1   Inferences With Longitudinal Data

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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

₂₇ <center>Inferences With Longitudinal Data</center>

₂₈   Organizational scientists recognize that psychological phenomena and processes unfold

₂₉ over time (Beal, 2015; Pitariu & Ployhart, 2010). Individuals in the workplace, over time,

₃₀ strive to accomplish work goals, team members collaborate so the whole eventually becomes

₃₁ greater than the sum of its parts, and managers repeatedly promote values to build vibrant,

₃₂ innovative work cultures. To better understand psychological phenomena, such as

₃₃ motivation, teamwork, and organizaitonal culture, researchers must attent not to static

₃₄ snapshots of behavior (Ilgen & Hulin, 2000; Kozlowski, Chao, Grand, Braun, & Kuljanin,

₃₅ 2013, 2016) but to variables and relationships as they move through time. They must

₃₆ observe or obtain longitudinal data capturing the unfolding set of events, interactions,

₃₇ behaviors, cognitions, or affective reactions responsible for psychological phenomena.

₃₈   Researchers have the opportunity to explore many inferences when they analyze

₃₉ longitudinal data. For example, researchers may examine the shape of trajectories on

₄₀ psychological constructs (e.g., Did job satisfaction generally increase or decrease over six

₄₁ months after a merger?), how two or more constructs relate to each other (e.g., Did team

₄₂ communication and cohesion positively correlate over time?), or whether changes in one

₄₃ variable relate to changes in another (e.g., Did changes in goal-setting lead to changes in

₄₄ employee performance? Dunford, Shipp, Boss, Angermeier, & Boss, 2012; Hardy, Day, &

₄₅ Steele, 2018; Jones et al., 2016; Judge, Simon, Hurst, & Kelley, 2014; Lanaj, Johnson, &

₄₆ Wang, 2016; Rosen, Koopman, Gabriel, & Johnson, 2016; Scott & Barnes, 2011). Given the

₄₇ variety of available inferences in longitudinal data, an organizing framework would elucidate

₄₈ their subtle differences, enhance theoretical insight, guide data collection, and facilitate

₄₉ sound analytical work.

₅₀   We developed a framework to capture these inferences, a way to organize the

₅₁ fundamental between-unit 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 research question that they are interested in. In summary, this paper exposes researchers to the span of between-unit 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, swift action teams; Wildman et al., 2012) 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 predictable pattern or whether trajectories 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 move through time as functions of themselves and each other and emphasize how the past constrains the future. 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.

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

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 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 in which the inferences present themselves simply by plotting – althought it is certainly possible. 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 in which researchers create an index of time and relate it to their response variable to understand the trajectory of the dependent variable. The first panel of Figure 1 shows a box-and-arrow model heuristic in which 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, increase or decrease 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 display a stable temporal pattern? 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 units – 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.

146   Correlating these trends between-units is the next inference. Correlating indicates

147 co-occuring patterns, where a large, positive, between-unit correlation between affect and

148 performance trends indicates that people with a positive affect trend (usually) have a

149 positive performance trend and people with a negative affect trend (usually) have a negative

150 performance trend.

151   Figure 2 shows the inuition behind this inference with a set of graphs. In Panel A, we

152 plot affect and performance across time for three individuals. Affect goes up while

153 performance goes down for person one, this pattern is reversed for person two, and person

154 three reports trendless affect and performance (i.e., zero trend). We use different colors to

155 label the trends for each person. The affect and performance trends for person one are

156 labeled with red lines, whereas person two has green lines and person three has blue lines.

157   Panel B then maps those pairings onto a scatterplot that demonstrates the

158 between-unit relationship among affect and performance trends. For example, person one

159 has a positive affect trend and a negative performance trend, so their value in Panel B goes

160 on the bottom right, whereas person two has the opposite pattern and therefore is placed on

161 the top left (where the performance trend is positive and the affect trend is negative).

162 Producing this bottom scatter plot tells us that the between-unit association among affect

163 and performance trends is negative. That is, people with a positive affect trend are expected

164 to have a negative performance trend, people with a negative affect trend are expected to

165 have a positive performance trend, and people with an affect trend of zero are expected to

166 have a performance trend of zero.

167   ————————

168   Insert Figure 2 about here

169   ————————

170   **Research Question 3:** What is the between-unit correlation among

171   two trends?

172   The final trend inference is about identifying covariates or predictors of trend. Does

173 gender predict depletion trends? Does the trend in unit climate covary with between-unit

174 differences in leader quality?

175   Figure 3 demonstrates the inference in a plot. We graph affect across time for six

176 employees, and these employees differ by job type. The first three individuals work in

177 research and development, whereas the final three work in sales. Affect trajectories tend to

178 decrease over time for employees in research and development, whereas affect trajectories

179 tend to increase for those in sales. An individual's job type, then, gives us a clue to their

180 likely affect trend – said formally, job type covaries with affect trend, such that we expect

181 individuals in sales to have positive affect trends and individuals in research and development

182 to have negative affect trends. The expected trends are plotted as the thick blue lines.

183   ———————

184   Insert Figure 3 about here

185   ———————

186   **Research Question 4:** What is the betweeen-unit correlation among

187   trend and a covariate?

188   Note the difference between research questions three and four. Both are between unit,

189 but three is about co-occuring trend patterns whereas four is about the relationship between

190 trend and a covariate/predictor. With respect to our examples, inference three (i.e., the

191 answer to research question three) says, on average, if an individual has a positive affect

192 trend then we expect her to have a negative performance trend. Inference four says, on

193 average, if an individual is in research and development then we expect him to have a

194 negative affect trend.

