Inferences With Longitudinal Data

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

This sentiment is reflected in our empirical literature, where repeated assessments are now common. For instance, Jones et al. (2016) observed the work attitudes of pregnant women in their second trimester every week until they gave birth. Meier and Spector (2013) examined counterproductive work behavior over five waves. Hardy, Day, and Steele (2018) investigated self-regulation over 20 lab trials. Finally, Johnson, Lanaj, and Barnes (2014) observed justice behavior and resource depletion across 10 consecutive workdays.

Armed with repeated observations, there are then different research questions that we can explore. Jones et al. (2016) ask about trend: they want to determine if the trajectories among certain variables increase or decrease over time. Johnson et al. (2014) about change: they are interested in how changes in one variable relate to changes in another across time. Hardy et al. (2018) inquire about dynamic relationships, where prior values on one variable predict subsequent values on another, and this second variable then goes back to predict the first at a later point in time. Finally, Meier and Spector (2013) examine how effect sizes change when they vary the time lag between their independent and dependent variable.

Researchers then evoke statistical models that are determined by their research questions. Meier and Spector (2013) present a sequence of path models that test increasingly longer time lags. Hardy et al. (2018) and Jones et al. (2016) employ bivariate

37 cross-lagged latent growth curves, an approach similar to the latent change model used by

38 Ritter, Matthews, Ford, and Henderson (2016). We also find complex hierarchical linear

39 models in many event-sampling studies (e.g., Koopman, Lanaj, & Scott, 2016; Rosen,

40 Koopman, Gabriel, & Johnson, 2016).

41 The spine of an investigation, finally, is to interpret the model and make an inference

42 regarding the original question. Jones et al. (2016) infer negative slopes for concealing

43 behaviors and positive slopes for revealing behaviors. Johnson et al. (2014) state that

44 justice behaviors fluctuate day to day and predict changes in depletion. Hardy et al. (2018)

45 find support for dynamic relationships between self-efficacy, metacognition, and exploratory

46 behaviors. Finally, Meier and Spector (2013) suggest that the effects of work stressors on

47 counterproductive work behaviors are not substantially different across different time lags.

48 None of these inferences perfectly discovers the data generating mechanism. Rather,

49 each asks an interesting and important question about how DVs relate to IVs. Only with

50 lots of asking about lots of different patterns of relationships across the variables could we

51 piece together one (of many) possible representation(s) of the data generating process –

52 hopefully having a good theory to guide the way.

53 We want to link inferences to models in this paper so that researchers know which of

54 the many models they can use when they are interested in one of the many possible

55 inferences in a longitudinal investigation. As should be clear to anyone reading our

56 literature, there is great excitement for the utility of longitudinal studies; they can pose

57 interesting questions and discover patterns that would otherwise be impossible to capture

58 in a static investigation. We bring attention to the span of questions available so that

59 researchers can fully appreciate and take advantage of their data. Although the inferences

60 concern trajectories or relationships over time, their small differences have large

61 implications for what we take away from them – what we ultimately conclude. Moreoever,

62 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.

Below, we do these things.

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 making a contrast with respect to either a) research designs or b) data structures. Longitudinal *research* is different from cross-sectional research because longitudinal designs entail three or more repeated observations (Ployhart & Vandenberg, 2010). We therefore emphasize differences on the number of observations when we distinguish longitudinal from other types of research. Longitudinal *data* are repeated observations on several units (i.e., N or $i > 1$), whereas panel data are observations of one unit over time – a distinction that focuses on the amount of people in our study (given repeated measures). Most organizational studies collect data on more than one unit, therefore our discussion below focuses on longitudinal research with longitudinal data, or designs with $N > 1$, $t >= 3$, and the same construct(s) measured on each i at each t.

Framework

Level. Trend. Dynamics. These are umbrella research foci, each has its own sub-inferences and models. Each section will have several inferences but they all gather

87 into two basic notions: 1) trying to understand the thing itself and variability about the

88 thing itself across units, and 2) correlates or predictors of the thing.

89 Each section will also point to models. But there is nuance. The models have different

90 names, some require stationary, some don't. You need to appreciate that and make sure

91 you are attending to all of its nuance. All we are doing here is pointing you in the direction.

Level

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

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

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

96 the specific value of a variable.

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

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

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

100 any span of t.

101 Figure 1 demonstrates this idea graphically. A variable is plotted across time, and the

102 color labels indicate levels – the red and green describe the variable at a specific moment

103 while the purple, average level, describes it across a window.

104 ————

105 Insert Figure 1 about here

106 ————

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

108 averaged across a window of time.

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

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

111 example – then we can look at the variability in level. Does everyone have high affect

112 across time? Is there variability in the level of skill among trainees at the beginning of a

113 training session?

