Inferences With Longitudinal Data

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Abstract

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Keywords: ....

Word count: 95

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 that we attend 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).

Option A. . . It's hard for newcomers

Although our field is increasingly interested in exploring patterns in longitudinal data, process-oriented methods are still relatively new to our field and newcomers without much longitudinal modeling training may be unfamiliar with the variety of questions they can ask. Consider a few recent longitudinal studies that all pose different questions. Jones et al. (2016) ask if the trajectories among certain variables increase or decrease over time. Johnson, Lanaj, and Barnes (2014) study how changes in one variable relate to changes in another across time. Hardy, Day, and Steele (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.

There are then complex statistical models that researchers evoke to examine their 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). Again, researchers without much longitudinal modeling training may not know when to apply each model – or which model is appropriate for a given question.

Finally, the spine of an investigation 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.

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 concern trajectories or relationships 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.

Option B. . . Just highlighting the literature

There are many interesting questions researchers can explore with longitudinal data. Consider a few recent longitudinal studies that all pose different questions. Jones et al. (2016) ask if the trajectories among certain variables increase or decrease over time. Johnson et al. (2014) study 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.

There are then complex statistical models that researchers evoke to examine their 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 et al. (2016). We also find complex hierarchical linear models in many event-sampling studies (e.g., Koopman et al., 2016; Rosen et al., 2016).

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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 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

We use three inference categories to partition our discussion, including level, trend, and dynamics. Each of these are broad categories, and they will all have their own sub-inferences and models. Our writing style will be the same throughout each section, where we first discuss the category itself and then sequentially walk through the inferences. During that sequence, we will pose questions to orient the reader as to what the inference captures, unpack graphs and figures, and then close with a table that provides example hypotheses that align with each inference. The figures we use in the level and trend sections are graphs that show what the inferences look like in data – we feel that graphing the inferences with respect to data is more informative than your usual box and arrow diagram. There is a caveat, however, that we want to make sure everyone is aware of. Data are always messy. It is rare to find data where the inferences expose themselves simply by plotting – although it is certainly possible. We are using these "data plots" to clearly convey what the inferences mean, but please be aware that field data will always be messy. When we discuss dynamics section we then use box and arrow diagrams because they better convey the ideas in that section.

Finally, we end each inference section by pointing researchers to respective statistical models. Although we direct researchers to models, our paper is not about statistical modeling only – it is about inferences – and researchers therefore need to be sure that they appreciate all of the nuance before applying a recommended model. There are many complex statistical issues that arise with longitudinal modeling – like stationarity – and the models differ in how they handle these issues, the assumptions they make, and the data format they require. There are plenty of great references on each model, what we are doing here is guiding researchers to those references based on the underlying inferences that interest them.

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.

Levels either describe the variable at one moment or averaged across a span 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 for a single person (i.e., unit), and the color labels indicate levels – the red and green describe the variable at a specific moment while the purple, average level, describes it across a window. The starting level is the value of the variable at the first time point, the ending level is its value at the last time point, and the average level is its average level across time.

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 examine 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 we now plot three units (people) across time. Each individual has a similar trajectory, but their ending levels of y are different. Said formally that is, "there is variability across units in level at the last time point."

Insert Figure 2 about here

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

> **Inference 2:** Across a span of t or at a specific t there is variability in the level of x.

Inferences one and two concern a single variable, but they can of course be iterated across any or all observed variables in the study (remember that variables are different than units). For example, we might discover that affect and performance have high average levels across time, but that affect has greater level variability across units. Or we might learn that affect has a low initial level whereas performance is initially high. What we are doing here is making descriptive comparisons between the level of one variable and the level of another. We can also produce a quantitative statement about the extent to which levels are related.

Correlating levels provides us with that quantitative statement. A large positive correlation between the initial levels of affect and performance would mean that people with greater initial levels of affect also tend to have greater intial performance, and people with lower initial affect also tend to have lower initial performance.