195 **Component 2 - Level.** Researchers that explore trend also assess its predicted

196 value at a given time t, and this second component is called level. Level is almost always

197 evaluated at the first or last observed time point – e.g., What is the predicted level of the

198 trainee skill trend, on average across units, at the beginning of a training session? On

199 average across units, what is the expected level of the unit climate trend at the end of a

200 two-week socialization process? – although researchers are free to asssess level at any t.

201   **Research Question 5:** On average across units, what is the expected

202   level of the y trend at time t?

203   After exploring the average (across units) trend level, we then move to its variability.

204 Trend lines have a beginning (or end) point, how consistent do we expect that point to be

205 across the sample? Is there variability in affect trend starting level? Are there large

206 between-unit differences in the expected level of the performance trend at the last time

207 point?

208   **Research Question 6:** Is there variability across units in the

209   expected level of the y trend at time t?

210   It is also possible to assess between-unit correlations among level and (a) trend in the

211 same variable or (b) level or (c) trend in a different variable. First, consider a relationship

212 among level and trend in the same variable. On average across units, do people with low

213 initial skill show positive skill trends whereas people with high initial skill show negative skill

214 trends? Do organizations with high initial CWBs, on average across units, tend to have

215 negative CWB trends?

216   **Research Question 7:** What is the between-unit correlation

217   between trend and level in y?

₂₁₈   Second, consider a between-unit correlation between level in one variable and level in

₂₁₉ another. On average across units, do people with low initial performance also have low initial

₂₂₀ depletion (based on the initial levels predicted by the performance and depletion trends)?

₂₂₁ Are organizations with high initial turnover also expected, on average across units, to have

₂₂₂ high burnout (based on the initial levels predicted by the turnover and burnout trends)?

₂₂₃   **Research Question 8:** What is the between-unit correlation

₂₂₄   between level of the x trend and level of the y trend at t?

₂₂₅   Finally, researchers are free to mix the inferences above and assess whether levels in

₂₂₆ one variable covary with trend in another. Are people with high initial voice (predicted by

₂₂₇ the voice trend) expected to have negative satisfaction trends?

₂₂₈   **Research Question 9:** What is the between-unit correlation

₂₂₉   between the level of the x trend at time t and the trend in y?

₂₃₀   A note on phrasing. The inferences we explored in this section have to do with

₂₃₁ correlating levels and trends, where a statement like, "affect and performance trends covary

₂₃₂ between-units, such that people with a negative affect trend have a positive performance

₂₃₃ trend" is appropriate. There is a less precise phrase that is easy to fall into – and we have

₂₃₄ seen it used in our literature. Sometimes, researchers will correlate trends and then state,

₂₃₅ "when affect decreases performance goes up." We urge researchers to avoid this second

₂₃₆ statement because it is not clear if it refers to a static relationship about trends or a

₂₃₇ dynamic statement about how trajectories move across time. That is, the phrase "when

₂₃₈ affect decreases performance goes up" could refer to between-unit correlated trends, but it

₂₃₉ could also mean something like, "when affect decreases performance immediately or

₂₄₀ subsequently goes up." This second statement is far different and it should not be used when

₂₄₁ an analysis only correlates trends or evokes predictors of trend. Again, we urge researchers

₂₄₂ to phrase their inferences as we show here.

Statistical Models for Trend

Currently, the dominant method for analyzing longitudinal data with respect to trend inferences in the organizational sciences is growth curve modeling (GCM; Braun, Kuljanin, & DeShon, 2013; Kuljanin et al., 2011a). 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 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 from our own field include Dunford et al. (2012) and Hülsheger (2016).

GCM is the longitudinal application of the more general statistical technique, random coefficient modeling (RCM; e.g, Hierarchical Linear Modeling; Latent Growth Modeling; Bollen & Curran, 2006; Raudenbush & Bryk, 2002; Singer et al., 2003). GCM (and RCM) can be applied through either a regression-based (e.g., Singer et al., 2003) or structural equation modeling-based (SEM; e.g., Bollen & Curran, 2006) approach. A complete discussion of these two approaches is beyond the scope of this paper; rather, this paper only focuses on the regression-based approach of GCM. All models presented have an equivalent representation within the SEM framework and can achieve identical inferences.

GCM models the dependent variable – performance, for example – as a result of predictors at multiple levels of analysis. Level one predictors vary at the same level as the depenent variable, meaning that if individual performance is the outcome of interest then level one predictors might include individual goal-striving and individual cognitive ability. If, on the other hand, the outcome is organizational performance then level one predictors might include organizational climate or culture. Level two predictors occur at higher units of

analysis – team cohesion if the dependent variable is individual performance or national

culture if the dependent variable is organizational performance. Variables at any level can

enter into the statistical model either as fixed or random. Fixed predictors estimate only the

average relationship across all units, whereas random predictors estimate not only the

average IV-DV relationship across units but also estimate the degree of between-unit

variability in the that relationship.

The most basic growth model is the unconditional means model (UMM). Using

notation from Singer et al. (2003), this statistical model is specified as

$$Y_{ij} = \pi_{0i} + \varepsilon_{ij} \tag{1}$$

$$\pi_{0i} = \gamma_{00} + \zeta_{0i} \tag{2}$$

where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ and $\zeta_{0i} \sim N(0, \sigma_0^2)$, Y_{ij} is the dependent variable measured for person i at

time j, π_{0i} is the mean of Y for individual i, γ_{00} is the mean of Y across everyone in the

population, ε_{ij} is the residual for individual i on occasion j, σ_ε^2 is the pooled within-person

variance of each individual's data around his or her mean, ζ_{0i} is the random effect for

individual i (i.e., deviation of the person-specific mean from the grand mean), and σ_0^2 is the

random effect variance.

