., did job satisfaction generally increase or decrease over six months after a merger?), how two or more psychological constructs relate to each other (e.g., did team communications and cohesion positively correlate during the last project?), or whether changes in one or more set of psychological constructs leads to changes in another set of psychological constructs (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 for longitudinal inferences not only facilitates longitudinal analytical work and elucidates nuanced differences between such inferences, but, also, enhances theoretical thought and guides data collection efforts.

We develop a framework to capture fundemental patterns researchers may explore with longitudinal data. Researchers often focus on one familiar inference despite possessing the data to explore many more fundamental patterns. Understanding the set of patterns one may explore with longitudinal data expands the possible insights into investigated phenomena and processes. We bring attention to the span of questions available so that researchers can fully appreciate and take advantage of their data. Furthermore, we describe statistical models useful for examining longitudinal inferences. This takes researchers from conceptually discussing their longitudinal inferences to evaluating them analytically while, at the same time, appropriately specifying longitudinal statistical models. In summary, this work organizes for researchers the span of inferences they may investigate when they collect longitudinal data, links longitudinal inferences to statistical models, and explains differences between various longitudinal inferences.

Longitudinal Research in Psychology

This work exclusively devotes its attention to inferences with respect to repeated measures on units of observation in psychological research. First, longitudinal data differs from cross-sectional data because longitudinal designs entail three or more repeated measurements on the same units of analysis on one or more constructs (Ployhart & Vandenberg, 2010). Two repeated measurements prohibits the evaluation of different trends as the linear trend perfectly fits all units of observation. Second, in most cases in psychological research, longitudinal data consists of repeated observations on more than one unit of observation, whereas panel data consists of observations on one unit over time such as one finds in economics research. Thus, we focus our attention to inferences researchers can make from longitudinal data consisting of at least three repeated measurements on one or more constructs observed on more than one unit.

We highlight longitudinal data in psychological research may cover short or long time horizons. In other words, we consider both an experiment tracking participant behavior on ten trials and a study tracking participant attitudes once every year for ten years as longitudinal research. Certain psychological phenomena and processes unfold over short time horizons (e.g., decision-making on simple tasks) whereas other psychological phenomena and processes unfold over long time horizons (e.g., team performance on complex tasks; Mitchell & James, 2001). Thus, longitudinal psychological research does not merely consist of long time horizon studies. Short time horizon studies can equally well inform researchers on suitable phenomena and processes operating at such time scales. Ultimately, the informativeness of a particular study depends on its rationale, research design, potent analytical work, and effective interpretation of results as with any study. When it comes to longitudinal research in psychology, short and long time horizons both offer valuable insights into psychological phenomena and processes.

Framework for Longitudinal Inferences

We use three broad inference categories to partition our discussion on construct: trends, relationships, and dynamics. Briefly, longitudinal inferences focusing on trends in constructs assess whether change on constructs follows linear or curvilinear trajectories or whether trajectories differ between individuals; longitudinal inferences focusing on relationships between constructs assess the extent to which two or more constructs associate with one another over time; 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 a discussion of its own set of sub-inferences and statistical models. We proceed by posing questions to illuniate what each broad inference category and its associated sub-inferences capture, visualize inferential ideas with figures, and provide inferential statements useful to guide longitudinal hypothesis development. We use diagrams to represent the broad inferences and graph hypothetical data to explicate differences between sub-inferences.

We intend for the hypothetical data plots to illuminate the meaning behind inferences and not to indicate actual longitudinal data looks this cleanly. Actual data tends to look noisier. To handle nosiy data, we turn to statistical models to facilitate inferences. Thus, we refer to respective statistical models useful to investigate discussed inferences. Although we direct researchers to statistical models, we primarily emphasize inferences with longitudinal data. We wish researchers better understand the available set of longitudinal inferences the may investigate before applying statistical models. Numerous complex statistical issues arise when modeling longitudinal data such as stationarity (see Braun et al., 2013a, 2013b; Kuljanin et al., 2011), and statistical models differ in how they handle these issues, the assumptions they make, and the data format they require. In this work, we cannot speak to these matters, and we refer readers to numerous 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 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, 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.

