Inferences With Longitudinal Data

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Abstract

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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 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 cross-lagged latent growth curves, an approach similar to the latent change model used by Ritter, Matthews, Ford, and Henderson (2016) We also find complex hierarchical linear models in many event-sampling studies (e.g., Koopman, Lanaj, & Scott, 2016; Rosen, Koopman, Gabriel, & Johnson, 2016).

The spine of an investigation, finally, is to interpret the model and make an inference regarding the original question. Jones et al. (2016) infer negative slopes for concealing behaviors and positive slopes for revealing behaviors. Johnson et al. (2014) state that justice behaviors fluctuate day to day and predict changes in depletion. Hardy et al. (2018) find support for dynamic relationships between self-efficacy, metacognition, and exploratory behaviors. Finally, Meier and Spector (2013) suggest that the effects of work stressors on counterproductive work behaviors are not substantially different across different time lags.

None of these inferences perfectly discovers the data generating mechanism. Rather, each asks an interesting and important question about how DVs relate to IVs. Only with lots of asking about lots of different patterns of relationships across the variables could we piece together one (of many) possible representation(s) of the data generating process – hopefully having a good theory to guide the way.

We want to link inferences to models in this paper so that researchers know which of the many models they can use when they are interested in one of the many possible inferences in a longitudinal investigation. 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 concern trajectories or relationships over time, their small differences have large implications for what we take away from them – what we ultimately conclude. Moreoever, 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 (potentially) each i at (potentially) each t.

Framework

Level. Trend. Dynamics. These are umbrella research foci, each has its own sub-inferences and models. Each section will basically have two notions: trying to understand the thing itself (one variable). Looking at trend or variability in trend. Then looking at correlates or predictors of the thing: correlates of trend, etc.

Each section will also point to models. But there is nuance. The models have different names, some require stationary, some don't. You need to appreciate that and make sure you are attending to all of its nuance. All we are doing here is pointing you in the direction.

Different literatures talk about the idea of level in different ways. In mathematical biology a variable is referred to as a state, the span of values that it can take is known as the state space, and its current value is called the condition of the state. Level is therefore synonymous with the condition of a state. Monge refers to it as magnitude.

In the statistical literature, level is called the intercept. Level, with respect to a certain point or window in time, is called the intercept in the statistical literature, and we can make an inference about the intercept at any observation point. Sometimes we are interested in the level at the beginning of the study, other times we are interested in the level at the last observation. We can of course also be interested in the average level across time.

Level

Is employee emotional exhaustion, on average, high across the study? Is trainee skill low at the beginning of a training session? What value are newcomer perceptions of unit climate at the end of a two-week socialization process? These are questions about level, or the specific value of a variable.

We can think about level at a specific moment or averaged across a window of time.

That is, if we put a variable on the y axis and plot its values against time on the x axis, we can explore the value that it takes at time t, or the value that it takes on average across any span of t. Figure 1 demonstrates this idea graphically. A variable is plotted across time, and the color labels indicate levels – two at specific t's and the third averaged across time – that we may be interested in.

Insert Figure 1 about here

Our first level inference, therefore, concerns the value of a variable at a specific time or averaged across a window of time.

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

When we retain one variable but add multiple units – people or organizations, for example – then we can look at the variability in level. Does everyone have high affect across time? Is there variability in the level of skill among trainees at the beginning of a training session? We demonstrate this idea in figure 2, where each unit (person) has a similar trajectory but different levels at the last time point.

Insert Figure 2 about here

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

Inference 2: There is variability in the level of x at time t, or across a span of t.

Inferences one and two concern a single variable, but they can of course be iterated across any or all observed variables in a study. For example, we might discover that x and y have high average levels across time, but that y has greater variability, suggesting individual differences in the sample. Or we might learn that x has a low initial level whereas y's initial level is high.

Correlating these levels is the next inference. When x on average is low at the initial time point and y on average is high at the initial time point, we can correlate them to discover if units (people) with low initial levels of x have high initial levels on y and people with high initial levels on x have low initial levels on y.

Figure **??** demonstrates this graphically. all about the graph.

Inference 3: There is a correlation between the level of x ***and*** y ***at*** t***.***

The final inference is horizontal. Rather than regressing a point estimate of the level on another level, we regress the values on a variable across time on another variable's values across time.