In words with individual performance as an example, this UMM says that performance

for Rachel at any time is a function of her across time individual performance mean and

error (equation one). Moreover, Rachel's individual performance mean is a function of the

population performance mean (i.e., the mean of everyone's individual performance) and error

(equation two). What this statistical model embodies is that (1) a reasonable prediction for

Rachel's performance given no other information, such as other predictors like goal-striving

or cognitive ability, is the mean of individual performance and (2) there are between-person

differences in individual performance.

290   The initial UMM model is typically used to calculate the intraclass correlation

291   coefficient (ICC(1)) which estimates the proportion of total variance attributed to

292   between-unit differences. Researchers, for example, would conduct an initial UMM on

293   individual performance and then state, perhaps, that 57% of the total variance resides

294   between individuals. It is also possible to conduct a χ^2 test to assess whether the estimated

295   between-person variance differs from zero. Both results are used to argue that it is

296   reasonable to move forward with more complicated statistical analyses, to include additional

297   predictors that may explain (in a statistical sense) the observed between-person variability.

298   Assuming differences across units exist, it is then recommended to conduct the

299   unconditional linear growth model (ULGM). The ULGM regresses the dependent variable on

300   a fixed linear time variable while allowing variability across units in intercepts. The

301   regression weight on the time variable (ie., slope) models the average trend across units and

302   is used to answer RQ1. It is then common to allow the Time-DV relationship to vary across

303   units by entering the time variable as a level one random predictor, as shown in the equation

304   below.

$$Y_{ij} = \pi_{0i} + \pi_{i1}Time_{ij} + \varepsilon_{ij} \tag{3}$$

$$\pi_{0i} = \gamma_{00} + \zeta_{0i} \tag{4}$$

$$\pi_{i1} = \gamma_{10} + \zeta_{1i} \tag{5}$$

305   where $\varepsilon \sim N(0, \sigma_{\varepsilon}^2)$ and $\begin{bmatrix} \zeta_{0i} \\ \zeta_{1i} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{10} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix} \right)$, π_{0i} is now the initial status (i.e.,

306   intercept) of Y for individual i, γ_{00} is the average initial status of Y across everyone in the

307   population, π_{1i} is the rate of change (i.e., slope) of Y for individual i, γ_{10} is the average rate

308   of change of Y across everyone in the population, σ_{ε}^2 is the pooled variance of each

309   individuals' data around his or her linear change trajectory, ζ_{0i} is the intercept random effect

310 for individual i, σ_0^2 is the variance of intercept random effects, ζ_{1i} is the slope random effect

311 for individual i, σ_1^2 is the variance of the slope random effects, σ_{10} is the population

312 covariance between intercepts and slopes, and all other terms are defined above.

313   In words with individual performance as example, this ULGM says that Rachel's

314 performance is a function of her initial level of performance (which is a function of the

315 population initial performance level and error) and time (equation 3). Time, therefore, can

316 be thought of as a predictor in the case of the ULGM which makes it an inherently static

317 statistical model (Voelkle & Oud, 2015). We moved beyond the unconditional means model

318 to "explain" more variation in Rachel's performance by including additional predictors. In

319 the case of the ULGM, our additional predictor is time and the estimate of the coefficient

320 relating it to the outcome describes both the expected trend and whether there are

321 between-unit differences in trend in the sample (research questions one and two). Time is a

322 level one predictor because it varies on the same level as the outcome (the individual level)

323 and it is incorporated in the statistical model as a random effect (equation 5).

324   To review, we first modeled individual performance as a function of across time

325 individual performance means (which, themselves, were functions of the population

326 individual performance). That basic statistical model was a UMM and we turned it into an

327 ULGM by incorporating time as a predictor. Once time enters the equation, we update our

328 view of performance and it becomes a function of initial performance level and time,

329 meaning that one-unit increases in time are seen as relating to increases or decreases in

330 performance. Those increases and decreases across time, in aggregate, form trend. In

331 practice, the statistical model returns one number for the estimate of the coefficient relating

332 time to the outcome and it describes the expected between-person performance trend.

333   Understanding the basic ULGM with time as a random level one predictor allows

334 researchers to explore, with simple extensions such as incorporating additional predictors or

335 modeling two or more variables as outcomes (multivariate systems), any number of further

inferences. Researchers can enter additional multiples of time as predictors – e.g., include $Time^2$ and/or $Time^3$ in equation 3 – to determine whether trajectories are curvilinear or follow other temporal patterns. Researchers can enter additional level one or two substantive predictors to determine whether there are covariates of trend. Consider, again, the example in Figure 3 which plots affect trends that differ by job type. Affect is the outcome that is regressed on time, forming the underlying ULGM. Entering job type as a random, level two predictor returns a coefficient that describes whether the expected affect trend differs according to this additional predictor. Statistically, the model estimates whether higher values on the level two predictor relate to stronger IV-DV relationships. In the case of growth models, time is the IV so "stronger IV-DV" relationships means different trend patterns. The level two predictor therefore estimates whether higher values – or in the case of job type, different types of jobs – demonstrate different trend (RQ4). Beyond incorporating more predictors of a single outcome, researchers can also model multiple outcomes with simultaneous ULGMs. Consider first two independent ULGMs, one with individual performance regressed on time and another with individual OCBs regressed on time. All inferences, research questions, and statitical models described above can be explored independently with these two outcomes. Typically, however, when random effects are incorporated covariances among all random effect variables are estimated, meaning that the two outcomes in the multivariate system are no longer viewed as independent. The covariance estimate between the slope term for performance and the slope term for OCBs, in this example, are used to answer research question three.

