1   Inferences With Longitudinal Data

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

3   [1] Michigan State University

4   [2] University of South Florida

5   [3] DePaul University

6   Author Note

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8   Correspondence concerning this article should be addressed to Christopher R. Dishop,

9   316 Physics Road, Psychology Building, Room 348, East Lansing, MI, 48823. E-mail:

10 dishopch@msu.edu

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 structures lend themselves to many different inferences – to different patterns that researchers may emphasize – and there are different 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 can also make 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, discuss the inferences, 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

₂₈ <center>Inferences With Longitudinal Data</center>

₂₉ Organizational phenomena unfold over time. They are processes that develop, change,

₃₀ and evolve (Pitariu & Ployhart, 2010) that create a sequence of events within a person's

₃₁ stream of experience (Beal, 2015). Moreover, organizations are systems with many connected

₃₂ parts, and systems are inherently dynamic. Studying these systems and processes, therefore,

₃₃ requires that we attend not to static snapshots of behavior (Ilgen & Hulin, 2000), but to

₃₄ variables and relationships as they move through time; doing so puts us in a better position

₃₅ to capture the sequence, understand it, and can lead to new and interesting insights

₃₆ (Kozlowski & Bell, 2003).

₃₇ We have noticed a variety of inferences emerging in our literature that researchers

₃₈ explore when they want to understand something over time. Some focus on whether

₃₉ trajectories increase or decrease, or the pattern of growth in a variable over time. Others

₄₀ turn their attention not to trends but to relationship patterns across time. There is also an

₄₁ increasing emphasis on dynamics. How are these ways of asking questions about patterns in

₄₂ longitudinal data different? We find these inferences everywhere, and their persistence has

₄₃ driven us to ask how to organize them.

₄₄ We developed a framework to capture these inferences; a way to organize the

₄₅ fundemental patterns researchers explore with longitudinal data despite focusing on different

₄₆ content areas or using different statistical models. Often research groups focus on one

₄₇ familiar inference despite having the data to explore many more fundamental patterns.

₄₈ There are also a number of complex statistical models lingering in our literature, and it is

₄₉ not always clear for which questions they are appropriate. We want to be sure researchers

₅₀ have a framework to expose the core patterns in longitudinal data as these data structures

₅₁ become more popular in our field.

₅₂ In this paper we discuss the common inferences that researchers in our field make when

they apply a model to longitudinal data. As should be clear to anyone reading our literature, there is great excitement for the utility of longitudinal studies; they can pose interesting questions and discover patterns that would otherwise be impossible to capture in a static investigation. 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. Moreover, there are many inferences, many models, and different models can be used to understand or explore the same inference. In this paper, 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 the inferences we make with 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

78   longitudinal research with longitudinal data, or designs with $N > 1$, $t >= 3$, and the same

79   construct(s) measured on each i at each t. In English, we focus on designs that measure their

80   variables repeatedly across many people – and every variable is measured at each time point.

Framework

82   We use four inference categories to partition our discussion, including level, trend,

83   relationships, and dynamics. Each of these are broad categories, and they will all have their

84   own sub-inferences and models. Our writing style will be the same throughout each section,

85   where we first discuss the category itself and then sequentially walk through the inferences.

86   During that sequence, we will pose questions to orient the reader as to what the inference

87   captures, unpack graphs and figures, and then close with a table that provides example

88   hypotheses that align with each inference. The figures we use in the level, trend, and

89   relationships sections are graphs that show what the inferences look like in data – we feel

90   that graphing the inferences with respect to data is more informative than your usual box

91   and arrow diagram. There is a caveat, however, that we want to make sure everyone is aware

92   of. Data are always messy. It is rare to find data where the inferences expose themselves

93   simply by plotting – although it is certainly possible. We are using these "data plots" to

94   clearly convey what the inferences mean, but please be aware that field data will always be

95   messy. When we discuss dynamics we then use box and arrow diagrams because they better

96   convey the ideas in that section.

97   Finally, we end each inference section by pointing researchers to respective statistical

98   models. Although we direct researchers to models, our paper is not about statistical

99   modeling only – it is about inferences – and researchers therefore need to be sure that they

100 appreciate all of the nuance before applying a recommended model. There are many complex

101 statistical issues that arise with longitudinal modeling – like stationarity – and the models

102 differ in how they handle these issues, the assumptions they make, and the data format they

103   require. There are plenty of great references on each model, what we are doing here is

104   guiding researchers to those references based on the underlying inferences that interest them.

Level

106   Is employee emotional exhaustion, on average, high across the study? Is trainee skill

107   low at the beginning of a training session? What value are newcomer perceptions of unit

108   climate at the end of a two-week socialization process? These are questions about level, or

109   the specific value of a variable.

110   Levels either describe the variable at one moment or averaged across a span of time.

111   That is, if we put a variable on the y axis and plot its values against time on the x axis, we

112   can explore the value that it takes at time t, or the value that it takes on average across any

113   span of t.

114   Figure 1 demonstrates this idea graphically. A variable is plotted across time for a

115   single person (i.e., unit), and the color labels indicate levels – the red and green describe the

116   variable at a specific moment while the purple, average level, describes it across a window.

117   The starting level is the value of the variable at the first time point, the ending level is its

118   value at the last time point, and the average level is its average level across time.

119   ————

120   Insert Figure 1 about here

121   ————

122   Our first level inference, therefore, concerns the value of a variable at a specific time or

123   averaged across a window of time.

124   **Inference 1:** What is the level of x at time t, or across a span of t?

125   When we retain one variable but add multiple units – people or organizations, for

126 example – then we can examine variability in level. Does everyone have high affect across

127 time? Is there variability in the level of skill among trainees at the beginning of a training

128 session?

129   We demonstrate this idea in figure 2, where we now plot three units (people) across

130 time. Each individual has a similar trajectory, but their ending levels of y are different. Said

131 formally that is, "there is variability across units in level at the last time point."

132   ————

133   Insert Figure 2 about here

134   ————

135 The second level inference, therefore, is about level variability across units.

136   **Inference 2:** Across a span of t or at a specific t there is variability in

137   the level of x.

138   Inferences one and two concern a single variable, but they can of course be iterated

139 across any or all observed variables in the study (remember that variables are different than

140 units). For example, we might discover that affect and performance have high average levels

141 across time, but that affect has greater level variability across units. Or we might learn that

142 affect has a low initial level whereas performance is initially high. What we are doing here is

143 making descriptive comparisons between the level of one variable and the level of another.

144 We can also produce a quantitative statement about the extent to which levels are related.

145   Correlating levels provides us with that quantitative statement. A large positive

146 correlation between the initial levels of affect and performance would mean that people with

147 greater initial levels of affect also tend to have greater intial performance, and people with

148   lower initial affect also tend to have lower initial performance.

149   Figure 3 demonstrates a correlation of starting levels. In Panel A we plot affect and

150   performance trajectories for three individuals across time, where the black solid line indicates

151   affect and the dashed line indicates performance. We indicate starting levels for both

152   variables in Panel A by placing colored circles on the graph for each individual. For example,

153   we indicate the starting levels of affect and performance for person one with red circles and

154   the starting levels for person two with green circles.

155   Panel B of figure 3 maps those starting levels onto a new plot that leads to our

156   inference. On the x-axis is initial level of affect where high values indicate a high starting

157   level of affect, and on the y-axis is initial level of performance where high values indicate a

158   high starting level of performance. The red circle for person one is on the bottom right

159   because that individual has a high initial level of affect and a low initial level of performance.