Figure 3 demonstrates a correlation of starting levels. In Panel A we plot affect and performance trajectories for three individuals across time, where the black solid line indicates affect and the dashed line indicates performance. We indicate starting levels for both variables in Panel A by placing colored circles on the graph for each individual. For example, we indicate the starting levels of affect and performance for person one with red circles and the starting levels for person two with green circles.

Panel B of figure 3 maps those starting levels onto a new plot that leads to our inference. On the x-axis is initial level of affect, where high values indicate a high starting level of affect, and on the y-axis is initial level of performance, where high values indicate a high starting level of performance. The red circle for person one is on the bottom right because that individual has a high initial level of affect and a low initial level of performance. Person two (the green circle) is on the top left because that individual has a high initial level of performance and a low initial level of affect, and person three is in the middle because they have roughly the same starting levels of affect and performance. The dots slope downward in Panel B, which tells us that there is a negative relationship between initial level of affect and initial level of performance.

Overall, figure 3 suggests that the starting levels of affect and performance are correlated. Panel A shows the actual starting levels, and Panel B shows that there is a strong negative correlation between initial affect and initial performance. This negative relationship means that we expect people with low initial affect to have high initial performance, whereas we expect people with high initial affect to have low initial performance.

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

Insert Figure 8 about here

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.

Insert Table 1 about here

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. Point to references.

Trend

Does affect go up or down across time, or is it relatively stable? Does trainee skill increase over the training session? These are questions about trend, and these first two are specifically about linear trend. It is also possible to explore how variables bend or curve across time. Do newcomer perceptions of climate increase and then plateau over time? Does the response time of a medical team decrease with each successive case but then remain stable once the team can no longer improve their coordination? These latter questions concern curvilinear trajectories.

Trend has to do with the 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, where the red line shows negative, decreasing trend, the blue line shows positive, increasing 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.

Insert Figure 4 about here

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

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

As with the level inferences, when we add more units we can examine trend variability. 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 facet all units (people) show the same positive trend, whereas everyone in the second facet shows different trend: person one's data appear to increase over time, person two's data decrease over time, and person three's data remain flat. With greater variability there is less consistency in trend across units.

Insert Figure 5 about here

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

Inferences one and two are about one variable, but they can also be iterated across all observed variables. For example, we might discover that affect and performance trends both decrease, but there is greater variability across units in the affect trend. Or we might learn that affect has a negative trend while performance has a positive trend.

Correlating these trends is the next inference. Correlating indicates co-occuring patterns, but this time we are focused on trends rather than levels. A large positive correlation between affect and performance trends indicates that people with a positive affect trend (usually) have a positive performance trend and people with a negative affect trend (usually) have a negative performance trend.

Figure 6 shows the inuition behind the inference with a set of graphs. In Panel A we plot affect and performance across time for three individuals. Affect goes up while performance goes down for person one, this pattern is reversed for person two, and person three reports trendless affect and performance (i.e., zero trend), 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.

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 research and development, whereas the final three individuals work in sales. Affect trajectories tend to decrease over time for employees in research and development, whereas affect trajectories tend to increase for those in sales. An individual's job type, then, gives us a clue to their likely affect trend – said formally, job type covaries with affect trends, such that we expect individuals in sales to have positive affect trends and individuals in research and development to have negative affect trends. The expected trends are plotted as the thick blue lines.

Inference 4: There are correlates of trend.

Trend Inference Table

The inference table below provides examples of each trend inference. Inference one is about the general direction or shape of a trajectory across time. Inference two is about variability in that shape across units. Inference three takes the trend in one variable and asks whether it co-occurs with trend in another. Inference four, finally, is about the relationship between trend in one variable and the raw values of one or more correlates.