Statistical Models for Level

Once time is included in the statistical model (e.g., the ULGM), the intercept value represents the level of the DV at the time point coded 0 (typically the first or last time point). The intercept value is almost always modeled as random whereby the analysis will

361 return a mean estimate which tells you the average level across units (answering RQ5), and

362 it will also return a variance estimate that indicates variability in level between units. As

363 such, the variance component on the intercept term determines whether there is significant

364 between-unit variability in the level of the DV when time equals zero, answering RQ6. As

365 previously stated, it is common to estimate covariance among random predictors, therefore

366 the covariance between the intercept and slope random effects is used to determine whether

367 units with higher (lower) initial values exhibit stronger (weaker) growth, answering RQ7.

368 Finally, it is also possible to estimate covariances among the intercept and slope among

369 different variables in multivariate systems, answering RQ8 and RQ9.

Relationships

371 A relationships inference explores between-unit relationships over time. The second

372 panel of Figure 1 shows a model heuristic, where a predictor is concurrently related to a

373 response variable at each time point and the relationship is typically constrained to equality

374 or is averaged over time. Essentially, the inference compiles single-moment between-unit

375 correlations. For example, we assess the between-unit correlation between, say, OCBs and

376 depletion at time one, again and times two and three, and then ultimately take the average

377 of each individual, between-unit correlation.

378 Questions about static relationships over time take the following forms. What is the

379 relationship between helping behaviors and incivility? Does burnout predict turnover

380 intention? Is unethical behavior related to self-control?

381 Figure 4 shows the inuition of the inference with data. Panel A plots affect and

382 performance trajectories for three people. The red circles in Panel A highlight each

383 individual's affect and performance values at time point six. Given that we have three people

384 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.

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Insert Figure 4 about here

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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 for Relationships

Time-varying covariates (TVC) analysis is the workhorse behind relationship inferences. TVC models are simply growth curve models that include level 1 predictors (either fixed or random). The equation below shows an ULGM ammended to include an additional level one predictor, X.

$$Y_{ij} = \pi_{0i} + \pi_{i1}Time_{ij} + \pi_{i2}X_{ij} + \varepsilon_{ij} \tag{6}$$

$$\pi_{0i} = \gamma_{00} + \zeta_{0i} \tag{7}$$

$$\pi_{i1} = \gamma_{10} + \zeta_{1i} \tag{8}$$

$$\pi_{i2} = \gamma_{20} + \zeta_{2i} \tag{9}$$

where X is the additional random predictor and it is related to the outcome, Y, through π_{i2}. The average relationship between X and Y across units is used to answer RQ1 whereas the variance component estimating the between-unit variaiblity in the X-Y relationship is used to answer RQ2. It is important to note that TVC analyses can either be conducted by building upon the ULGM, as is presented here (and seen in Braun, Kozlowski, Brown, & DeShon, in press), or can be done by building directly upon the UMM (e.g., Judge, Scott, & Ilies, 2006). The difference is whether the predictor time is included to control for growth in the DV. Typically, if it is anticipated or observed that the DV exhibits a consistent trajectory over time, then time is included and TVC models build from the ULGM. Alternatively, if the DV is not expected or observed to exhibit linear (or curvilinear) growth, then level one predictors are added directly to the UMM. A complete discussion of TVC models is in Schonfeld and Rindskopf (2007) and Finch, Bolin, and Kelley (2016) and two relatively straight-forward empirical examples are in Barnes, Schaubroeck, Huth, and Ghumman (2011) and Chi, Chang, and Huang (2015).

₄₂₆   **Dynamics**

₄₂₇   Dynamics refers to a specific branch of mathematics, but the term is used in different

₄₂₈ ways throughout our literature. It is used informally to mean "change", "fluctuating,"

₄₂₉ "volatile," "longitudinal," or "over time" (among others), whereas formal definitions are

₄₃₀ presented within certain contexts. Wang (2016) defines a dynamic *model* as a

₄₃₁ "representation of a system that evolves over time. In particular it describes how the system

₄₃₂ evolves from a given state at time t to another state at time $t + 1$ as governed by the

₄₃₃ transition rules and potential external inputs" (p. 242). Vancouver, Wang, and Li (2018)

₄₃₄ state that dynamic *variables* "behave as if they have memory; that is, their value at any one

₄₃₅ time depends somewhat on their previous value" (p. 604). Finally, Monge (1990) suggests

₄₃₆ that in dynamic *analyses*, "it is essential to know how variables depend upon their own past

₄₃₇ history" (p. 409). In this section we discuss a number of inferences couched in the idea that

₄₃₈ the past constrains future behavior.

₄₃₉   Does performance relate to itself over time? Do current helping behaviors depend on

₄₄₀ prior helping behaviors? Does unit climate demonstrate self-similarity across time? Does

₄₄₁ income now predict income in the future? These are questions about the relationship of a

₄₄₂ single variable with itself over time – does it predict itself at each subsequent moment? Is it

₄₄₃ constrained by where it was in the past?