160   Person two (the green circle) is on the top left because that individual has a high initial level

161   of performance and a low initial level of affect, and person three is in the middle because

162   they have roughly the same starting levels of affect and performance. The dots slope

163   downward in Panel B, which tells us that there is a negative relationship between initial level

164   of affect and initial level of performance.

165   Overall, figure 3 suggests that the starting levels of affect and performance are

166   correlated. Panel A shows the actual starting levels, and Panel B shows that there is a strong

167   negative correlation between initial affect and initial performance. This negative relationship

168   means that we expect people with low initial affect to have high initial performance, whereas

169   we expect people with high initial affect to have low initial performance.

170   **Inference 3:** There is a correlation between the level of x and the

171   level of y at t.

172   ———————

173   Insert Figure 3 about here

174   ———————

Level Inference Table

176   The inference table below provides examples of each level inference. Inference one is

177 about level itself – a single value that describes the variable at one time or averaged across

178 time. Inference two is about variability across units in level. Inference three takes the level

179 in one variable and asks whether it tends to co-occur with the level in another. Think of

180 inference three as creating a latent level variable at a single moment and asking how it

181 relates to another latent variable from a single moment.

182   ———————

183   Insert Table 1 about here

184   ———————

Models

186   Level is called the intercept in the statistical modeling literature. That is, when a

187 researcher estimates a model to explore the starting level of a variable, like performance, she

188 is estimating the intercept at the initial time point. The analysis will return a mean estimate

189 which tells you about level, and it will also return a variance estimate that indicates

190 variability across units. Typically you will hear researchers refer to models that only explore

191 level as intercept-only models. Intercept-only models are almost always paired with more

192 complex growth models, so we will save our reference recommendations for the next section.

193 If a researcher is interested in level he or she can look to the references we point to in the

194 next, "trend" section, all of those models also examine intercepts.

₁₉₅   **Trend**

₁₉₆   Does affect go up or down across time, or is it relatively stable? Does trainee skill

₁₉₇ increase over the training session? These are questions about trend, and these first two are

₁₉₈ specifically about linear trend. It is also possible to explore how variables bend or curve

₁₉₉ across time. Do newcomer perceptions of climate increase and then plateau over time? Does

₂₀₀ the response time of a medical team decrease with each successive case but then remain

₂₀₁ stable once the team can no longer improve their coordination? These latter questions

₂₀₂ concern curvilinear trajectories.

₂₀₃   Trend has to do with the global shape of the trajectory across time. If we put a

₂₀₄ variable on the y-axis and plot its values against time on the x-axis, do the values tend to go

₂₀₅ up or down over time? It can be thought of as the coarse-grained direction of a trajectory.

₂₀₆   Figure 4 demonstrates trend, where the red line shows negative, decreasing trend, the

₂₀₇ blue line shows positive, increasing trend, and the green line shows a curvilinear trajectory.

₂₀₈ Keep in mind that curvilinear and linear trajectories are both *linear in parameters* and

₂₀₉ should not be confused with non-linear systems.

₂₁₀   ———————

₂₁₁   Insert Figure 4 about here

₂₁₂   ———————

₂₁₃   Our first trend inference, therefore, concerns the shape of the trajectory.

₂₁₄   **Inference 1:** There is positive/negative/curvilinear trend in a

₂₁₅   variable across time.

₂₁₆   As with the level inferences, when we add more units we can examine trend variability.

217 Do all trainees develop greater skill across time? Is there variability in the trend of helping

218 behaviors, or counterproductive work behaviors over time?

219   Figure 5 shows differences in trend variability. In the first facet all units (people) show

220 the same positive trend, whereas everyone in the second facet shows different trend: person

221 one's data appear to increase over time, person two's data decrease over time, and person

222 three's data remain flat. With greater variability there is less consistency in trend across

223 units.

224   ———————

225   Insert Figure 5 about here

226   ———————

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

228   Inferences one and two are about one variable, but they can also be iterated across all

229 observed variables. For example, we might discover that affect and performance trends both

230 decrease, but there is greater variability across units in the affect trend. Or we might learn

231 that affect has a negative trend while performance has a positive trend.

232   Correlating these trends is the next inference. Correlating indicates co-occuring

233 patterns, but this time we focus on trends rather than levels. A large positive correlation

234 between affect and performance trends indicates that people with a positive affect trend

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

236 have a negative performance trend.

237   Figure 6 shows the inuition behind the inference with a set of graphs. In Panel A we

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

239 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), but both variables fluctuate across time for this individual. 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 figure that shows the relationship between the affect and performance trend. 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 relationship between the affect and performance trend is negative. That is, people with a positive affect trend usually have a negative performance trend, people with a negative affect trend are more likely to have a positive performance trend, and people with no affect trend usually have no performance trend.

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Insert Figure 6 about here

—————

Inference 3: There are correlated trends.

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? Notice the difference between this inference and inference three. Inference three asks how one trend is related to another, whereas this inference asks how one trend relates to a covariate.

Figure 7 demonstrates the inference in a plot. We plot affect across time for six employees, and these employees differ by job type. The first three individuals work in

264 research and development, whereas the final three individuals work in sales. Affect

265 trajectories tend to decrease over time for employees in research and development, whereas

266 affect trajectories tend to increase for those in sales. An individual's job type, then, gives us

267 a clue to their likely affect trend – said formally, job type covaries with affect trends, such

268 that we expect individuals in sales to have positive affect trends and individuals in research

269 and development to have negative affect trends. The expected trends are plotted as the thick

270 blue lines.

271 ————————

272 Insert Figure 7 about here

273 ————————

274   **Inference 4:** There are correlates of trend.

275 **Trend Inference Table**

276   The inference table below provides examples of each trend inference. Inference one is

277 about the general direction or shape of a trajectory across time. Inference two is about

278 variability in that shape across units. Inference three takes the trend in one variable and

279 asks whether it co-occurs with trend in another. Inference four, finally, is about the

280 relationship between trend in one variable and the raw values of one or more correlates.

281 ————————

282 Insert Table 2 about here

283 ————————

284   We want to close this section with a note on phrasing. The inferences we explored in

285 this section have to do with correlating trends, where a statement like "affect and

286 performance trends covary, such that people with a negative affect trend have a positive

287 performance trend" is appropriate. There is a less precise phrase that is easy to fall into –

288 and we have seen it used in our literature. Sometimes, researchers will correlate trends and

289 then state, "when affect decreases performance goes up." We urge researchers to avoid this

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

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

292 affect decreases performance goes up" could refer to correlated trends, but it could also mean

293 something like, "when affect decreases performance immediately or subsequently goes up."

294 This second statement is far different and it should not be used when an analysis only

295 correlates trends or evokes predictors of trend. Again, we urge researchers to phrase their

296 inferences as we have shown here.

297 **Models**

298   Trend is called the slope in the statistical modeling literature. That is, when a

299 researcher estimates a model to explore whether a variable goes up or down over time she is

300 estimating the trend coefficient. Again, the mean estimate will tell you about the trend itself

301 and the variance estimate refers to the trend variability across units. In the statistical

302 modeling literature these models are called growth-models or growth-curves. Keep in mind,

303 however, that researchers use the word "change" informally to mean growth as well, so when

304 you read a theoretical discussion you may see words like "change" and "increase" despite the

305 researcher using a "growth" model.