114 We demonstrate this idea in figure 2, where each unit (person) has a similar

115 trajectory but different levels at the last time point.

116 ————

117 Insert Figure 2 about here

118 ————

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

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

121 ***the level of x.***

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

123 across any or all observed variables in the study. For example, we might discover that

124 affect and performance have high average levels across time, but that affect has greater

125 level variability. Or we might learn that affect has a low initial level whereas performance

126 is initially high. What we are doing here is making descriptive comparisons between the

127 level of one variable and the level of another. We can also produce a quantitative

128 statement about the extent to which levels are related.

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

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

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

132 with lower initial affect also tend to have lower initial performance.

133 Figure **??** (no figure yet) demonstrates this graphically. Paragraph about the graph.

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

135   ***y at t.***

136   The final level inference is horizontal. Rather than correlating values from a single

137   moment or a single averaged moment, we correlate values across time. For example, we

138   might ask if affect is related to performance across time; i.e., when affect is high is

139   performance also high, and when affect is low is performance also low?

140   This inference sounds similar to the one just presented, but their difference is

141   important. With inference three we ask about affect and performance at t or at an

142   averaged window of t – we examine, for example, how averaged values across time relate to

143   averaged values across time. Here, we retain all of the information and examine the

144   relationship between affect and performance across all t.

145   Figure 3 shows this inference graphically. The top panel plots affect and performance

146   trajectories across time. The colored squares represent levels at different points in time.

147   The green squares highlight low values of both variables, the blue high values, and the red

148   middle values. The bottom panel shows how those respective values map onto a graph that

149   describes the relationship between affect and performance across time. Notice that there

150   appears to be a positive relationship in the scatterplot, which tells us that when affect is

151   high performance also tends to be high, and vice versa.

152   ———————

153   Insert Figure 3 about here

154   ———————

155   ***Inference 4: There is a relationship between x and y across time.***

Level Inference Table

The inference table below provides examples of each level inference. Inference one is about level itself – a single value that describes the variable at one time or averaged across time. Inference two is about variability across units in level. Inference three takes the level in one variable and asks whether it tends to co-occur with the level in another. Think of inference three as creating a latent level variable at a single moment and asking how it relates to another latent variable from a single moment. Inference four, finally, is about the relationship between raw values across time.

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.
4	Affect relates to performance across time.
	Helping behaviors predict depletion across time.

Models

Level is called intercept in the statistical modeling literature. Typically the mean estimate tells you about the level, and the variance estimate tells you about the variability across units. Intercept only models in HLM or SEM. Time-varying or invariant covariates analyses. Point to references.

₁₇₀ **Trend**

₁₇₁ Does affect go up or down across time, or is it relatively stable? Does trainee skill

₁₇₂ increase over the training session? These are questions about trend, and these first two are

₁₇₃ specifically about linear trend. It is also possible to explore how variables bend or curve

₁₇₄ across time. Do newcomer perceptions of climate increase and then plateau over time?

₁₇₅ Does the response time of a medical team decrease with each successive case but then

₁₇₆ remain stable once the team can no longer improve their coordination? These latter

₁₇₇ questions concern curvilinear trajectories.

₁₇₈ Trend has to do with the global shape of the trajectory across time. If we put a

₁₇₉ variable on the y-axis and plot its values against time on the x-axis, do the values tend to

₁₈₀ go up or down over time? It can be thought of as the coarse-grained direction of a

₁₈₁ trajectory.

₁₈₂ Figure 4 demonstrates trend, where the red line shows positive, increasing trend, the

₁₈₃ blue line shows negative, decreasing trend, and the green line shows a curvilinear trajectory

₁₈₄ (ADD GREEN LINE). Keep in mind that curvilinear and linear trajectories are both

₁₈₅ *linear in parameters* and should not be confused with non-linear systems.

₁₈₆ —————

₁₈₇ Insert Figure 4 about here

₁₈₈ —————

₁₈₉ Our first trend inference, therefore, concerns the shape of the trajectory.

₁₉₀ ***Inference 1: There is positive/negative/curvilinear trend in a variable***

₁₉₁ ***across time.***

₁₉₂ As with the level inferences, when we add more units we can examine trend

₁₉₃ variability. Do all trainees develop greater skill across time? Is there variability in the

₁₉₄ trend of helping behaviors, or counterproductive work behaviors over time?

195   Figure 5 shows differences in trend variability. In the first panel all units (people)

196 show the same positive trend, whereas everyone in the second panel shows different trend:

197 person one's data appear to increase over time, person two's data remain flat, and person

198 three's data decrease over time. With greater variability there is less consistency in trend

199 across units.