> **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 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?

> **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 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

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 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?

> **Inference 6:** There is variability 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, 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 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, to have high burnout (based on the initial levels predicted by the turnover and burnout trends)?

> **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 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. 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" 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, and the second panel of Figure 1 shows a 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 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 correlation coefficients for the rest of the time points. Often these 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.

> **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. How consistent across the sample is the relationship between distractions and fatigue? Is there variability in the relationship between emotions and volunteering behaviors?

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

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 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. Note that the statistical term to capture self-similarity or memory is called autoregression.

Inference 1: On average, there is self-similarity (autoregression) 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 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.

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.

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.

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). 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 multiple-unit, longitudinal data structures. What is the average trend in performance? Is it consistent across people or organizations? What is its initial or ending level? Does the performance trend covary with a predictor or trend in another variable? Does performance show self-similarity or memory? Or a lagged relationship with other variables? Is it part of a reciprocal system? 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 inferences that they can explore with rich, multiple-unit longitudinal data.

Within-Persons Modeling

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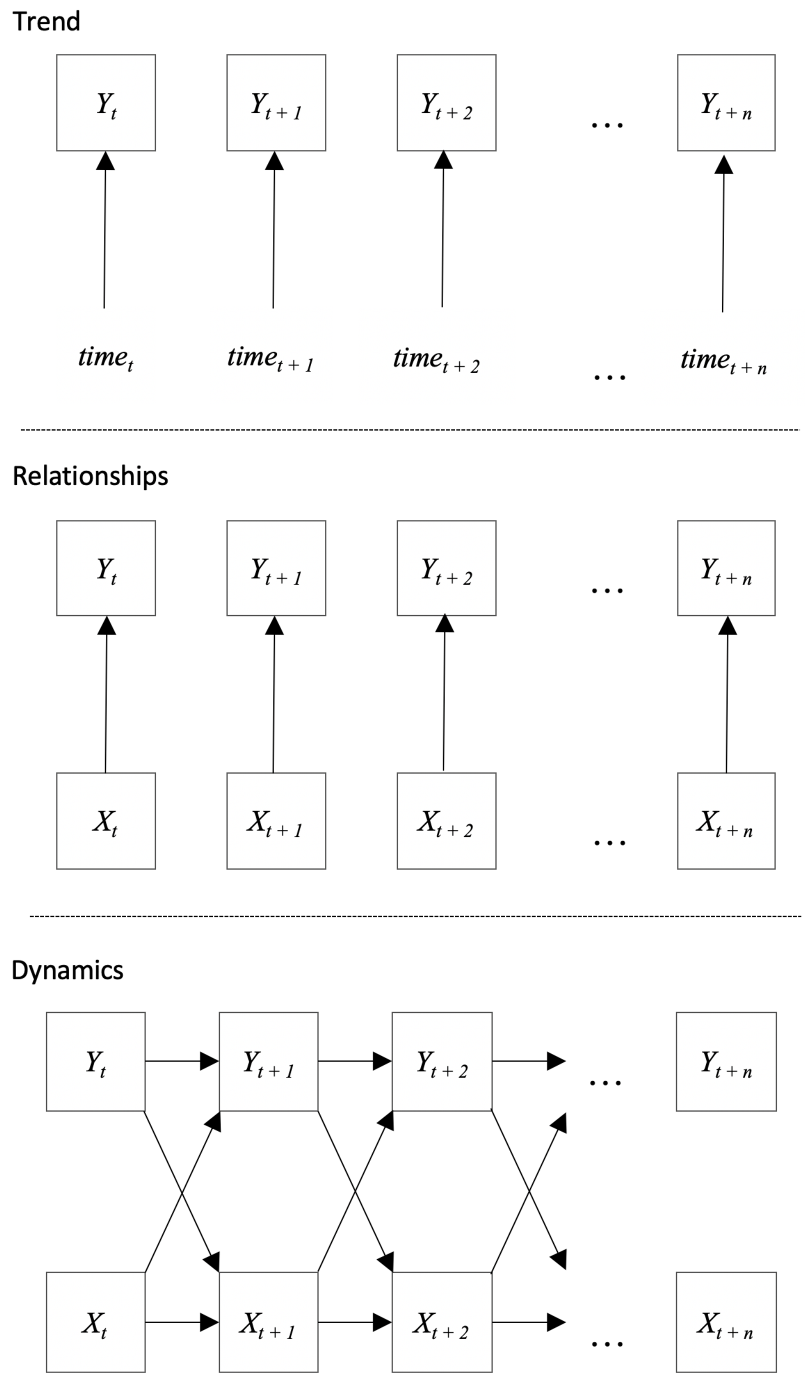