Questions. Is the level of affect related to the level of helping behaviors across time? That is, when affect is high, are helping behaviors also high or are they low? When team cohesion is low, is team performance low as well, or is it high?

Figure 3

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

Level Inference Table

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

Intercept only models: these can be done in HLM or SEM. Time-varying or invariant covariates analysis, these can be done in HLM or SEM. Point to references.

One variable, multiple units

Muliple Variables

When affect is low performance is low. When affect is high performance is high.

Trend

Does affect go up or down across our measurement period, or is it relatively stable? Does trainee skill increase over the training session? These first two examples are questions about linear trend; we can also explore curvilinear trajectories. Do newcomer perceptions of climate increase and then plateua 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?

Trend has to do with the global shape of the trajectory across time. If we put a variable on the y-axis and plot its values against time on the x-axis, do the values tend to go up or down over time? It can be thought of as the coarse-grained direction of a trajectory. Figure 4 demonstrates trend differences, where the red line shows positive, increasing trend, the blue line shows negative, decreasing trend, and the green line shows a curvilinear trajectory. Keep in mind that curvilinear and linear trajectories are both **linear in parameters** and should not be confused with non-linear systems.

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

Inference 1: There is positive/negative/curvilinear trend in a variable across time.

We can also examine trend variability when we observe more than one unit. Do all trainees develop greater skill across time? Is there variability in the trend of helping behaviors, or counterproductive work behaviors over time?

Figure 5 shows differences in trend variability. In the first panel all units (people) show the same positive trend, whereas everyone in the second panel shows different trend: person one's data appear to increase over time, person two's data remain flat, and person three's data decrease over time. With greater variability there is less consistency in trend across units.

Inference 2: There is variability in the trend of a variable across time. Trend differs across units.

Just like our discussion of the "level" inferences, inferences one and two were about one variable, but they can be iterated across all observed variables. For example, we might discover that x and y both have decreasing trend, but that y has greater variability, suggesting individual differences in the sample. Or we might learn that x has negative trend whereas y has positive trend.

Correlating these trends is the next inference. People with positive trend in x also have positive trend in y.

Figure **??**. Explain.

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

Correlates/predictors of trend.

Figure 6

Inference 4: There are correlates/predictors of trend.

Trend Inference Table

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.

Models

Growth curves in SEM or HLM. Bivariate growth curves.

Dynamics

Dynamics refers to systems with memory. When the past matters, dynamics are at play.

Stuff about change.

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.

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

Inference 2: There is a cross-lag relationship, where one variable relates to another at a different point in time. x__t is associated with y__t+1 across time.

Inference 3: There is a change relationship, where one variable relates to the change in another. x__t is associated with delta y__t.

Inference 4: There is a cross-lag relationship of change, where one variable relates to the change of another at a different point in time. x__t is associated with change at y__t+1.

Dynamics Inference Table

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 changes in performance.
4	Affect relates to subsequent change in performance.
	Helping behaviors predict subsequent depletion changes.

Inference List

A variable has autoregression.

Level relationships with lags: x_t is associated with $y_t + 1$ across time. There are cross-lag effects, where one variable relates to another at a different point in time. Distinguish this from one measurement at t_1 and one measurement of y at t_2. . . this inference is not that. This inference is about a bunch of repeated measurements, and at each of those x predicts the next moment of y.

The inference above can be extended to include reciprocal relationships or multiple variables.

Change relationships. x is associated with a change in y. This implies that x_t predicts y_t, but y_t is no longer just the straight observation, it is the difference between y_t and $y_t - 1$ (or with $y_t - 1$ partialled).

Change relationships with lags. Same thing as above but now a different lag of x is predicting change in y.

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.