₄₄₄   Panel A of Figure 5 shows the concept with a box-and-arrow model heuristic. y

₄₄₅ predicts itself across every moment – it has self-similarity and its value now is constrained by

₄₄₆ where it was a moment ago. In our diagram, we show that y at time t is related to y at time

₄₄₇ $t + 1$. In other words, we posit that y shows a lag-one relationship, where y is related to its

₄₄₈ future value one time-step away. Researchers are of course free to suggest any lag amount

₄₄₉ that they believe captures the actual relationship. Note that the statistical term to capture

₄₅₀ 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, $t-1$, $t-3$); 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, in which 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).

Statistical Models for Dynamics

Much like the models presented for relationship inferences, one way to view dynamic models is as extensions of the ULGM or UMM. The principle addition for dynamic models is the inclusion of a lagged version of the DV as a predictor (Y_{t-1}). The inclusion of Y_{t-1} controls for prior observations of the DV when predicting current values, essentially modeling the change in the DV from one time point to another without relying on difference scores due to their statistical pitfalls (e.g., Edwards & Parry, 1993). As such, the first research question is answered by evaluating the average relationship between the DV and a prior version of itself as a level one predictor. Similarly, once the autoregressive term is modeled as random, evaluating the variance component answers RQ2 regarding whether the autoregressive relationship differs across units. To answer the subsequent research questions, the inclusion of an additional substantive predictor, X_t, is required. When X_t is modeled at only the concurrent time point with the DV, then the $X_t \rightarrow Y_t$ relationship determines whether values of X at a given time point relate to the change in Y, addressing RQ3. The variance component on X_t when it is modeled as a random level one preditor determines whether the relationship varies across units, answering RQ4. Finally, if the researcher is interested in determining whether changes in the predictor, X, relate to changes in the DV, Y, an additional level one predictor in included in the model that represnts prior realizations of X, X_{t-1}. With the inclusion of X_{t-1}, the paramater on the predictor X_t now determines whether changes in X relate to changes in Y, answering RQ5 whereas the variance component on X_t determines whether significant variability in the relationship exists (RQ6). There are many additional dynamic models that can be estimated within the GCM framework. Wang et al. (2016) reviews many of the different types of dynamic models and, although the paper does not provide readers will specific code, is an excellent resource to observe the variety of potential 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 among a set of constructs (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 emphasizes 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

571 within-person perspective of organizational citizenship behaviors.

572   Within-unit perspectives have their own research questions and inferences. For
573 example, Ilies, Johnson, Judge, and Keeney (2011) hypothesize that "interpersonal conflict
574 at work immediately influences employee's negative affect, such that employees will report
575 heightened negative affect after periods when they experience more conflict, compared to
576 periods when they experience less conflict" (p. 3). There are many within-person inferences
577 accumulating in our literature, but they often apply a between-person model and are
578 dispersed among different content areas. An immediate next step for research is to write the
579 within-unit version of this paper, a paper that organizes and explains within-unit inferences.

580   When researchers explore patterns in longitudinal data, regardless of whether they
581 emphasize between or within-unit inferences, there are additional statistical complexities to
582 consider that influence the veracity of a researcher's conclusions. For example, consider a
583 researcher interested in inference one from the "relationships" section of this paper. To
584 explore it, she collects data on 400 subjects across eight time points, applies a recommended
585 statistical model, and then evaluates the results and makes an inference about the
586 underlying process. Although she aligned her question with an appropriate statistical model,
587 there is an issue related to her data that she did not assess. The longitudinal data that she
588 collected may not contain the statistical characteristics that merit her inference. She can ask
589 questions about its patterns, apply a statistical model to it and make statements that are
590 appropriate *given only the statistical model that she applied*, but we do not know if her
591 inference is appropriate *given the statistical characteristics of the data that she applied her*
592 *model to.* Do the data merit her inference in the first place?

593   The statistical complexities that we discuss below include stationarity and ergodicity.
594 Stationarity and ergodicity are statistical characteristics that can be assessed with
595 longitudinal data, and we discuss both below in the context of advocating for greater T, for
596 researchers to collect more observations over time because statistical models alone do not

reveal stationarity or ergodicity if the analyst is not meticulously looking for them. They require tests of their own and the tests are facilitated by data structures with more time points.

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). Full explanations of stationarity are in Kuljanin et al. (2011b), Braun et al. (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 of 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. Both are complex ideas and merit entire papers of their own, but for now 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

649 course gives researchers the ability to explore both frameworks, but our field will need to

650 recognize that a small samples (e.g., five or fewer participants) measured across many time

651 points does allow a researcher to make within-person inferences (by definition) and is useful.

652 Given the resource constraints that come with conducting research, we cannot shy away from

653 few participants measured across many time points as viable techniques to assessing

654 within-person relationships.