306   Broad theoretical discussions of growth and change are found in Pitariu and Ployhart

307 (2010) and Ployhart and Vandenberg (2010), whereas Bliese and Ployhart (2002) describe

308 how to go about running an analysis. Growth curves are a core topic in developmental

309 psychology, so there are many great articles and textbooks to read from their field. See

310 Grimm, Ram, and Estabrook (2016) and Singer, Willett, and Willett (2003) for two great

311 textbooks on growth curve modeling, and McArdle and Epstein (1987) for an empirical

312 discussion. For two straight-forward empirical examples in our own field see Dunford, Shipp,

313 Boss, Angermeier, and Boss (2012) and Hülsheger (2016).

Relationships

315 In the sections above we explored covariance at a single moment, general trends, and

316 covariance between trends. Here, we explore relationship patterns between two variables over

317 time. Does affect relate to performance across time? Over time, does unit climate covary

318 with shared mental models? Do the fluctuations in voice match the fluctuations in

319 commitment over time – i.e., when voice is high is commitment also high?

320 Our first inference focuses on a single unit – one person, one team, or one organization

321 over time. The trajectory of a single unit over time is called a time-series, and two are

322 plotted simultaneously in figure 8. The solid line shows a time-series of affect over time, and

323 the dashed line plots a time-series of performance. Notice that, across time, when affect is

324 high respective to itself performance is also high (and vice versa). The colored squares

325 represent values of each variable at different points in time. The green squares highlight low

326 values of both variables, the blue high values, and the red middle values.

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Insert Figure 8 about here

—————

330 Panel B shows how those respective values map onto a scatterplot of affect and

331 performance – which again will lead to the inference. The blue values indicate that high

332 values of affect tend to co-occur with high values of performance (shown respectively by the

333 blue squares in Panel A). The red values indicate that middle values of affect tend to

334 co-occur with middle values of performance. The green values, finally, indicate that low

335 values of affect tend to co-occur with low values of performance. Across time, affect and

336 performance covary and the relationship is positive.

337 **Inference 1:** There is a relationship between x and y across time.

338 What happens when we add more units? Doing so changes the question from "what is

339 the relationship across time" to, "at each moment, what is the relationship across units?"

340 Ultimately we move from a within-unit question to a between-unit focus, and we apply that

341 between unit focus to each time point.

342 In the prior inference we asked if affect relates to performance across time – on a single

343 person/unit. Now imagine that we gather data on multiple people across time, so we have

344 many affect and performance trajectories. One of the most popular inferences in our

345 literature is to take those time series and slice them into individual time points, look at

346 between-person correlations among affect and performance at a single moment, and then

347 repeat that analysis for each time point. At time one, what is the correlation between affect

348 and performance? At time two, what is the correlation between affect and performance? At

349 time three, what is the correlation between affect and performance? Because we have

350 multiple people we can explore correlations at a single moment. Researchers then typically

351 report the average of these single moment correlations, or they constrain them to be equal

352 across time.

353 Figure 9 shows the inference with data. Panel A plots affect and performance

354 trajectories for each person. The red circles in Panel A highlight each individual's affect and

355 performance values at time point six. Given that we have three people for time point six, we

356 can calculate a correlation between affect and performance at that moment (granted, it is a

357 small sample). The calculated correlation coefficient is then mapped onto 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 9 about here

———

Panel B then 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 second 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 relationships among one or more variables (and they are not evoking a growth curve) they are more than likely making this inference.

Inference 2: There is a relationship between x and y across units over time.

Relationships Inference Table

Table 3 reports example inferences with respect to relationships. Inference one focuses on within-unit relationships across time, whereas inference two focuses on between-unit relationships at each moment.

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Insert Table 3 about here

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378 **Models**

379   The workhorse of relationship inferences comes from time-varying covariates analyses.

380 A discussion of these models is found in Schonfeld and Rindskopf (2007) and Finch, Bolin,

381 and Kelley (2016). Relatively straight-forward empirical examples are in Barnes,

382 Schaubroeck, Huth, and Ghumman (2011) and Chi, Chang, and Huang (2015).

383   **Dynamics**

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

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

386 "volatile," "longitudinal," or "over time" (among others), whereas formal definitions in our

387 literature are presented within certain contexts. Wang (2016) defines a dynamic *model* as a

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

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

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

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

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

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

394 history" (p. 409).

395   The crucial notion to take from dynamics, then, is memory. When the past matters,

396 and future states are constrained by where they were at prior points in time, dynamics are at

397 play. In this section, we unpack a variety of inferences that are couched in this idea.

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

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

400 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 10 shows the concept with a box and arrow diagram. x 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 x at time t is related to x at time $t + 1$. In other words, we posit that x shows a lag-one relationship, where x is related to its future value one time step away. Modelers and theorists are of course free to suggest any lag amount that they believe captures the actual relationship.

Inference 1: There is self-similarity in x; x relates to itself across time.

————

Insert Figure 10 about here

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Inference one was about a single variable, and in the level and trend inference sections we saw that when we moved to multiple variables we started asking how variables relate to one another at t, or at an average window of t, or across t. With dynamics, where memory is a fundamental concept, we instead ask how variables relate to one another at different lags. Does affect predict subsequent performance? Do prior counterproductive work behaviors relate to current incivility? When goal discrepancy is large is effort at the subsequent time point high? When prior depletion is low, is current emotional exhaustion high?

We can capture this second inference by relating current values on one variable to future values on another. Equivalently, we can relate prior values on one variable to current values on another. Panel B of figure 10 shows this second dynamics inference. x still shows self-similarity across time, but it now predicts y at the subsequent moment. We are positing

425 a lag-one relationship between x and y. Said formally, we believe that x_t is related to y_{t+1}

426 (or equivalently, x_{t-1} is related to y_t). Relating current to future (or prior to current) values

427 from one variable to another is called a "cross lag" relationship.

428   **Inference 2:** There is a cross-lag relationship, where one variable

429   relates to another at a different point in time.

430   Inference two tells us whether the patterns in one variable co-occur with the patterns

431 in another at a subsequent time point. Across time, when affect is low is subsequent

432 performance also low? A related question is as follows: across time, when affect is low does

433 performance increase or decrease? This second question is about change. How does one

434 variable relate to the change in another?

435   When goal discrepancy is large does effort increase or decrease? When unit climate is

436 low do perceptions of the leader change? When performance is high does self efficacy go up

437 or down?

438   All of these questions are about change, but notice that change can be construed across

439 different lags. Change from what? Baseline? The prior time point? The last three time

440 points? Typically change is construed with respect to the last time point. When affect is low,

441 does performance from the last to the current time point increase or decrease? How does

442 effort change from the prior to the current time point when goal discrepancy is high?

443   Panel C of figure 10 demonstrates this idea. We are positing the same self-similarity in

444 x and the same cross-lag relationship that we saw before, but now y also has self-similarity

445 across time. The cross-lag relationship, therefore, is now capturing how y has changed from

446 the last point in time.

447   It is typical to think of change from the prior to the current time point, but researchers

448 are free to move it as they please. Here are the two final inferences that capture change in

449 different locations.

450   **Inference 3:** There is a change relationship, where one variable

451   relates to the change in another.

452   **Inference 4:** There is a cross-lag relationship of change, where one

453   variable relates to the change of another at a different point in time.

Dynamics Inference Table

455   We provide an inference table below – this time with respect to dynamic inferences.

456 Inference one is about autoregression, or memory in a single variable. Inference two asks how

457 a variable at one time co-occurs with another at a different time. Inferences three and four

458 focus on change: when one variable is high or low, does it relate to the change (an increase

459 or decrease) in the values of another variable?

460   ————

461   Insert Table 4 about here

462   ————

Extensions

464   We described a simple set of inferences above, but the ideas generalize to more complex

465 dynamics as well. Often researchers are interested in reciprocal relationships, where x

466 influences subsequent y, which then goes back to influence x at the next time point. Said

467 formally, x_t influences y_{t+1}, which then influences x_{t+2}. Said informally, current performance

468 influences subsequent self-efficacy, which then influences performance on the next trial.