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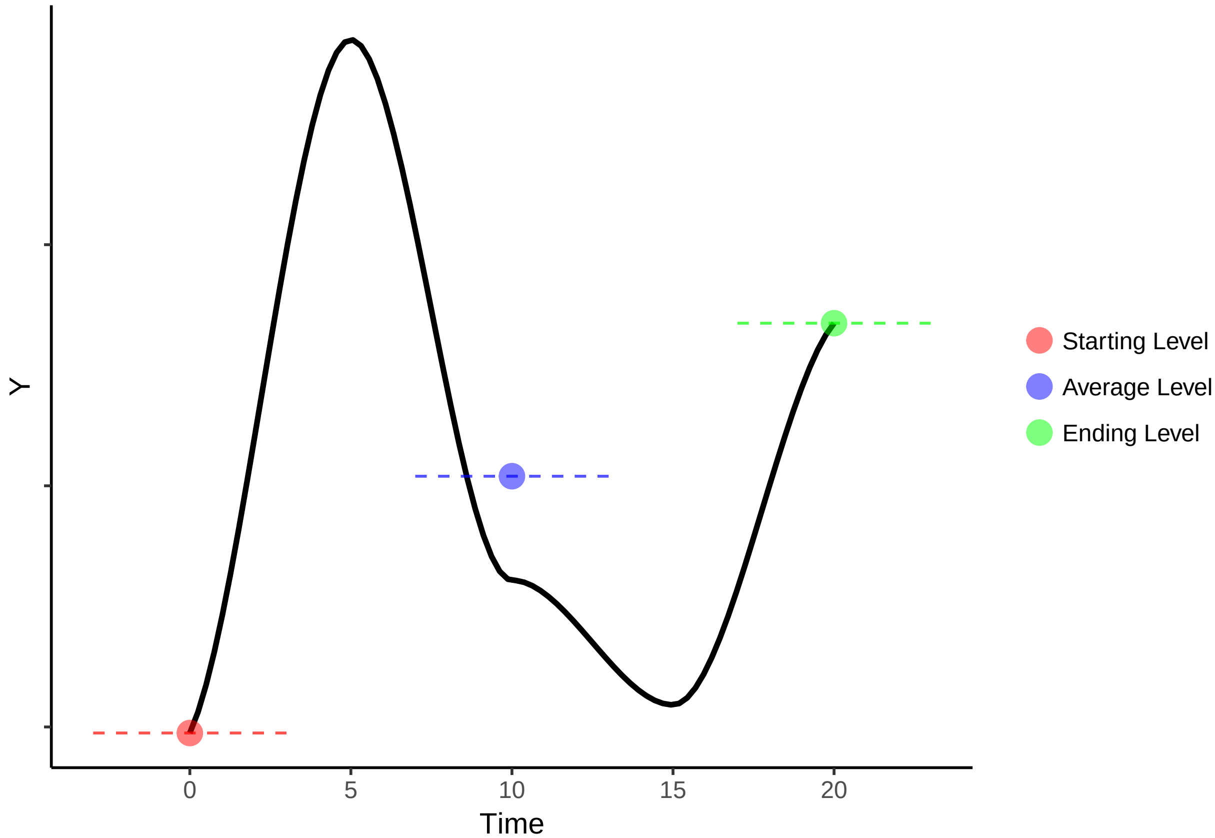