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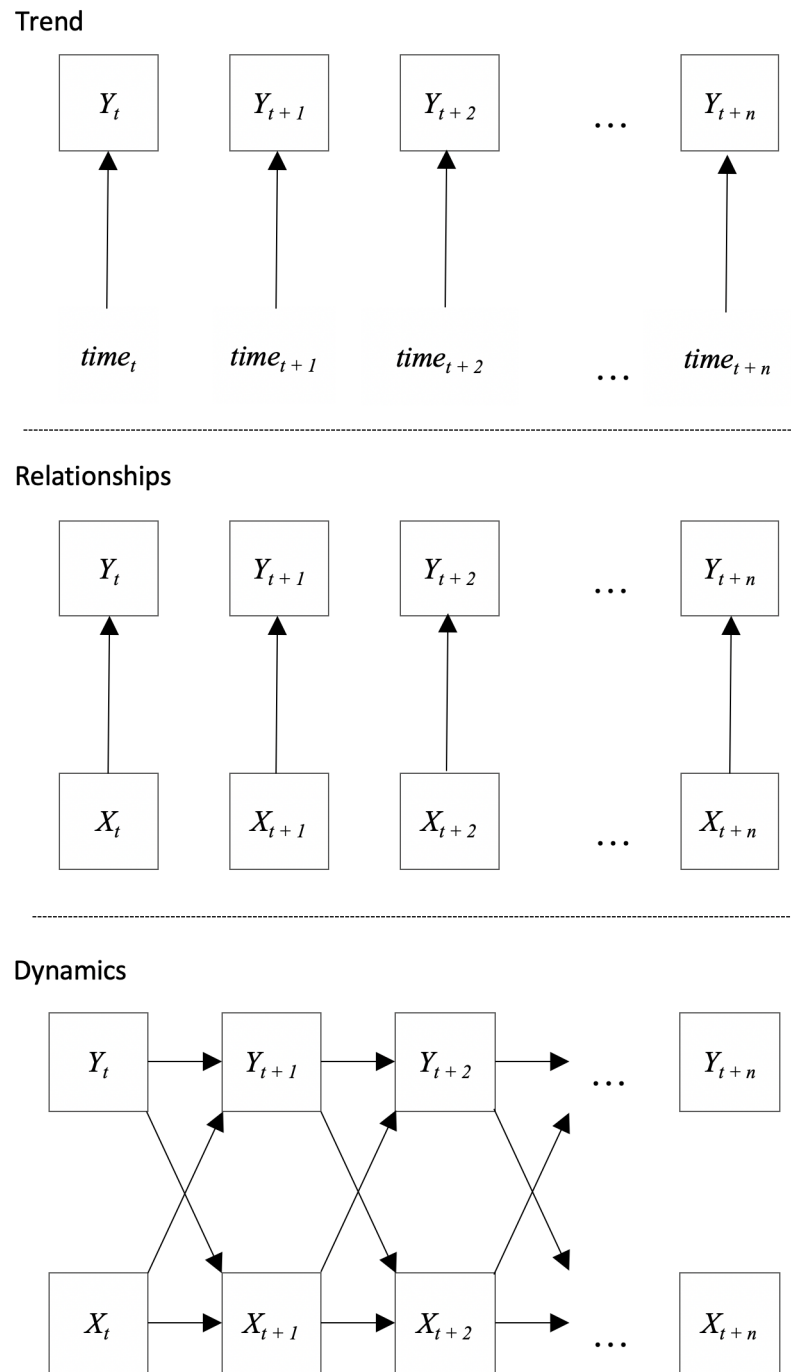811 framework. *Group & Organization Management*, *37*(2), 137–170.

Trend

Relationships

Dynamics

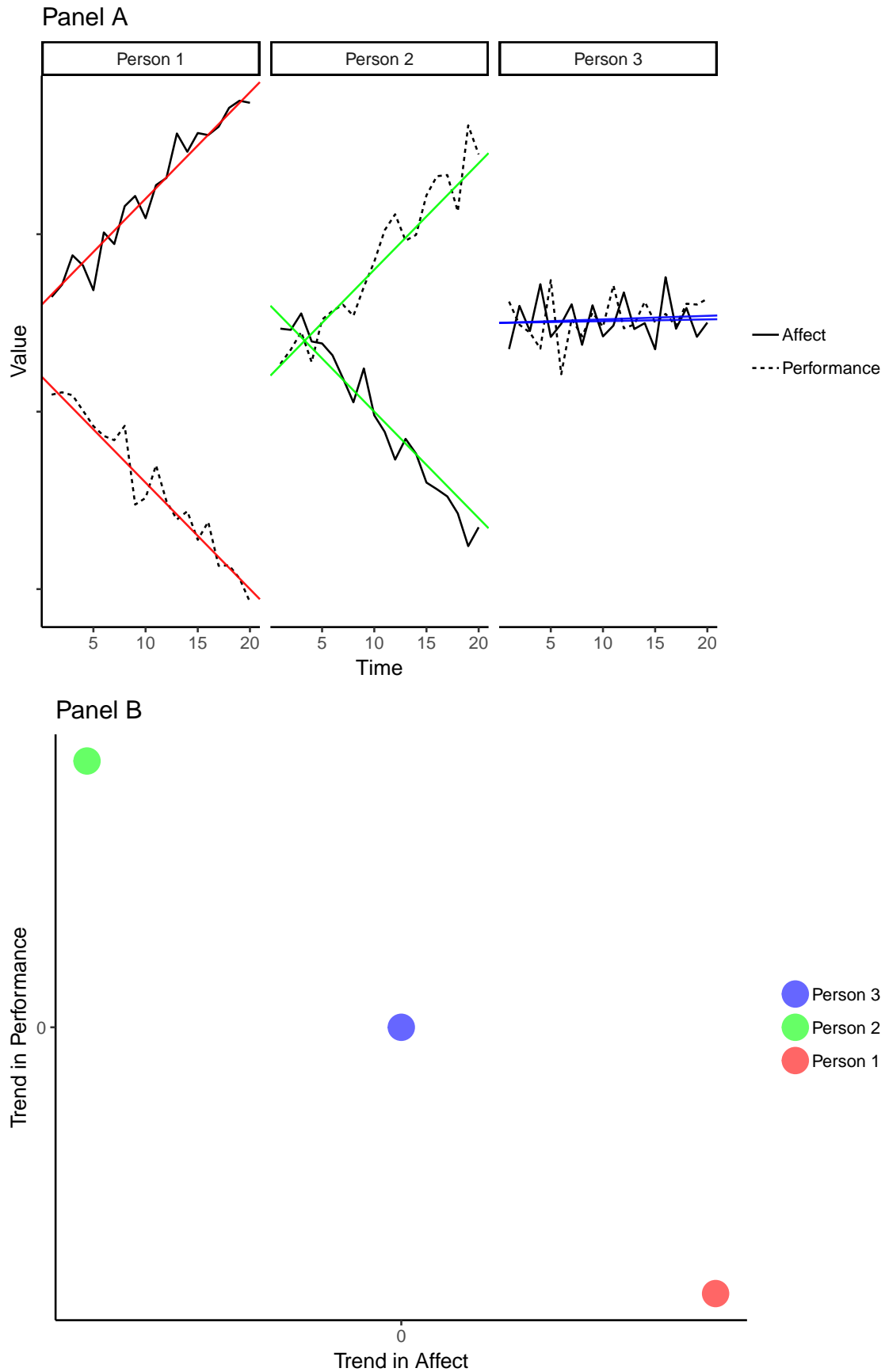*Figure 1*. Common inference categories with models applied to longitudinal data.