200   —————

201   Insert Figure 5 about here

202   —————

203   ***Inference 2: There is variability in the trend of a variable across time;***

204 ***trend differs across units.***

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

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

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

208 learn that affect has a negative trend while performance has a positive trend.

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

210 patterns, but this time we are focused on trends rather than levels. A large positive

211 correlation between affect and performance trends indicates that people with a positive

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

213 trend (usually) have a negative performance trend.

214   Figure 6 shows the inuition behind the inference with a set of graphs. On the top

215 panel, affect and performance are plotted across time for three individuals. For individual

216 one, affect goes up while performance goes down, this pattern is reversed for person two,

217 and person three reports fluctuating affect and performance but with no trend. The

218 bottom panel then maps those pairings onto a figure that shows the relationship between

219 the affect and performance trend. For example, person one has a positive affect trend and

220 a negative performance trend, so their point on the bottom panel goes on the bottom right,

221 whereas person two has the opposite pattern and therefore is placed on the top left (where

222 performance trend is positive and affect trend is negative). Producing this bottom scatter

223 plot tells us that the relationship between affect and performance trend is negative. That

224 is, people with a positive affect trend usually have a negative performance trend.

225 ————————

226 Insert Figure 6 about here

227 ————————

228 ***Inference 3: There are correlated trends. There is a relationship between***

229 ***two trends.***

230 The final trend inference is about identifying covariates or predictors of trend. Do

231 helping behaviors predict the trend in depletion? Does the trend in unit climate covary

232 with perceptions of leader quality?

233 Notice the difference between this inference and inference three. Inference three asks

234 how one trend is related to another, whereas this inference asks how raw values relate to or

235 predict the trend in a different variable.

236 Figure **??** (no figure yet). Paragraph about graph. **Not sure how to graph. Slope**

237 **is a single term, like 0.5. It is being predicted by the raw values of X across**

238 **time. . .**

239 ***Inference 4: There are correlates/predictors of trend.***

240 **Trend Inference Table**

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

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

²⁴³ variability in that shape across units. Inference three takes the trend in one variable and

²⁴⁴ asks whether it tends to co-occur with trend in another. Inference four, finally, is about the

²⁴⁵ relationship between trend in one variable and the raw values of one or more predictors.

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 positive health status trends have positive happiness trends.
	People with positive performance trends have negative anxiety trends.
4	Affect relates to the performance trend across time.
	Helping behaviors predict depletion trends.

²⁴⁷ **A note on phrasing. Correlating trends, statement (a): "people with a**

²⁴⁸ **negative affect trend have a positive performance trend." Some use phrases like**

²⁴⁹ **statement (b), "when affect decreases performance goes up; and when affect**

²⁵⁰ **increases performance goes down." You could construe statements (a) and (b)**

²⁵¹ **as equivalent, but usually they are not. When people state (b) they actually**

²⁵² **mean "when affect decreases performance immediately or subsequently goes**

²⁵³ **up, and at a later point in time when the same trajectory of affect goes down**

²⁵⁴ **performance immediately or subsequently goes up." These are very different**

²⁵⁵ **statements. Correlating trends only gives you (a).**

Models

Trends are called slope estimates in the statistical modeling literature. They are also referred to as growth. Mean estimates of slopes, or trends, or growth will tell you about trend, whereas the variance estimates will tell you about variability across units. Growth curves in SEM or HLM. Bivariate growth curves.

Dynamics

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

The crucial notion to take from dynamics, then, is memory. When the past matters, and future states are constrained by where they were at prior points in time, dynamics are at play. In this section, we unpack a variety of inferences that are couched in this idea.

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

Figure (no graph yet) shows the concept graphically. Paragraph about the graph.

281   The statistical term used to describe self-similarity is autoregression, and we use it to
282 put a label on this first inference.

283   ***Inference 1: There is autoregression in x.***

284   Inference one was of course about a single variable. When we apply the notion of
285 memory to multivariate systems we move away from asking how variables relate to one
286 another at t, or at an average window of t, or across t, and instead ask how variables to one
287 another at different lags. Does affect predict subsequent performance? Do prior
288 counterproductive work behaviors relate to current incivility? When goal discrepancy is
289 large (high), is effort at the subsequent time point also high? When prior depletion is low,
290 is current emotional exhaustion high?

291   We can capture this second inference by relating current values on one variable to
292 future values on another. Equivalently, we can relate prior values on one variable to current
293 values on another. Figure **??** (no figure yet) plots. . . Paragraph about the graph.

294   Relating current to future (or prior to current) from one variable to another is called
295 a "cross lag" relationship.

296   ***Inference 2: There is a cross-lag relationship, where one variable relates***
297 ***to another at a different point in time. x_t is associated with y_t+1 across***
298 ***time.***

299   Inference two tells us whether the patterns in one variable co-occur with the patterns
300 in another at a subsequent time point. Across time, when affect is low is subsequent
301 performance also low? A related question is as follows: across time, when affect is low does
302 performance increase or decrease? This second question is about change. How does one
303 variable relate to the change in another?