Figure 1. Level examples

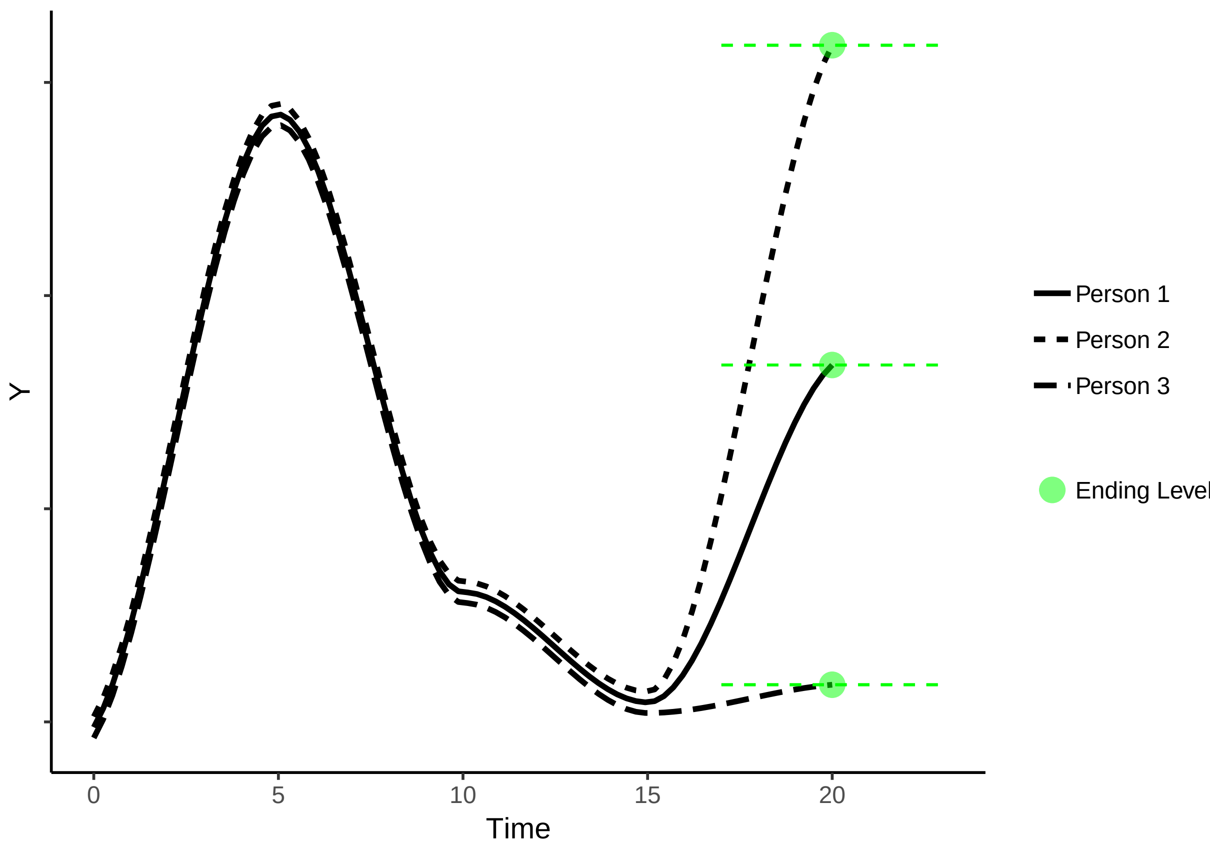

Figure 2. Trajectories with similar starting and average levels but different ending levels