Figure 1. Common inference categories with models applied to longitudinal data.

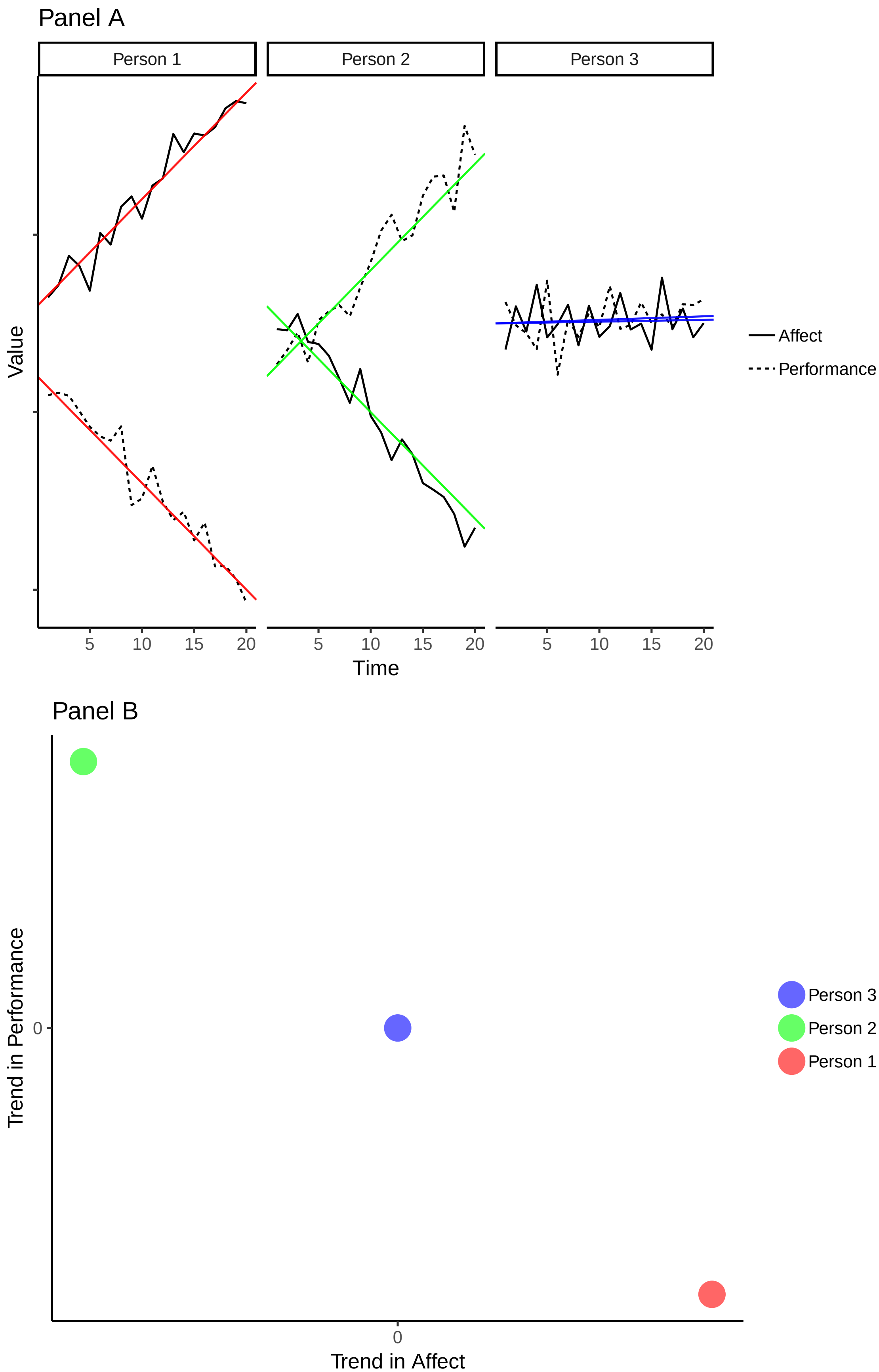