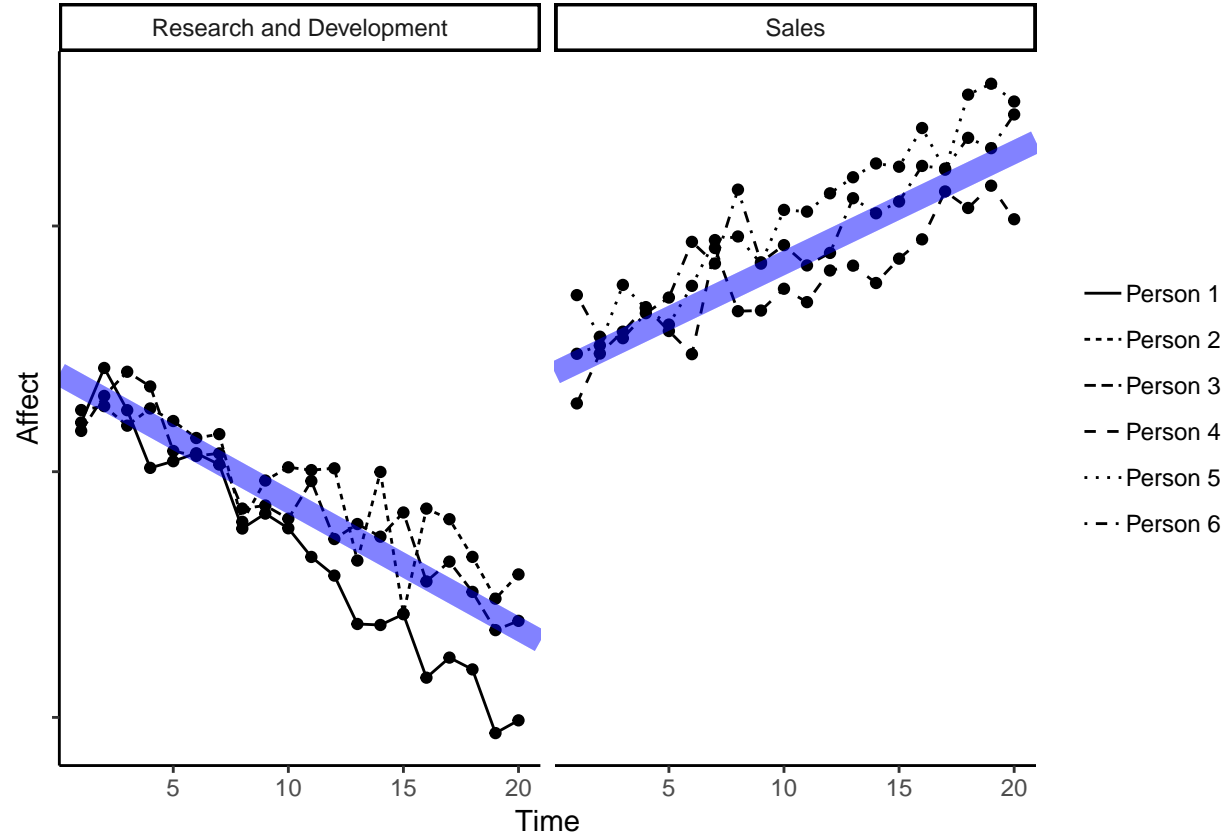*Figure 2*. Between-unit correlation of trend in affect and performance.