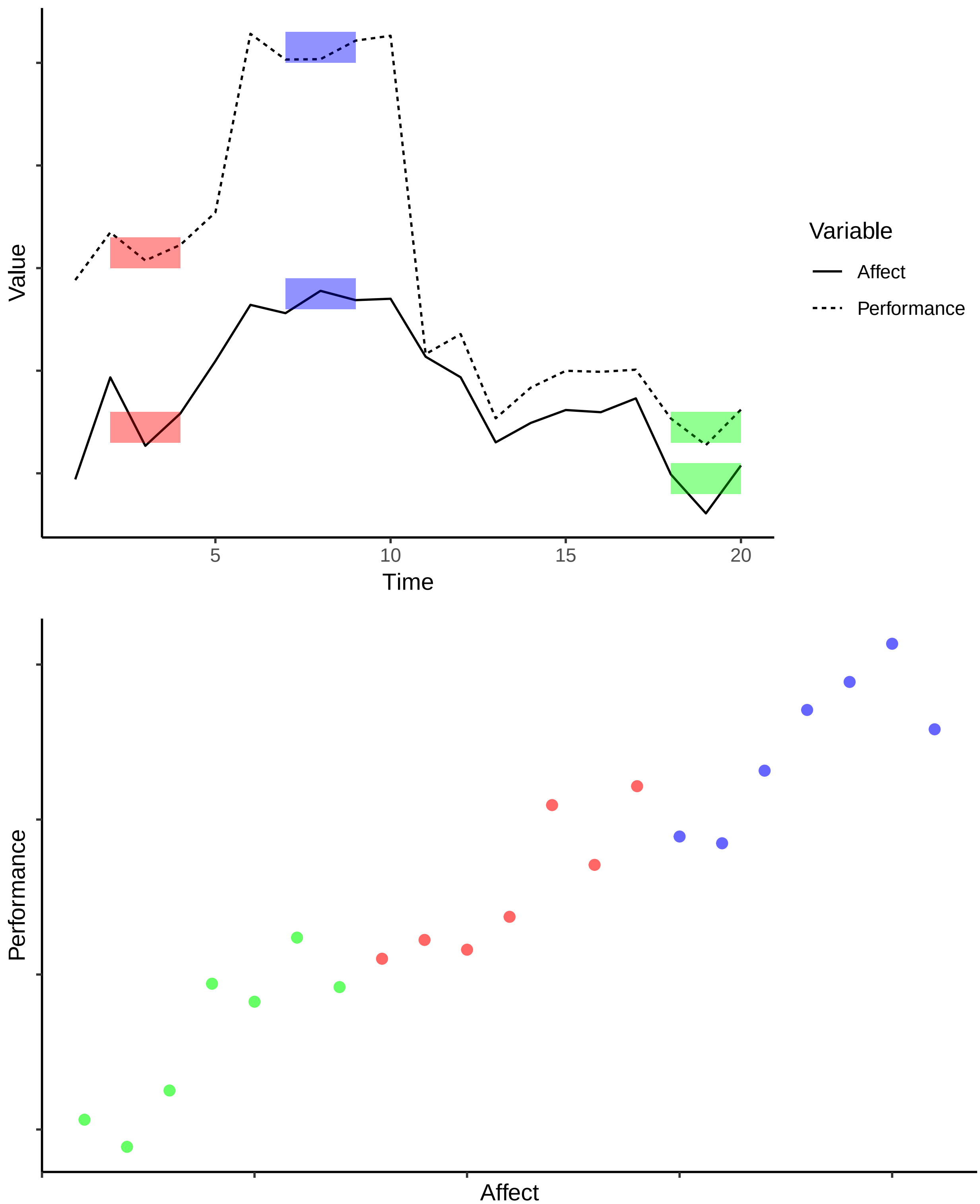

Figure 3. Relating affect to performance levels

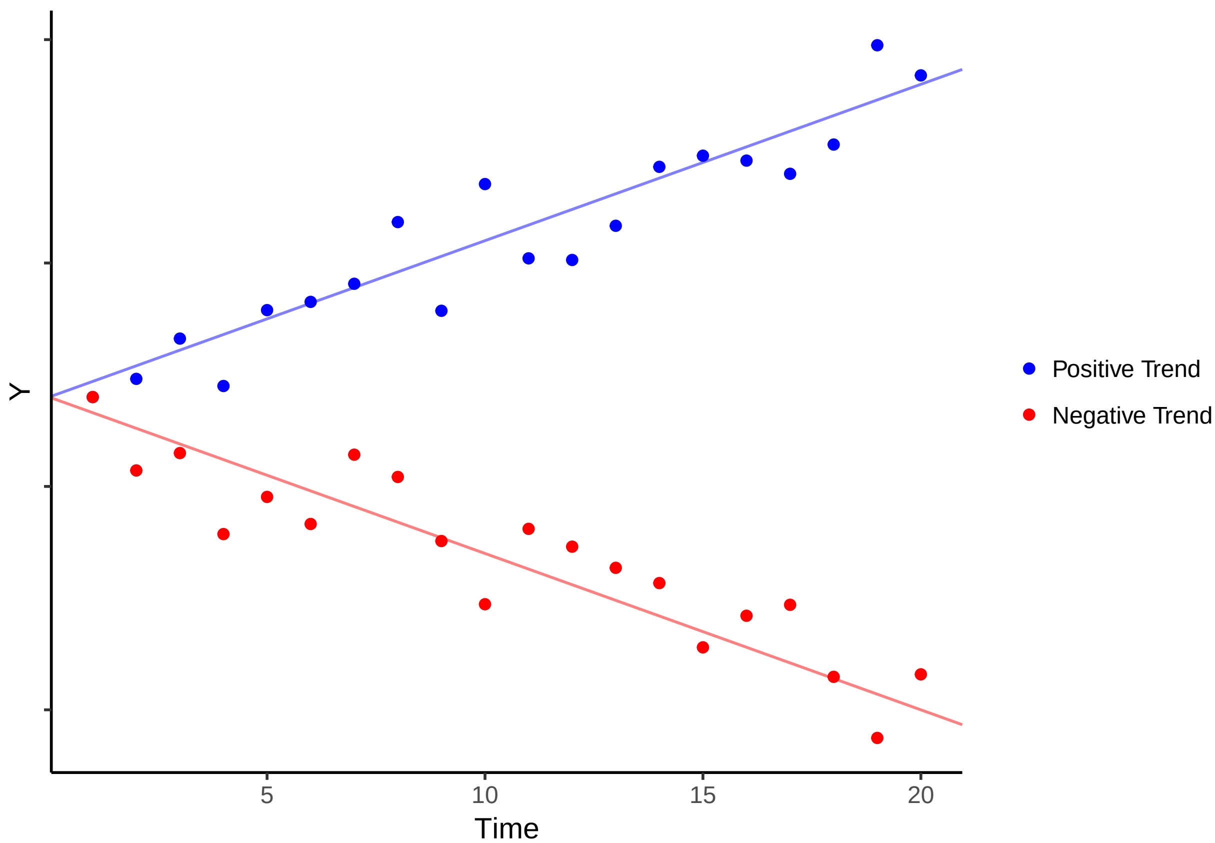