Figure 2. Between-unit correlation of trend in affect and performance.

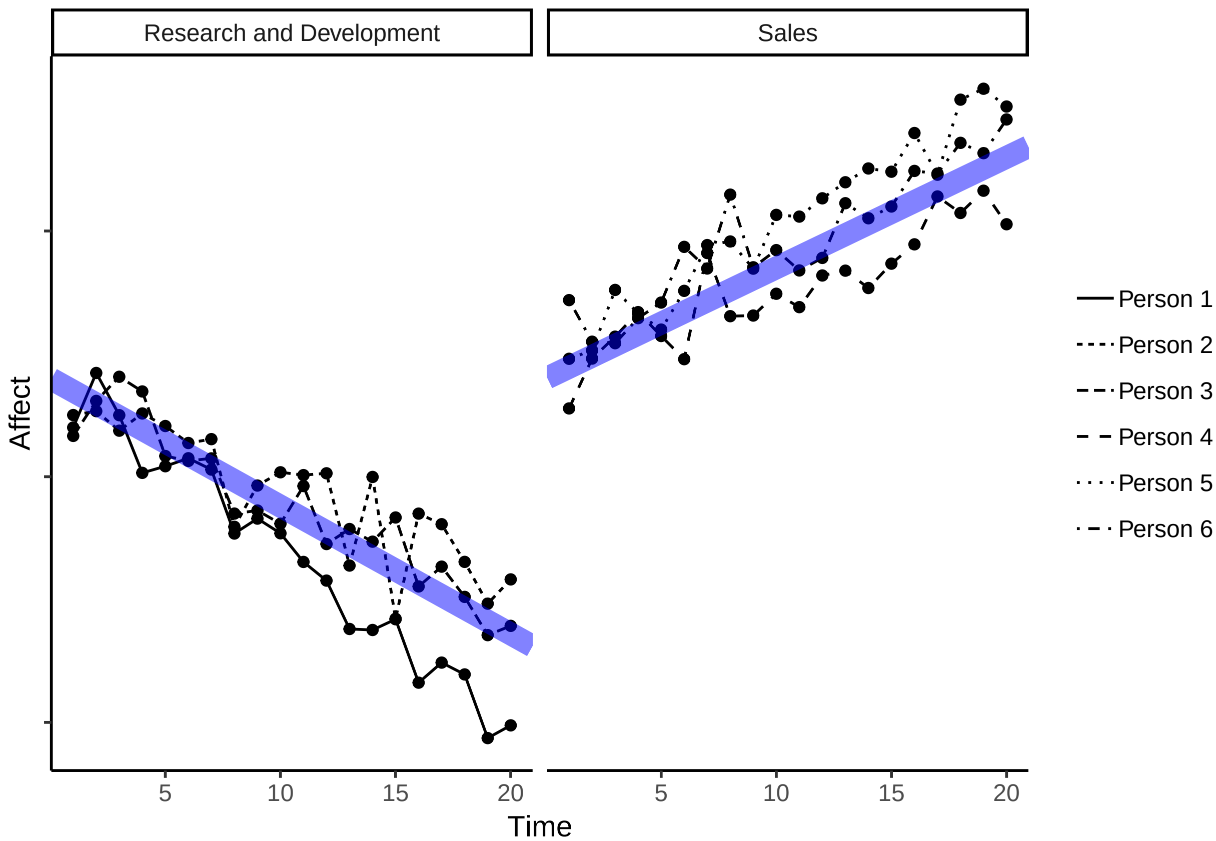

Figure 3. Job type as a covariate of affect trend.