469 These inferences are no different than what we saw above – they are cross-lag predictions –

all we did here was add more of them. Panel D of figure 10 shows reciprocal dynamics, where both x and y show self-similarity and cross-lag relationships with one another.

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. There could be a sequence of influence where initial dyadic exchanges influence subsequent team perceptions, which then influences later performance, and performance changes the structure of task which ultimately 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.

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Table 1

Examples of level inferences.

Inference	Examples
1	Burnout is high at the last time point.
	Performance is low, on average, across time.
2	Average affect across time differs across people (units).
	There is variability in the initial level of turnover across organizations.
3	People with greater initial health status also have greater initial happiness.
	People with high performance on average across time have lower anxiety on average across time.

Table 2

Examples of trend inferences.

Inference	Examples
1	Burnout decreases over time.
	Performance increases over time.
2	Affect trends differ across people (units).
	There is variability in turnover trends across organizations.
3	People with a positive health status trend have a positive happiness trend.
	People with a positive performance trend have a negative anxiety trend.
4	Gender correlates with depletion trends.
	Unit climate covaries with unit performance trends.

Table 3

Examples of Relationship inferences.

Inference	Examples
1	Affect relates to performance across time.
	Helping behaviors predict depletion across time.
2	Affect relates to performance across people (and it is consistent over time/and averaged over time it is positive).

Table 4

Examples of dynamic inferences.