Figure 4. Trend across time

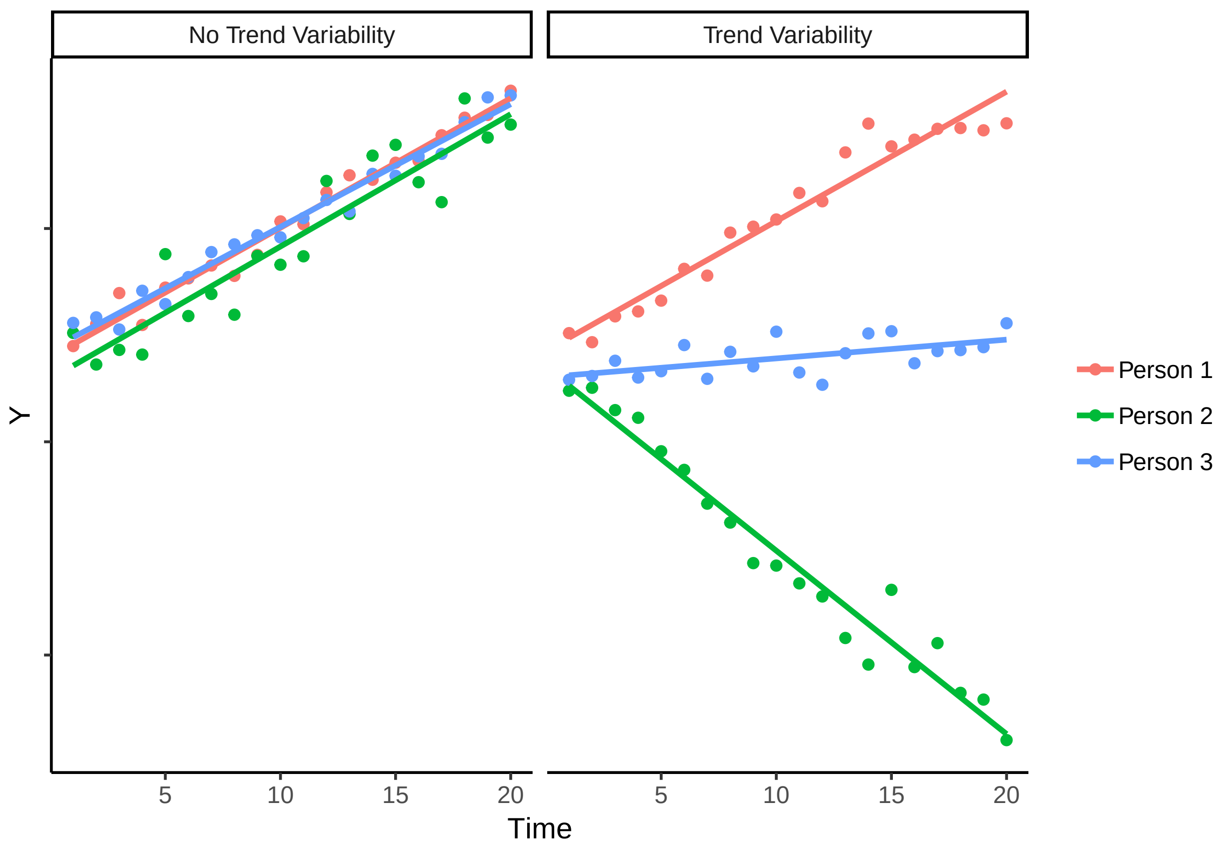

Figure 5. Differences in trend variability across units