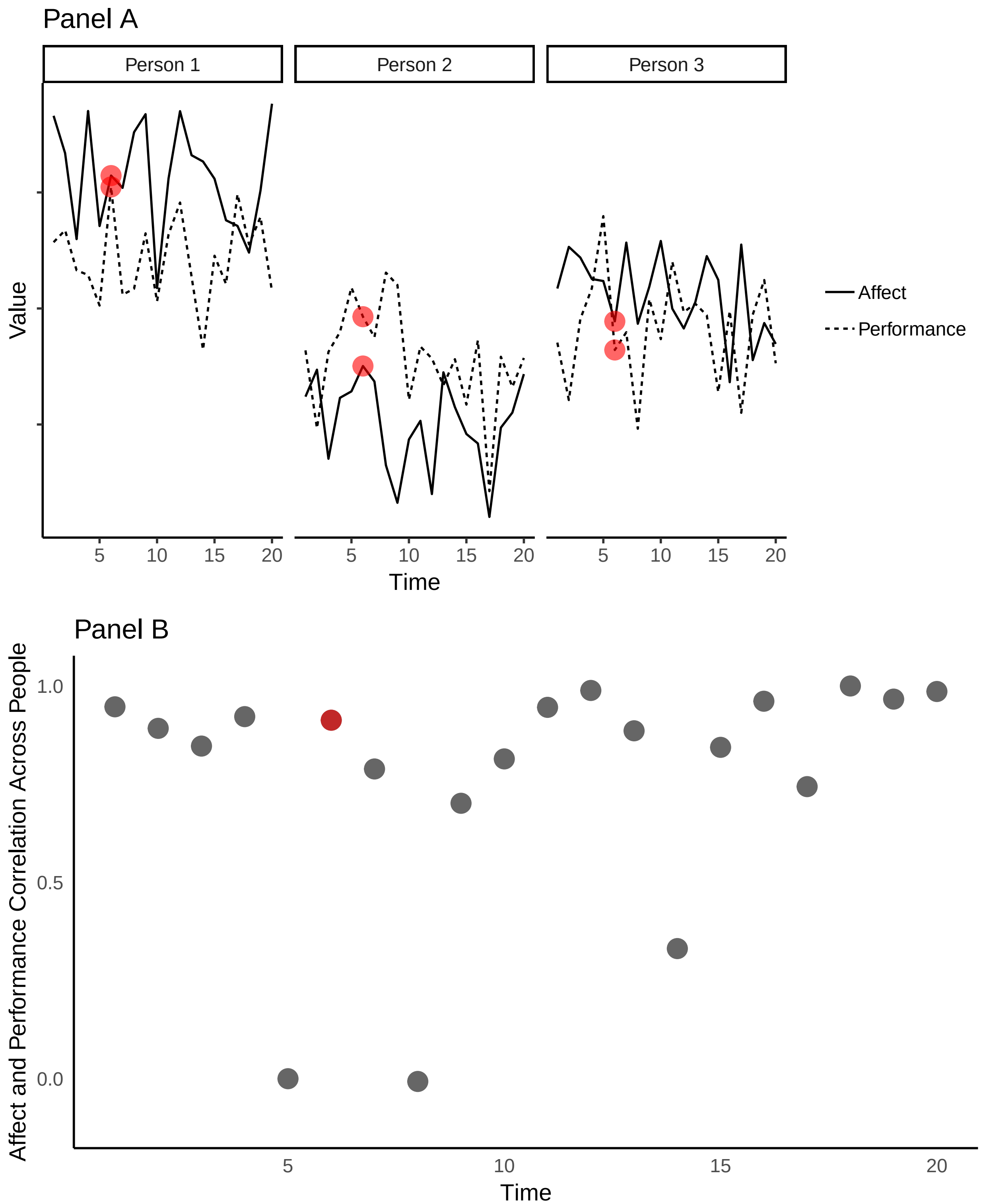

Figure 4. Relating affect to performance across units over time. The red circles demonstrate the between unit correlation at time point six. A typical time-varying covariates model constrains the correlation to be equivalent across time. Here, the relationship is unconstrained at each time point.