Inference	Examples
1	Burnout demonstrates self-similarity across time.
	Performance relates to subsequent performance.
2	Affect predicts subsequent counterproductive work behaviors.
	Turnover relates to subsequent firm performance.
3	Positive health status relates to change in happiness.
	Anxiety relates to change in performance.
4	Affect relates to subsequent change in performance.
	Helping behaviors predict subsequent depletion changes.
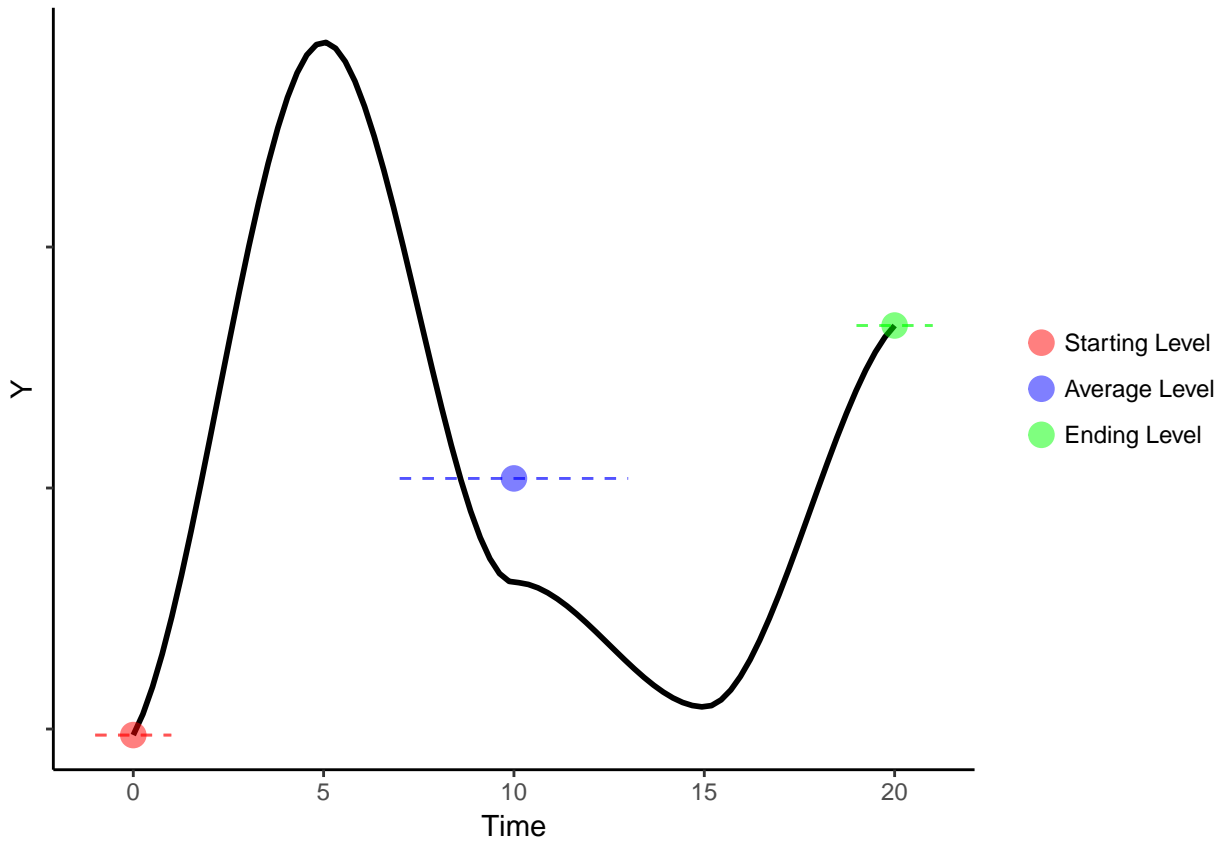
Figure 1. Level examples.
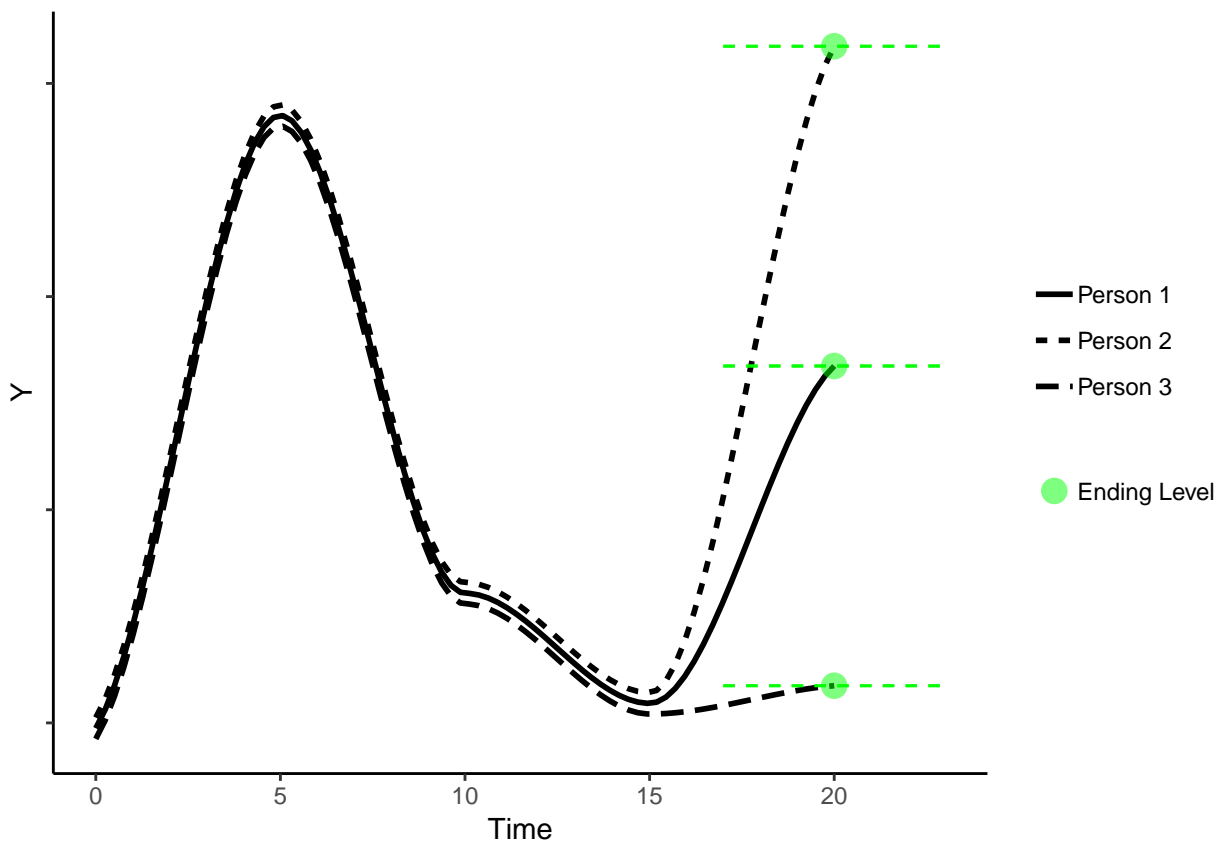
Figure 2. Trajectories with variability in ending level across units.
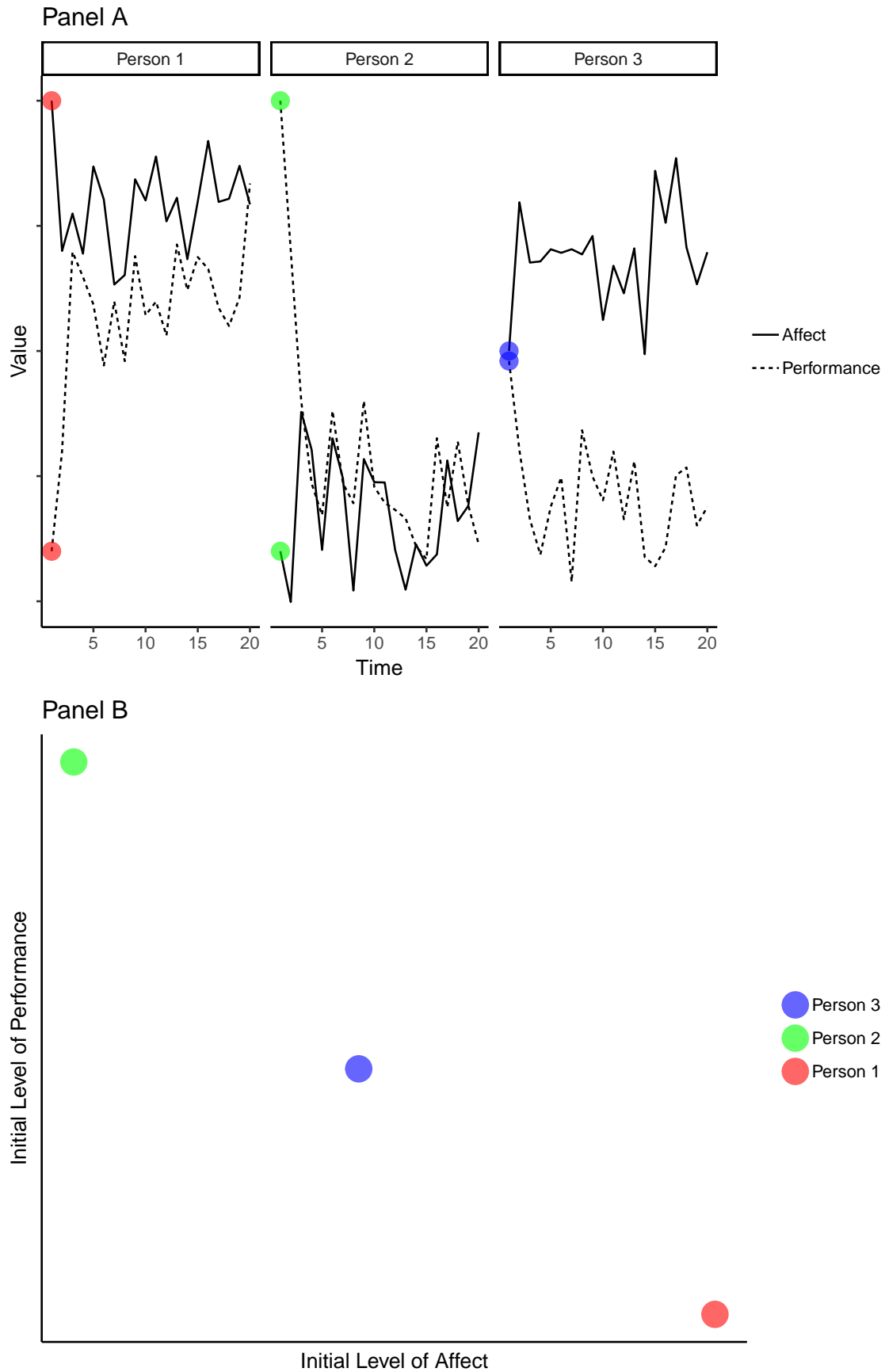
Figure 3. Correlating starting levels, or relating initial affect to initial performance.
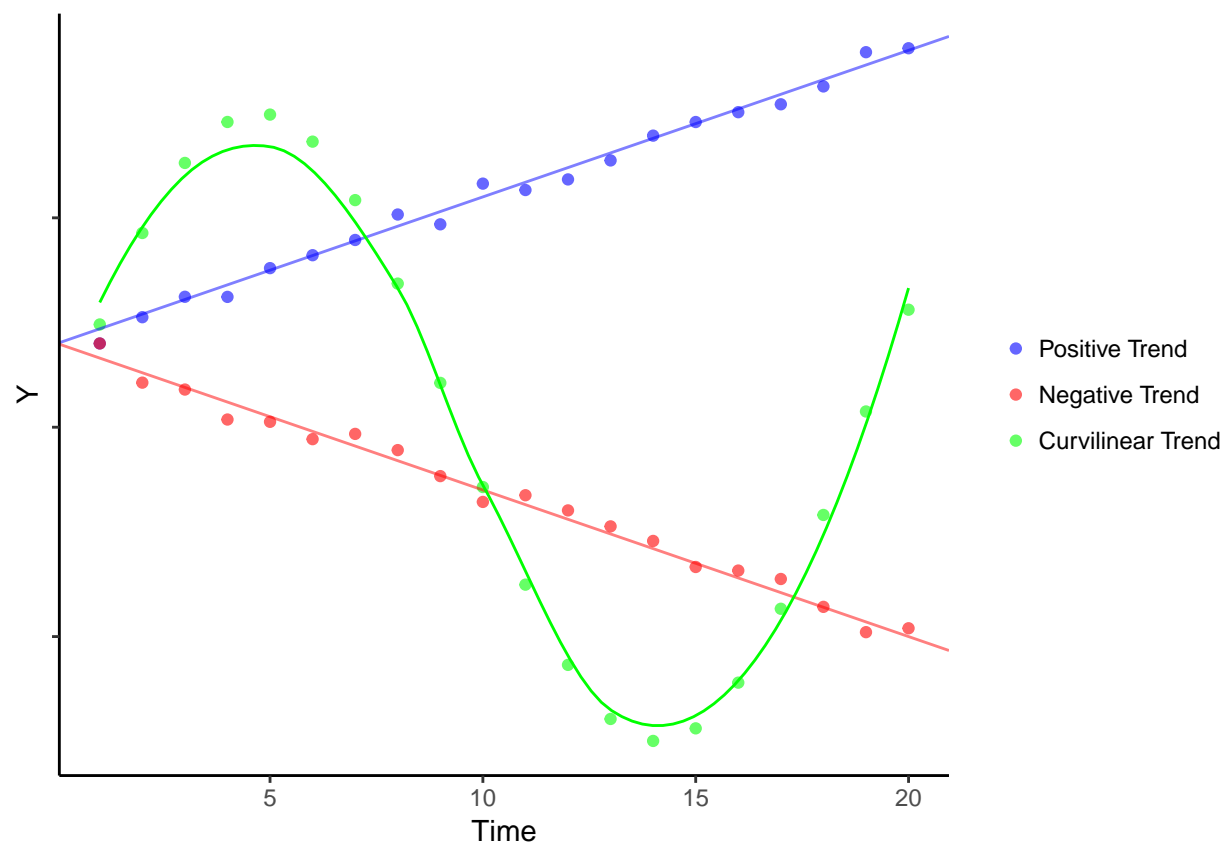
Figure 4. Trend across time.
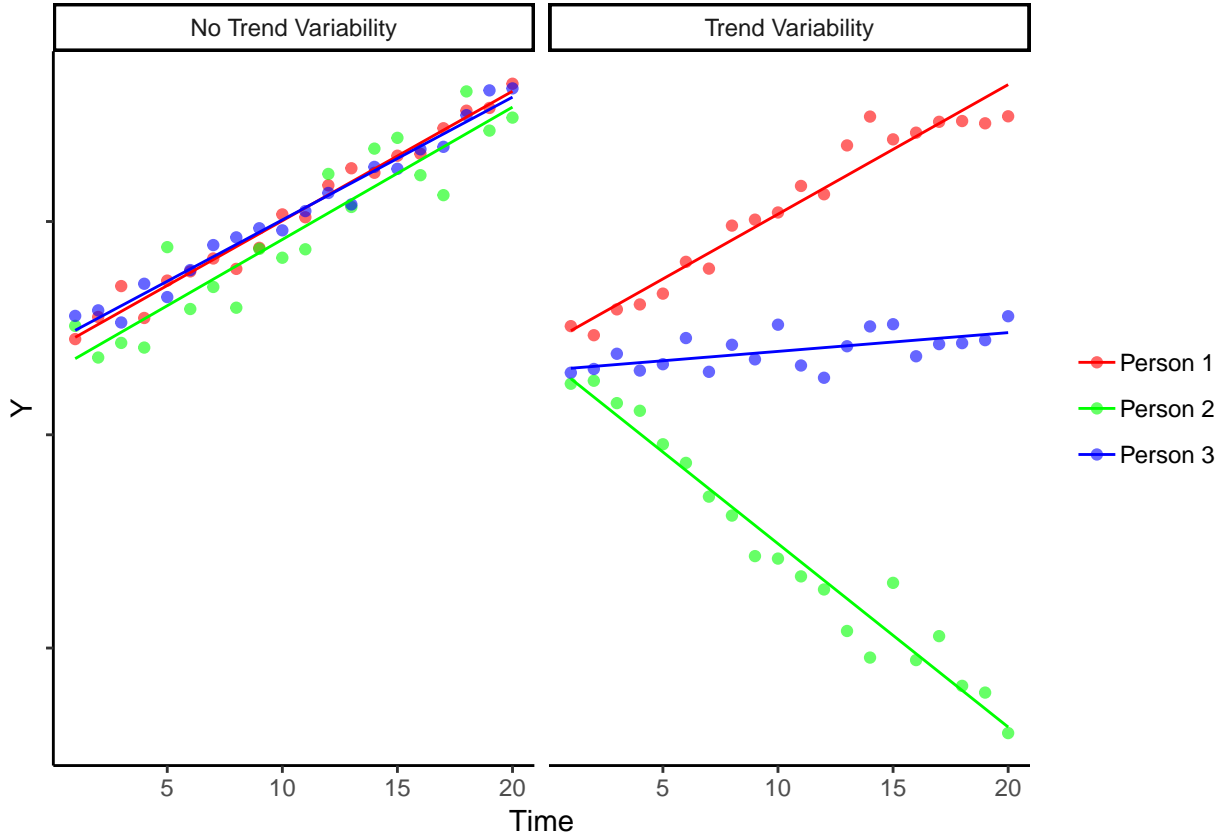
Figure 5. Differences in trend variability across units.
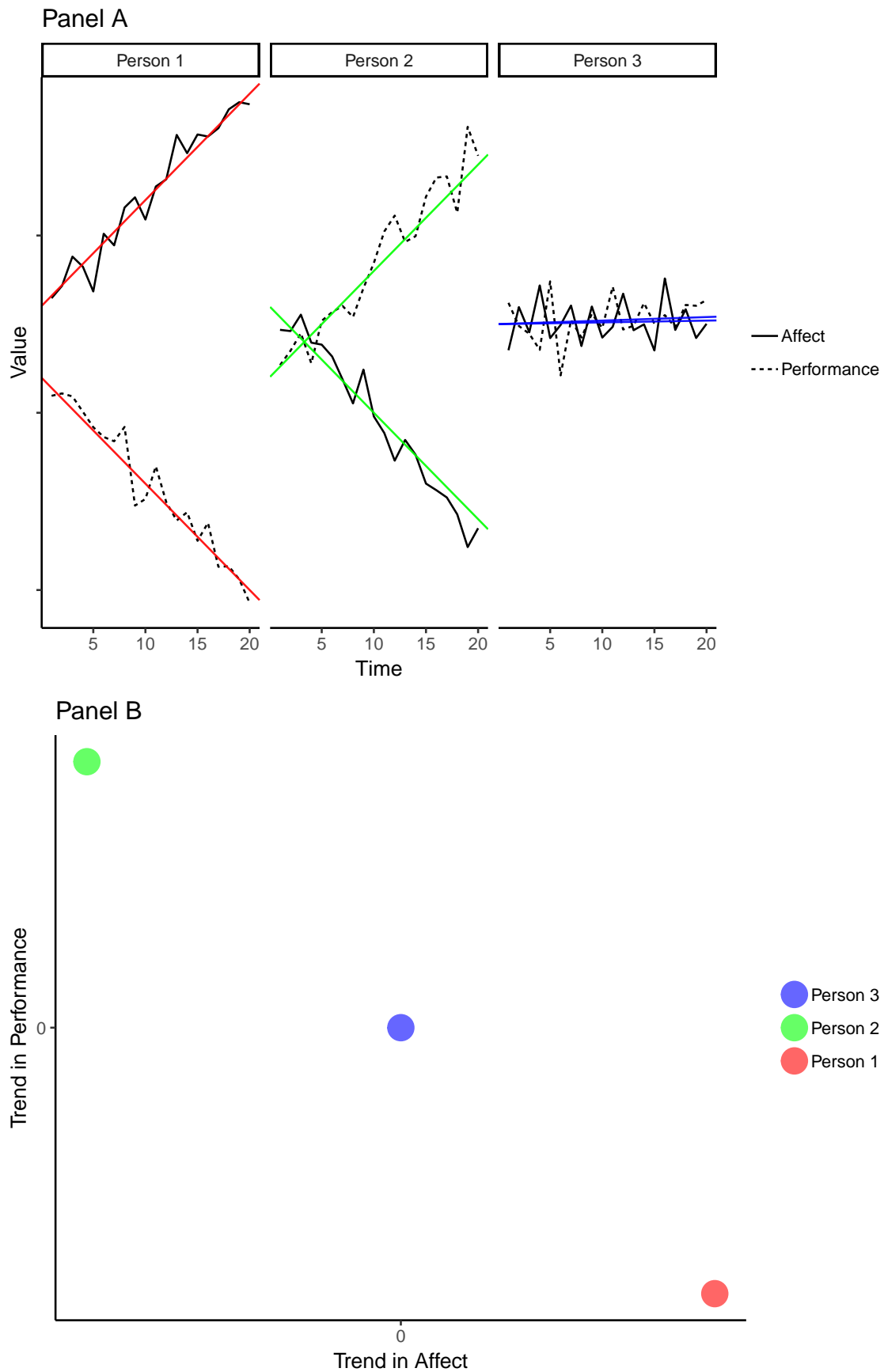
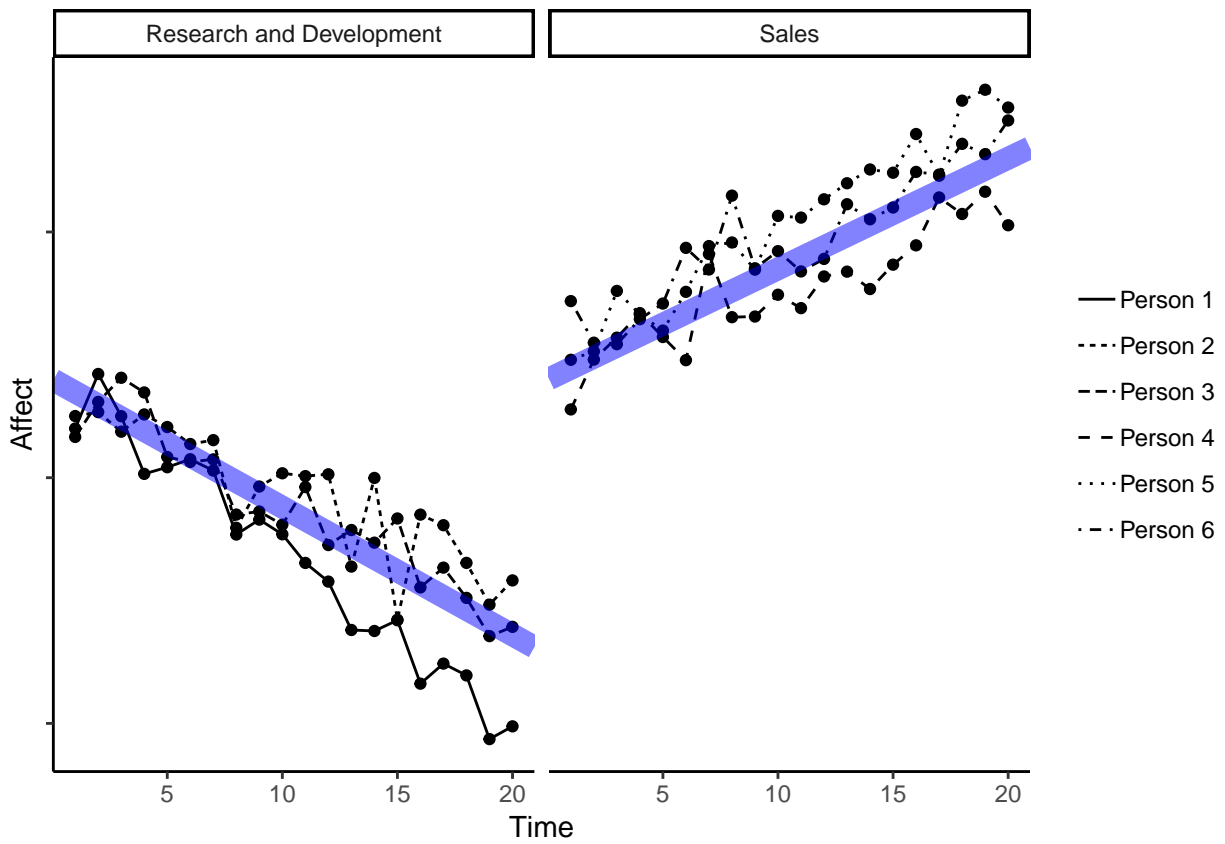*Figure 6*. Correlating slopes, or relating the affect to performance trend.