304   When goal discrepancy is large (high), does effort increase or decrease? When unit
305 climate is low, do perceptions of the leader change? When performance is high, does self
306 efficacy go up or down?

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

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

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

310 is low, does performance from the last to the current time point increase or decrease? How

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

312   Figure **??** demonstrates these ideas. Paragraph about the graph.

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

314 researchers are free to move it as they please. Here are the two final inferences that capture

315 change in different locations.

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

317 ***to the change in another. x_t is associated with Δ y_t.***

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

319 ***variable relates to the change of another at a different point in time. x_t is***

320 ***associated with Δ y_t+1.***

321 **Dynamics Inference Table**

322   Again, we provide an inference table below – this time with respect to dynamic

323 inferences. Inference one is about autoregression, or memory in a single variable. Inference

324 two asks how a variable at one time co-occurs with another at a different time. Inferences

325 three and four try to understand change: when one variable is high or low, does it relate to

326 the change (an increase or decrease) in the values of another variable.

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.

Models

Our literature has a history with difference scores and partialling. We debated difference scores so we have converged to partialling models. Typical we create a model with prior values of the response variable as a predictor.

Mediation

Systems of variables. Reciprocal relationships.

Somehow say that mediation kind of goes away when you get into reciprocal dynamics – without making it sound like we don't care about mediation.

Discussion

Points to include. 1) Econometrics modeling levels vs. modeling differences.

2) Keep in mind you might see weird stuff in the literature. X at time 1 relates to Z at time 2, which relates to Y at time 3, but none are measured repeatedly across time. This is no good. We opened with "we couch ourselves by only discussing studies

341 where constructs were measured on each i at each t." Sometimes this doesn't

342 happen...