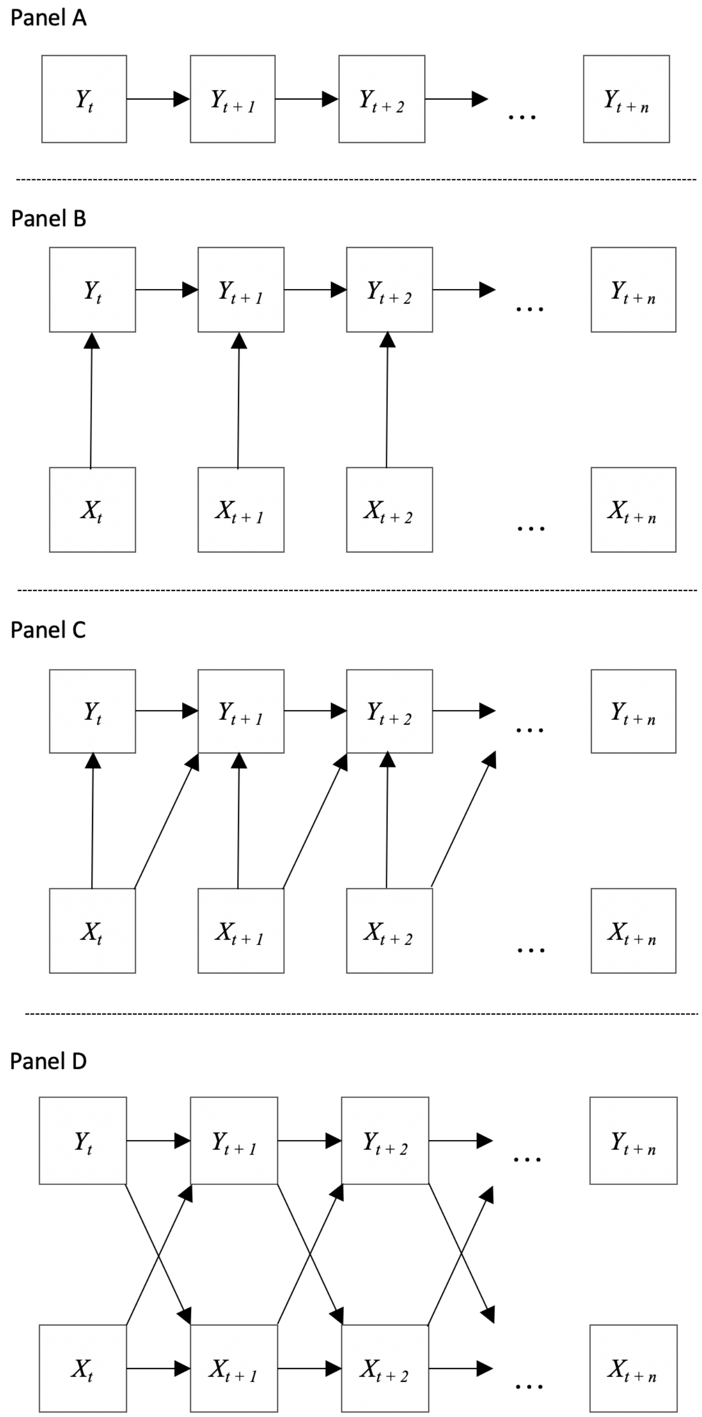

Figure 5. Univariate and bivariate dynamics adapted from DeShon (2012). Panel A shows self-similarity or autoregression in Y across time. Panel B shows concurrent X predicting change in Y. Panel C shows lagged change relationships. Panel D shows reciprocal dynamics between X and Y.