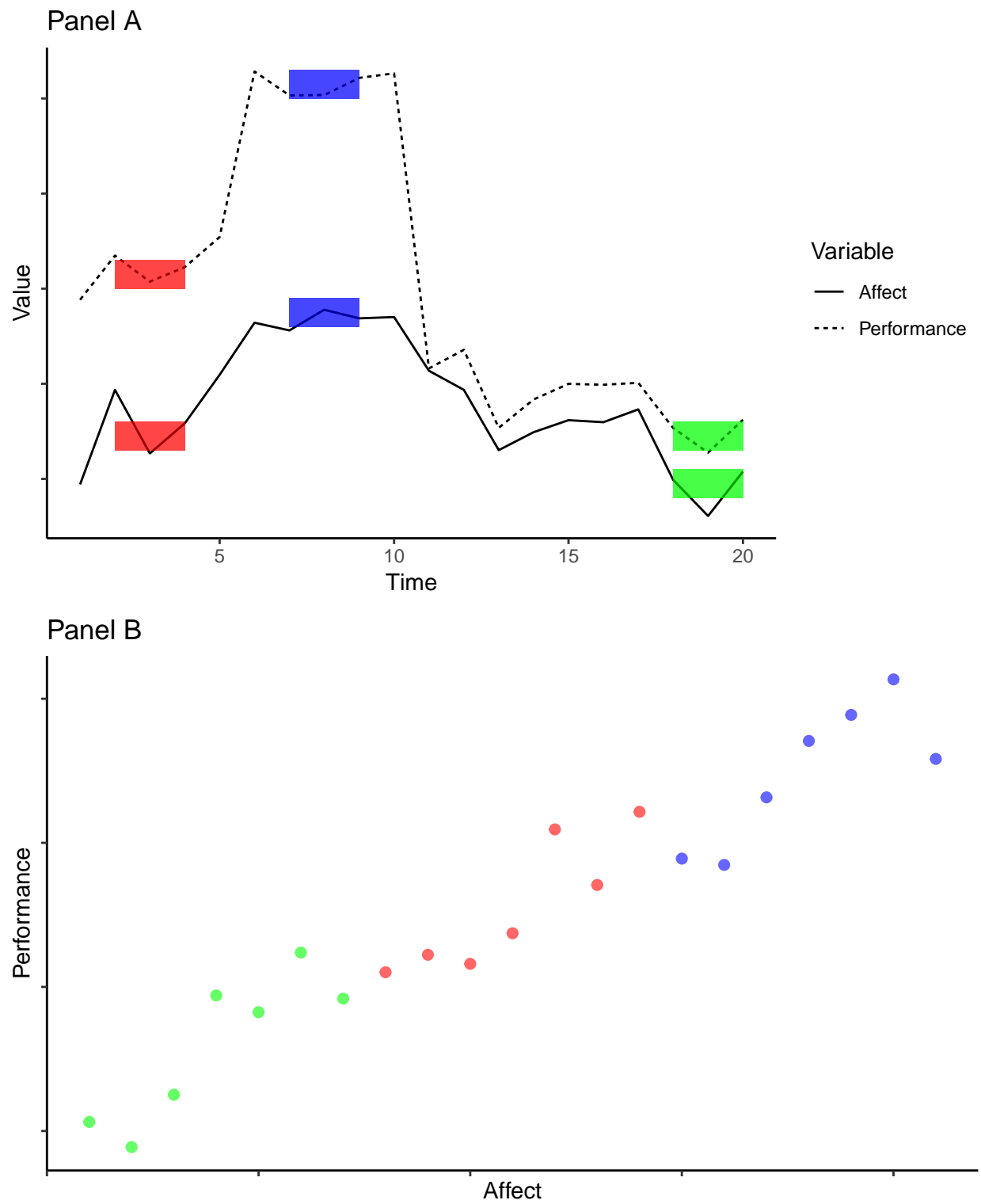*Figure 7.* Job type as a covariate of affect trend.