References

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r_refs(file = "references.bib")
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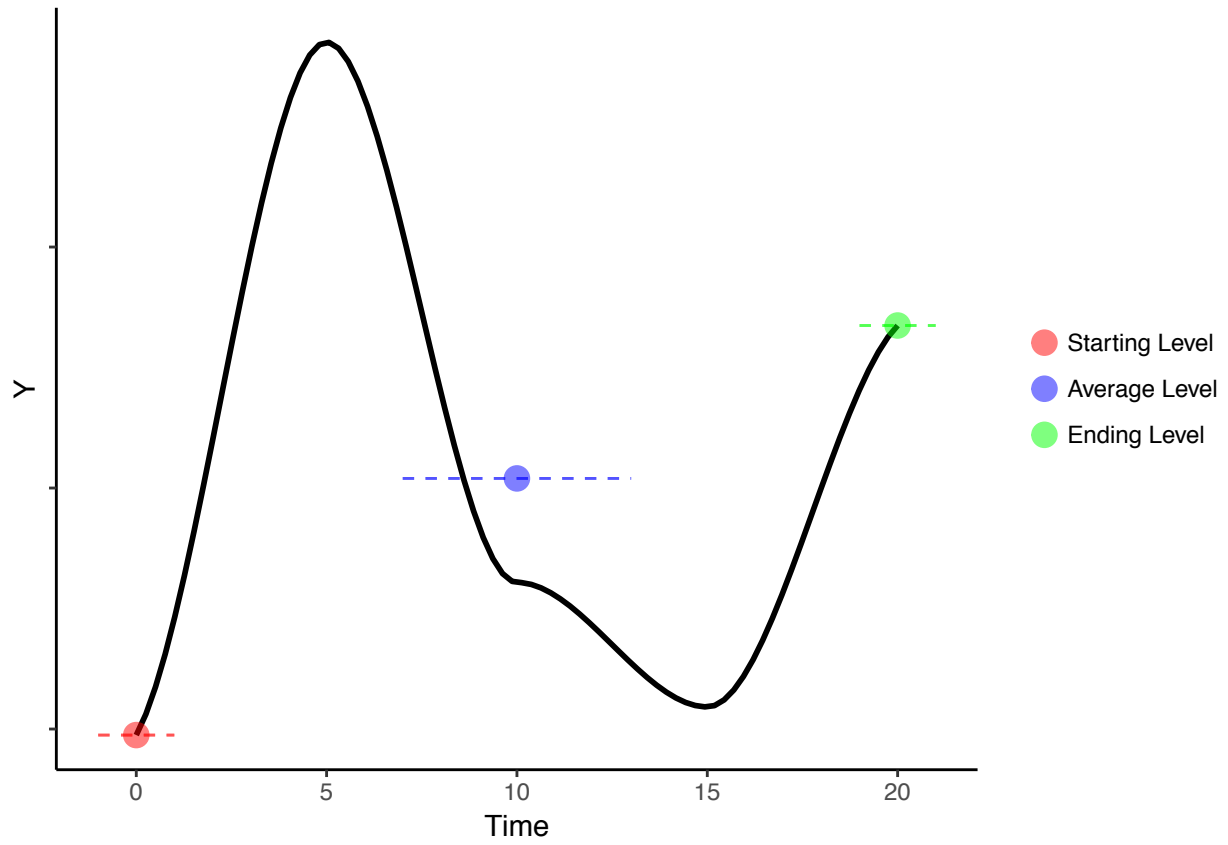
Figure 1. Level examples
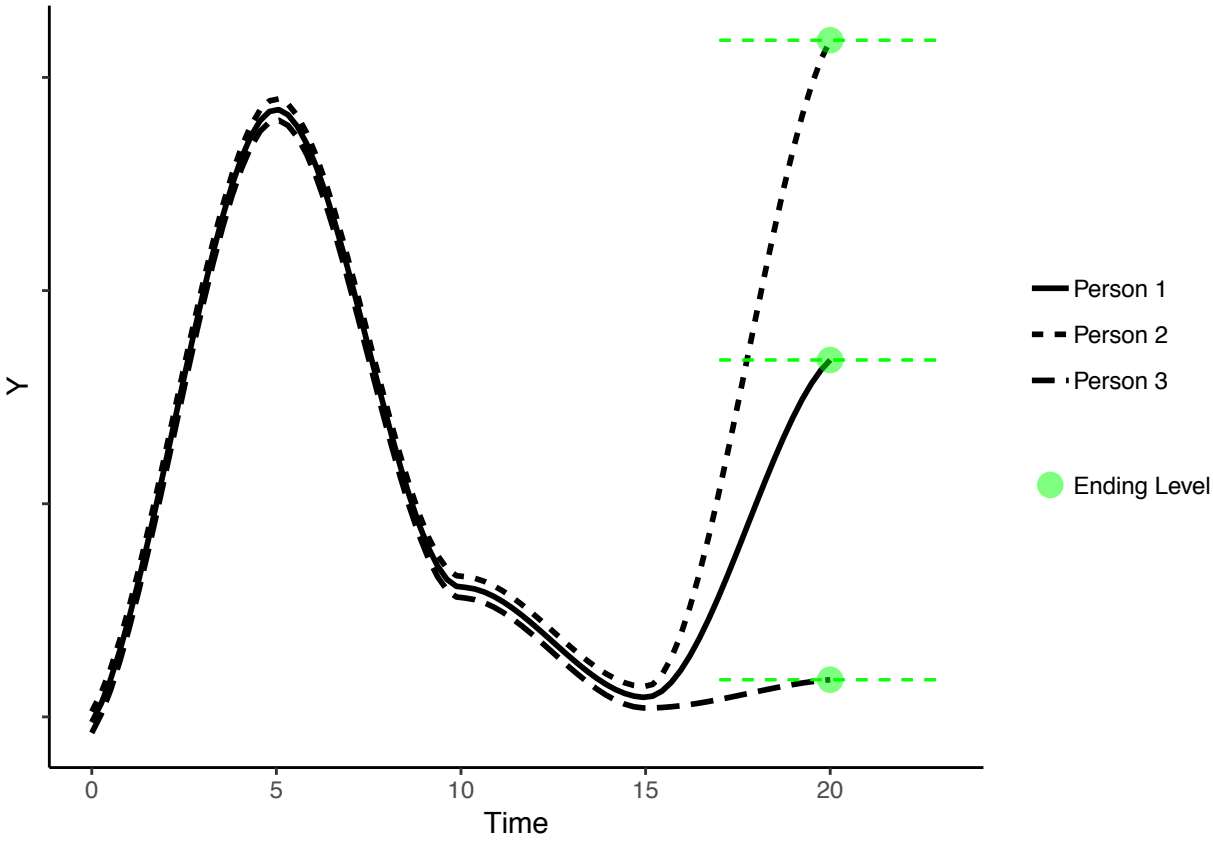
Figure 2. Trajectories with variability in ending level across units