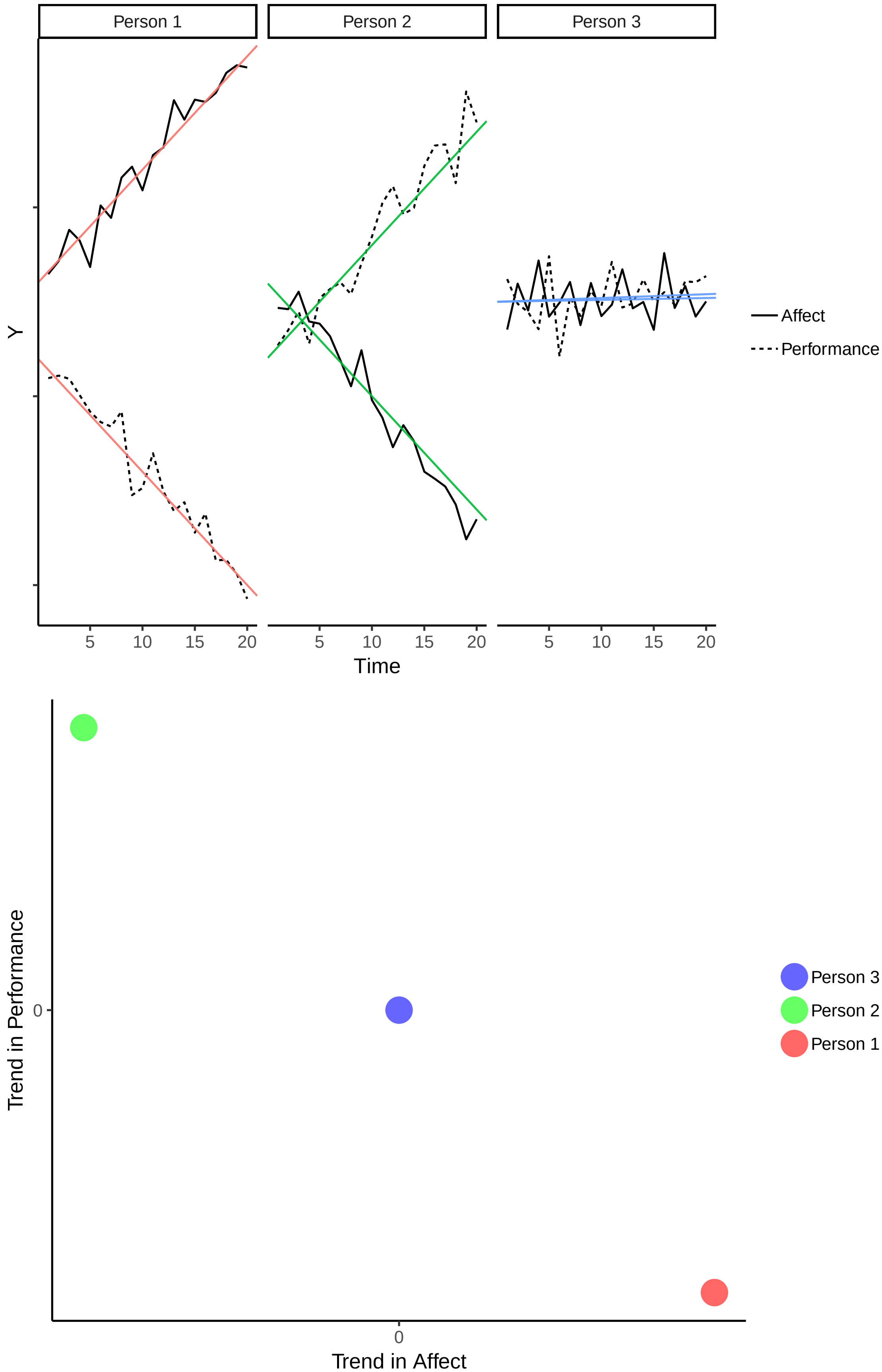

Figure 6. Correlating slopes, or relating the affect to performance trend