Insert Table 2 about here

We want to close this section with a note on phrasing. The inferences we explored in this section have to do with correlating trends, where a statement like "affect and performance trends covary, such that people with a negative affect trend have a positive performance trend" is appropriate. There is a less precise phrase that is easy to fall into – and we have seen it used in our literature. Sometimes, researchers will correlate trends and then state, "when affect decreases performance goes up." We urge researchers to avoid this second statement because it is not clear if it refers to a static relationship about trends or a dynamic statement about how trajectories move across time. That is, the phrase "when affect decreases performance goes up" could refer to correlated trends, but it could also mean something like, "when affect decreases performance immediately or subsequently goes up." This second statement is far different and it should not be used when an analysis only correlates trends or evokes predictors of trend. Again, we urge researchers to phrase their inferences as we have shown here.

Models

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.

Relationships

In our final level inference we correlate values across time rather than correlating values from a single moment or a single averaged moment. For example, we might ask if affect is related to performance across time; i.e., when affect is high is performance also high, and when affect is low is performance also low?

This inference sounds similar to the one just presented, but their difference is important. With inference three we ask about affect and performance at t or at an averaged window of t – we examine, for example, how ending performance relates to ending affect, or how affect averaged across time relates to performance averaged across time. Here, we retain all of the information and examine the relationship between affect and performance across all t.

Figure 8 shows this inference graphically. In Panel A we plot affect and performance trajectories across time, where the solid line indicates affect and the dashed line indicates performance – this time we only focus on a single individual or unit. The colored squares represent levels at different points in time. The green squares highlight low values of both variables, the blue high values, and the red middle values.

Panel B shows how those respective values map onto a scatterplot of affect and performance – which again will lead to the inference. The blue values indicate that high values of affect tend to co-occur with high values of performance (shown respectively by the blue squares in Panel A). The red values indicate that middle values of affect tend to co-occur with middle values of performance. The green values, finally, indicate that low values of affect tend to co-occur with low values of performance. Across time, affect and performance covary.

Inference four, finally, is about the relationship between raw values across time.

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

Figure 9 shows the inference.

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

Relationships Inference Table

Text.

Insert Table 3 about here

Models

Time-varying or invariant covariates analyses.

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 (2016) defines a dynamic *model* as a “representation of a system that evolves over time. In particular it describes how the system evolves from a given state at time *t* to another state at time *t + 1* as governed by the transition rules and potential external inputs” (p. 242). Vancouver, Wang, and Li (2018) state that dynamic *variables* “behave as if they have memory; that is, their value at any one time depends somewhat on their previous value” (p. 604). Finally, Monge (1990) suggests that in dynamic *analyses*, “it is essential to know how variables depend upon their own past history” (p. 409).

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? 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.

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 a lag-one relationship between x and y. Said formally, we believe that x_t is related to y_{t+1} (or equivalently, x_{t-1} is related to y_t). Relating current to future (or prior to current) values from one variable to another is called a "cross lag" relationship.

> **Inference 2:** There is a cross-lag relationship, where one variable relates to another at a different point in time.

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

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

All of these questions are about change, but notice that change can be construed across different lags. Change from what? Baseline? The prior time point? The last three time points? Typically change is construed with respect to the last time point. When affect is low, does performance from the last to the current time point increase or decrease? How does effort change from the prior to the current time point when goal discrepancy is high?

Panel C of figure 10 demonstrates this idea. We are positing the same self-similarity in x and the same cross-lag relationship that we saw before, but now y also has self-similarity across time. The cross-lag relationship, therefore, is now capturing how y has changed from the last point in time.

It is typical to think of change from the prior to the current time point, but researchers are free to move it as they please. Here are the two final inferences that capture change in different locations.

> **Inference 3:** There is a change relationship, where one variable relates to the change in another.

> **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.

Dynamics Inference Table

Again, we provide an inference table below – this time with respect to dynamic inferences. Inference one is about autoregression, or memory in a single variable. Inference two asks how a variable at one time co-occurs with another at a different time. Inferences three and four focus on change: when one variable is high or low, does it relate to the change (an increase or decrease) in the values of another variable?