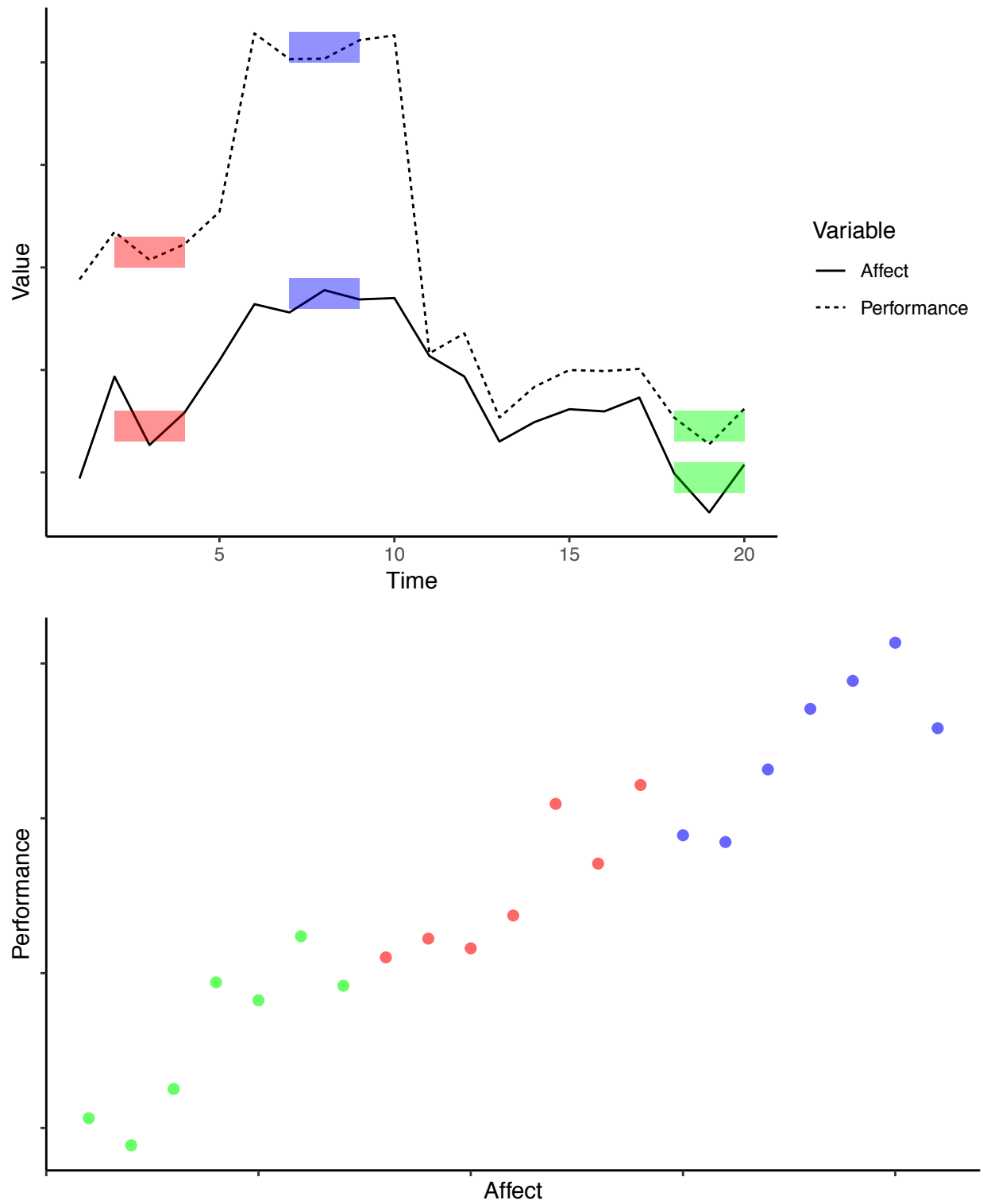
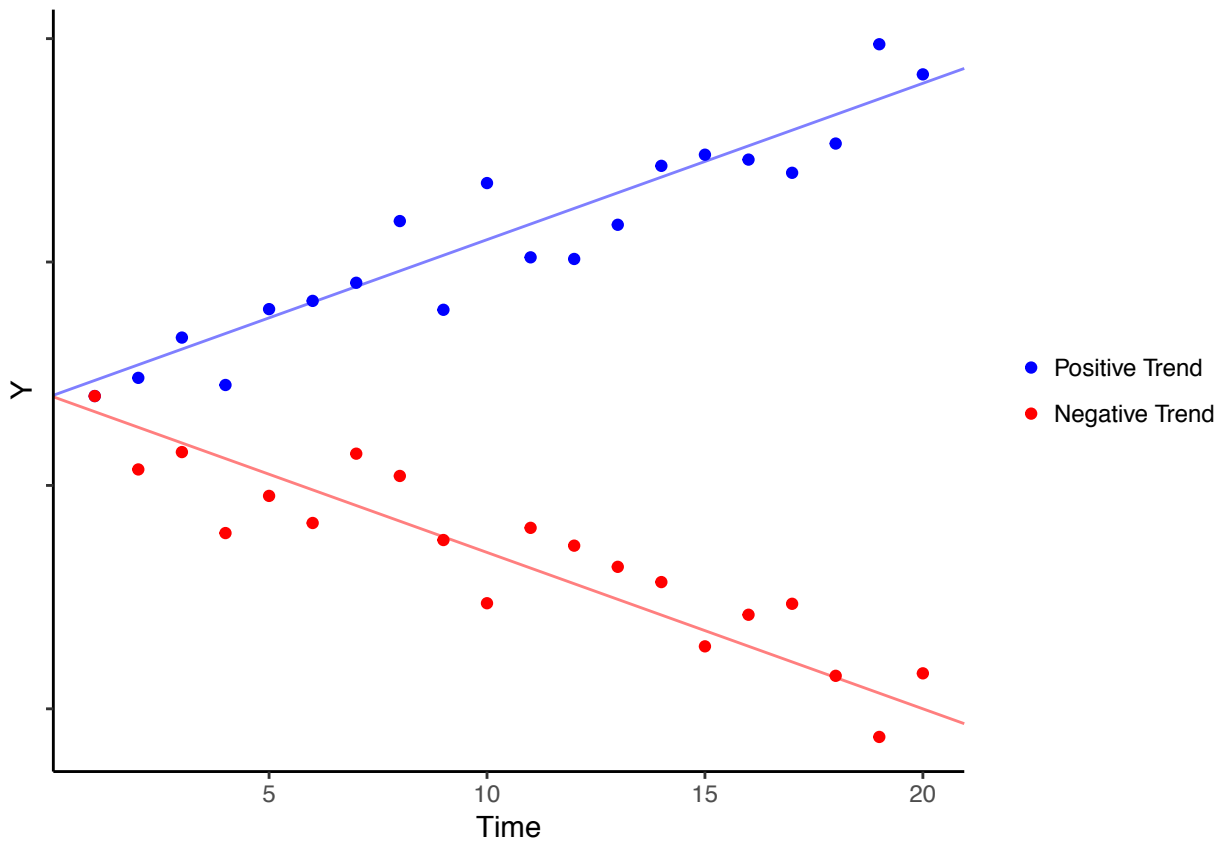*Figure 3*. Relating affect to performance levels