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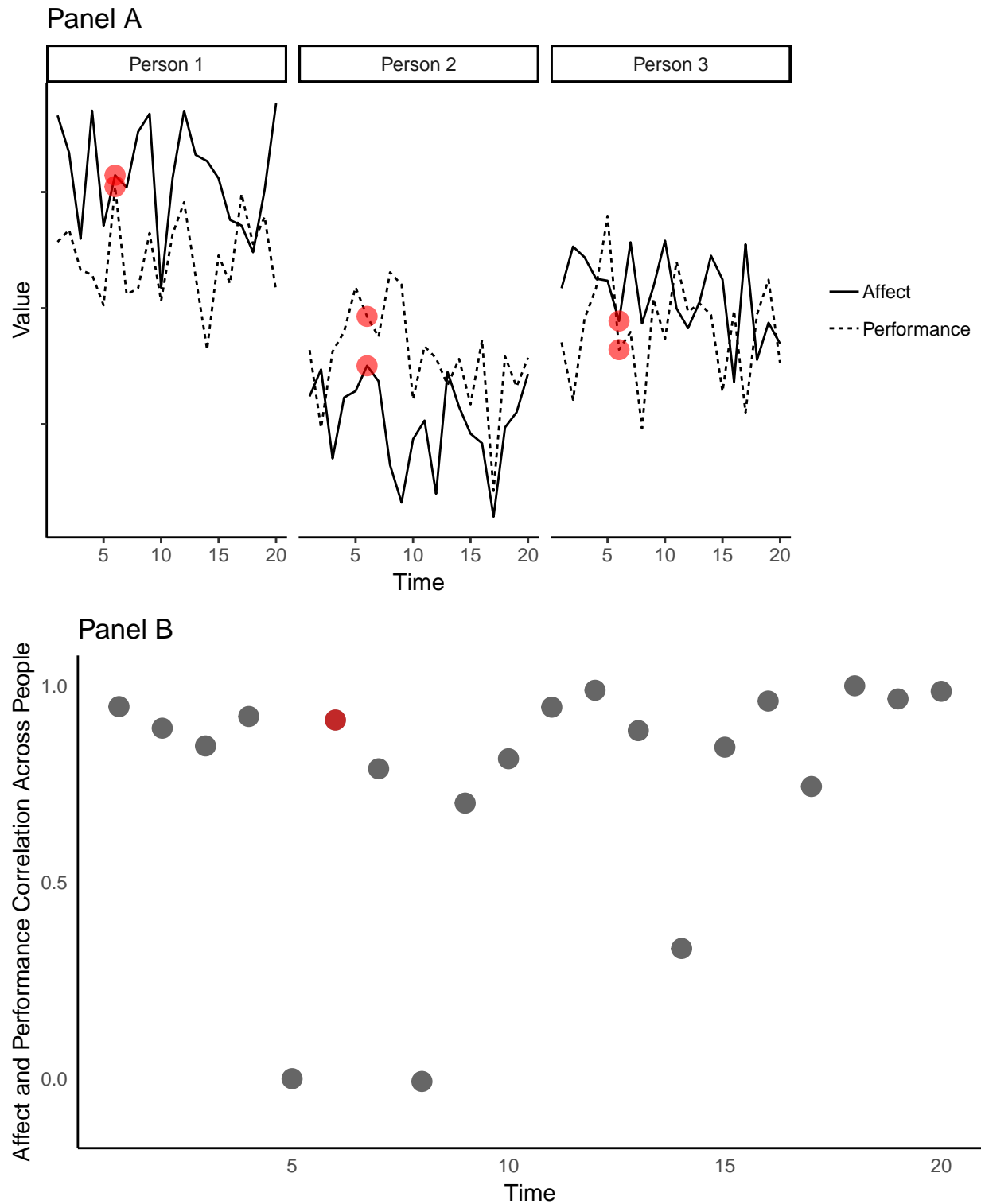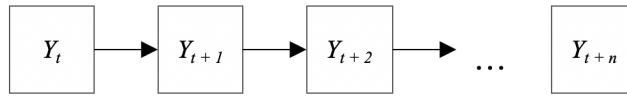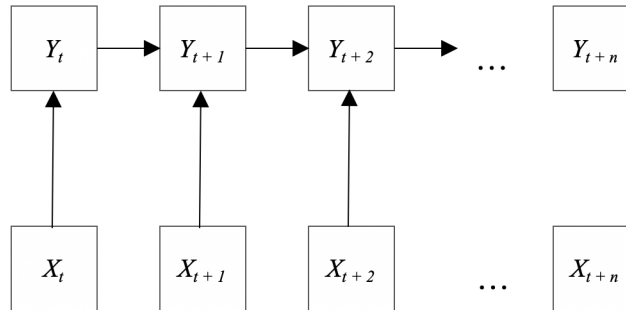
Panel A

Panel B

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.
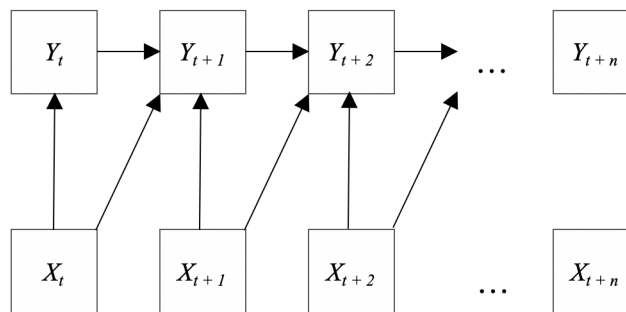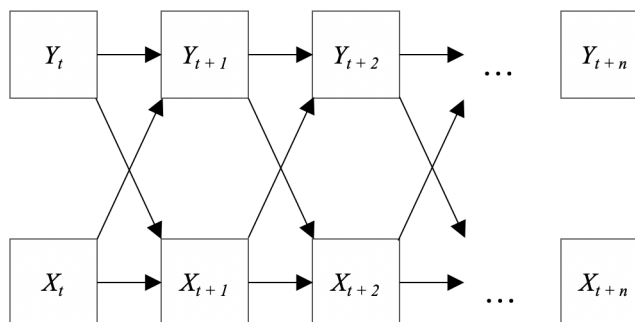
Panel A

Panel B

Panel C

Panel D

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.