Insert Table 4 about here

Extensions

We described a simple set of inferences above, but the ideas generalize to more complex dynamics as well. Often researchers are interested in reciprocal relationships, where x influences subsequent y, which then goes back to influence x at the next time point. Said formally, x_t influences y_{t+1}, which then influences x_{t+2}. Said informally, current performance influences subsequent self-efficacy, which then influences performance on the next trial. These inferences are no different than what we saw above – they are cross-lag predictions – all we did 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.

Moreover, the dynamic inferences shown here 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

Autoregression is the statistical word for the estimate of self-similarity in a variable, the relationship between a variable now and its future value. Our literature has a history with difference scores and partialling. We debated difference scores so we have converged to partialling models. Typically we create a model with prior values of the response variable as a predictor.

Discussion

Summary paragraph. We talked about these things.

Other possible discussion pieces. 1) 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 where constructs were measured on each i at each t." Sometimes this doesn't happen… 2) Econometrics modeling levels vs. modeling differences.

A section about our opinions of static versus dynamic research. We don't want to get into the difference between explaining a mechanism vs describing an observed "longitudinal" pattern, and we don't want to say that static research is useless…but can we close with some of our opinions? Some of the ways we hope researchers will go?

References

Beal, D. J. (2015). ESM 2.0: State of the art and future potential of experience sampling methods in organizational research. *Annu. Rev. Organ. Psychol. Organ. Behav.*, *2*(1), 383–407.

Hardy, J. H., Day, E. A., & Steele, L. M. (2018). Interrelationships Among Self-Regulated Learning Processes: Toward a Dynamic Process-Based Model of Self-Regulated Learning. *Journal of Management*, 0149206318780440. doi:10.1177/0149206318780440

Ilgen, D. R., & Hulin, C. L. (2000). *Computational modeling of behavior in organizations: The third scientific discipline.* American Psychological Association.

Johnson, R. E., Lanaj, K., & Barnes, C. M. (2014). The good and bad of being fair: Effects of procedural and interpersonal justice behaviors on regulatory resources. *Journal of Applied Psychology*, *99*(4), 635.

Jones, K. P., King, E. B., Gilrane, V. L., McCausland, T. C., Cortina, J. M., & Grimm, K. J. (2016). The baby bump: Managing a dynamic stigma over time. *Journal of Management*, *42*(6), 1530–1556.

Koopman, J., Lanaj, K., & Scott, B. A. (2016). Integrating the Bright and Dark Sides of OCB: A Daily Investigation of the Benefits and Costs of Helping Others. *Academy of Management Journal*, *59*(2), 414–435. doi:10.5465/amj.2014.0262

Kozlowski, S. W., & Bell, B. S. (2003). Work groups and teams in organizations. *Handbook of Psychology*, 333–375.

Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, *12*(1), 23.

Maxwell, S. E., Cole, D. A., & Mitchell, M. A. (2011). Bias in cross-sectional analyses of longitudinal mediation: Partial and complete mediation under an autoregressive model. *Multivariate Behavioral Research*, *46*(5), 816–841.

Meier, L. L., & Spector, P. E. (2013). Reciprocal effects of work stressors and counterproductive work behavior: A five-wave longitudinal study. *Journal of Applied Psychology*, *98*(3), 529.

Monge, P. R. (1990). Theoretical and analytical issues in studying organizational processes. *Organization Science*, *1*(4), 406–430.

Pitariu, A. H., & Ployhart, R. E. (2010). Explaining change: Theorizing and testing dynamic mediated longitudinal relationships. *Journal of Management*, *36*(2), 405–429.

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management*, *36*(1), 94–120.

Ritter, K.-J., Matthews, R. A., Ford, M. T., & Henderson, A. A. (2016). Understanding role stressors and job satisfaction over time using adaptation theory. *Journal of Applied Psychology*, *101*(12), 1655.

Rosen, C. C., Koopman, J., Gabriel, A. S., & Johnson, R. E. (2016). Who strikes back? A daily investigation of when and why incivility begets incivility. *Journal of Applied Psychology*, *101*(11), 1620.

Stone-Romero, E. F., & Rosopa, P. J. (2008). The relative validity of inferences about mediation as a function of research design characteristics. *Organizational Research Methods*, *11*(2), 326–352.