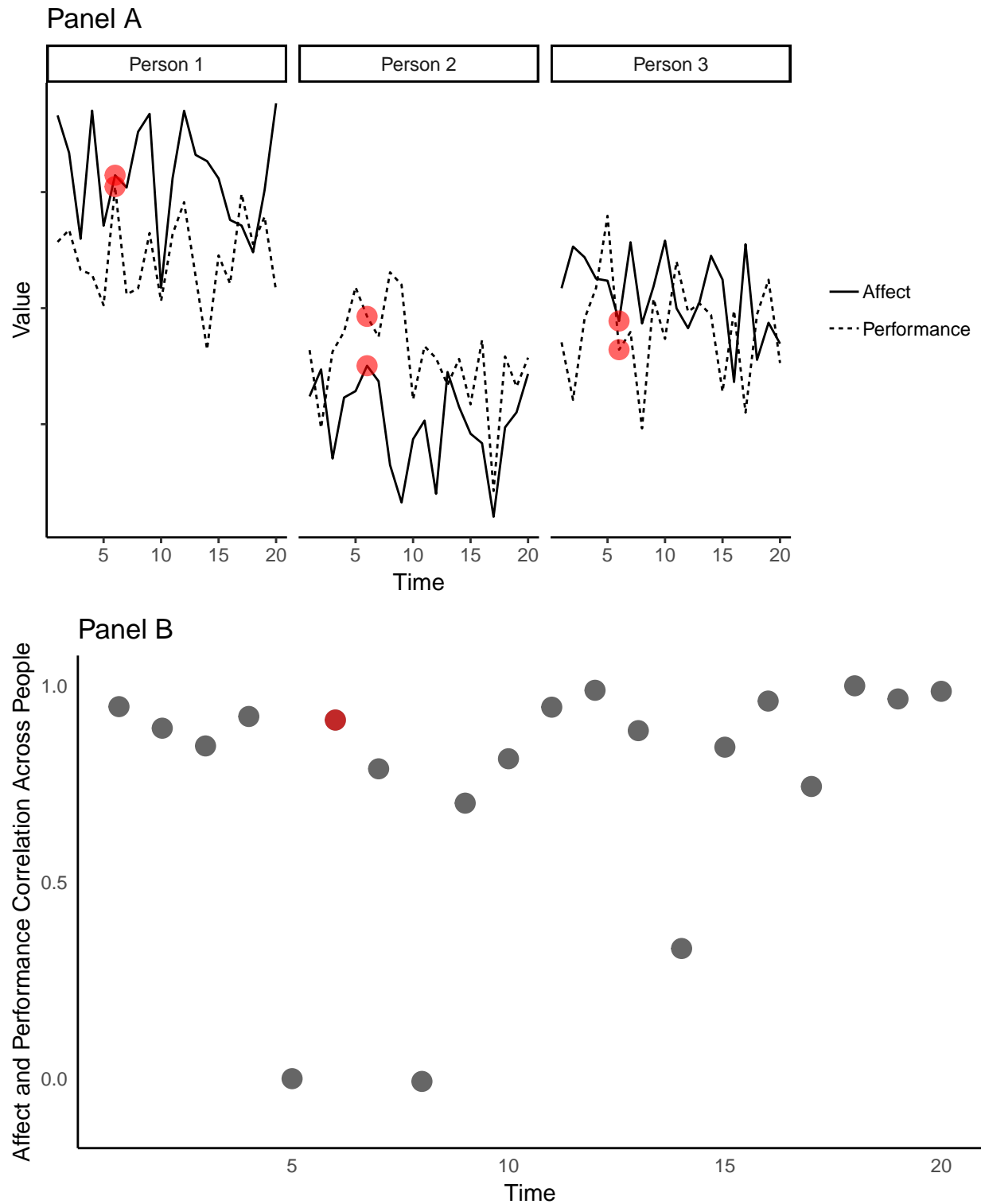*Figure 8*. Relating affect to performance on one unit across time.