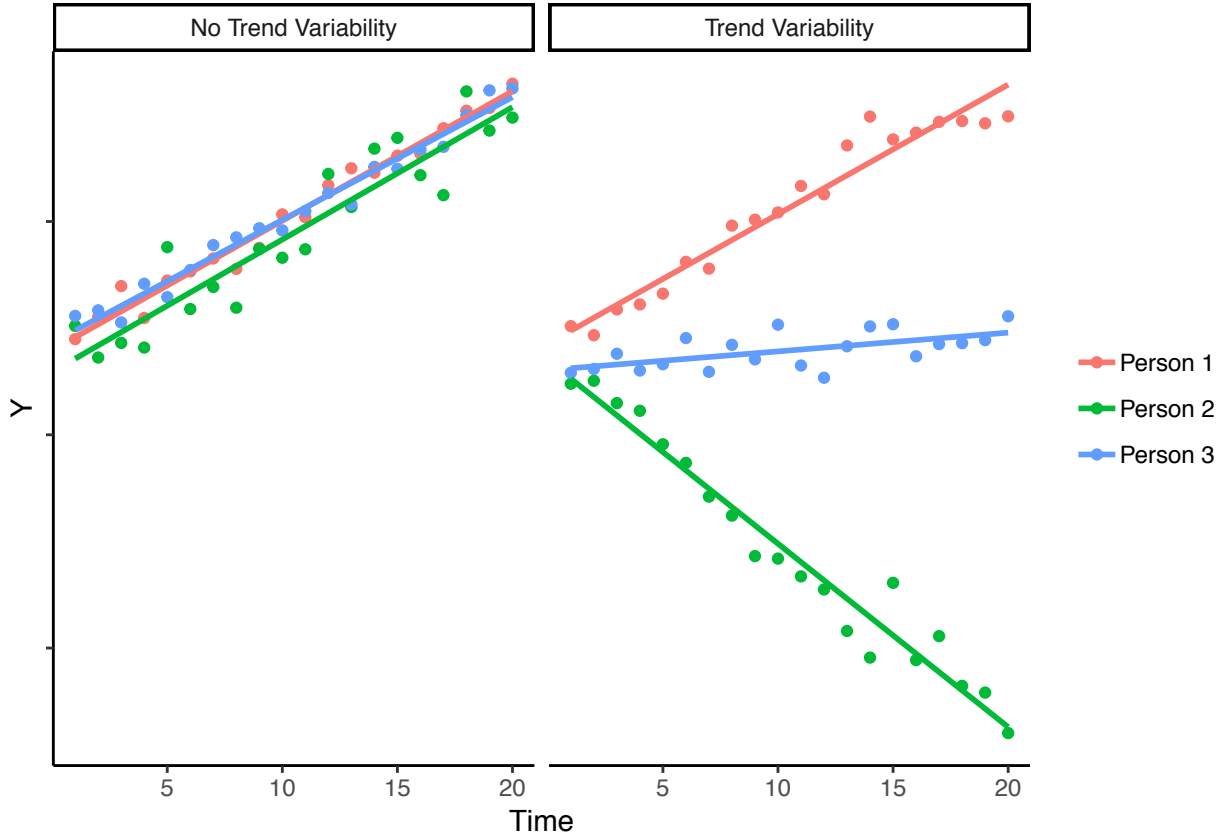*Figure 4*. Trend across time

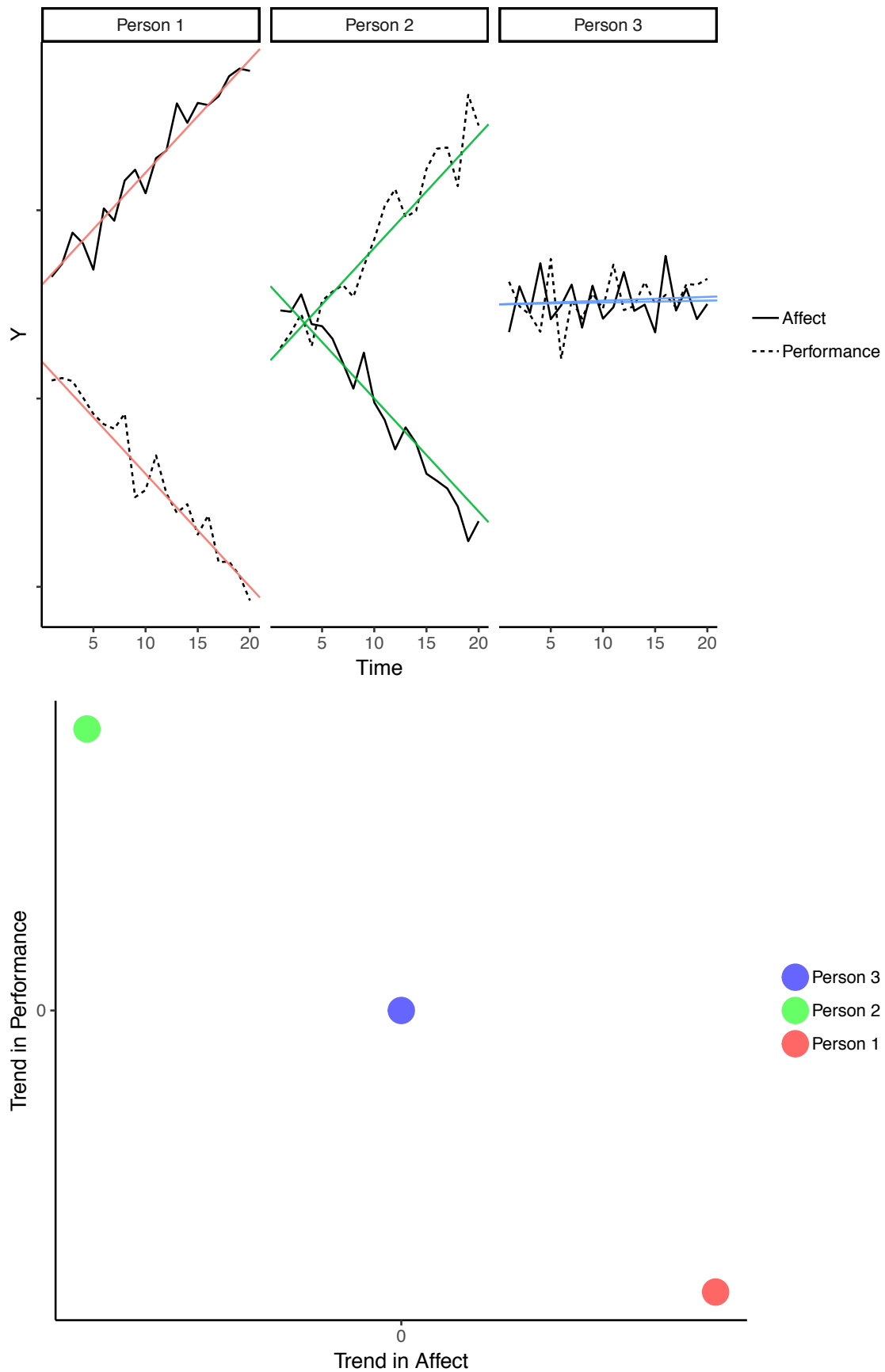*Figure 5*. Differences in trend variability across units

Figure 6. Correlating slopes, or relating the affect to performance trend