Figure 9. Relating affect to performance across units over time. The red circles demonstrate the between unit correlation for 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.
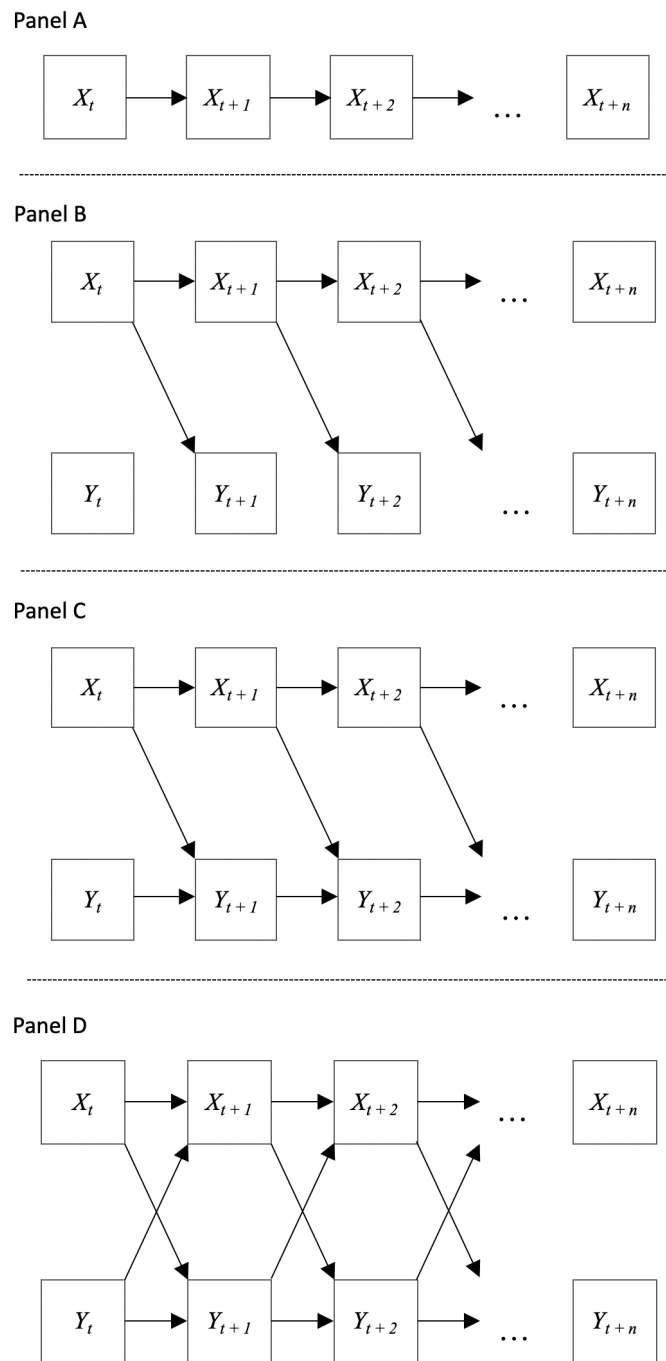
Figure 10. Univariate and bivariate dynamics adapted from DeShon (2012). Panel A shows self-similarity or autoregression in X across time. Panel B shows X predicting subsequent Y. Panel C shows X predicting subsequent change in Y. Panel D shows reciprocal dynamics between X and Y.