Vancouver, J. B., Wang, M., & Li, X. (2018). Translating Informal Theories Into Formal Theories: The Case of the Dynamic Computational Model of the Integrated Model of

Work Motivation. *Organizational Research Methods*, 109442811878030. doi:10.1177/1094428118780308

Wang, M., Zhou, L., & Zhang, Z. (2016). Dynamic modeling. *Annual Review of Organizational Psychology and Organizational Behavior*, *3*(1), 241–266. doi:10.1146/annurev-orgpsych-041015-062553

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.

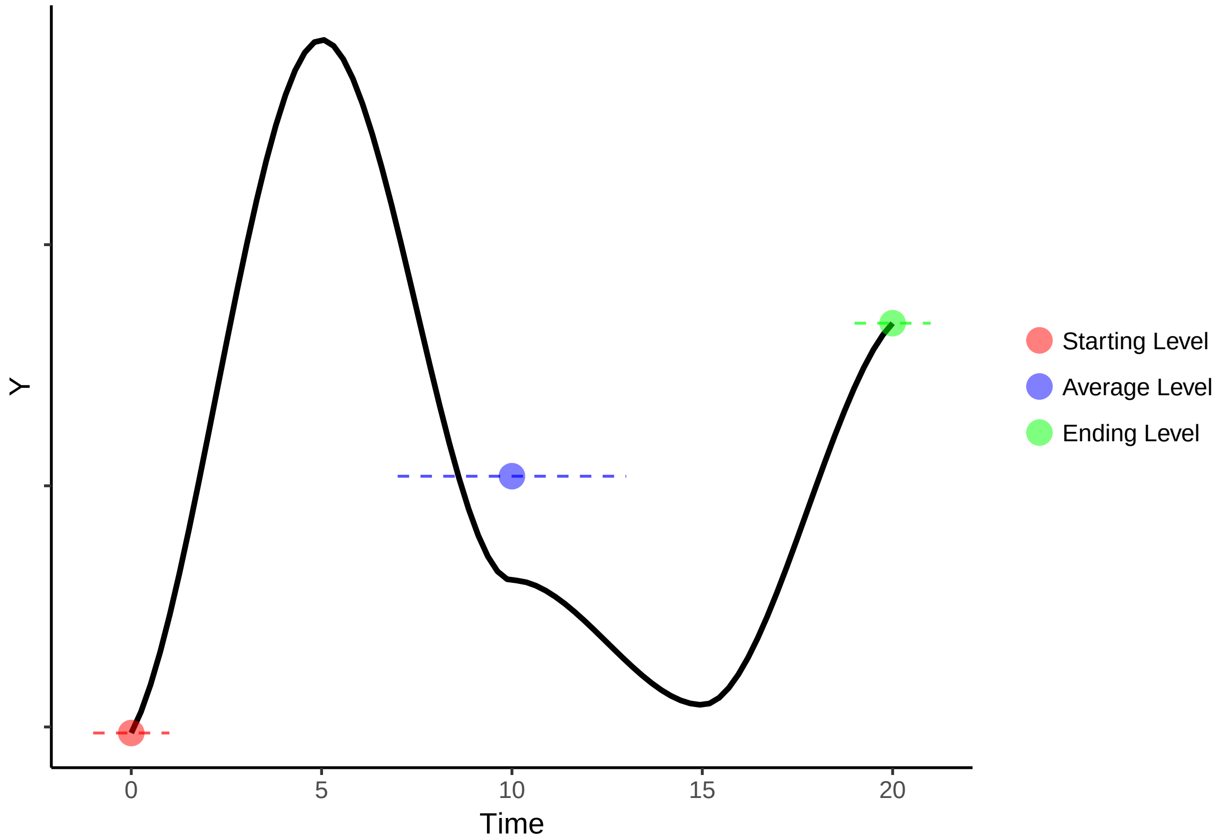

Figure 1. Level examples.

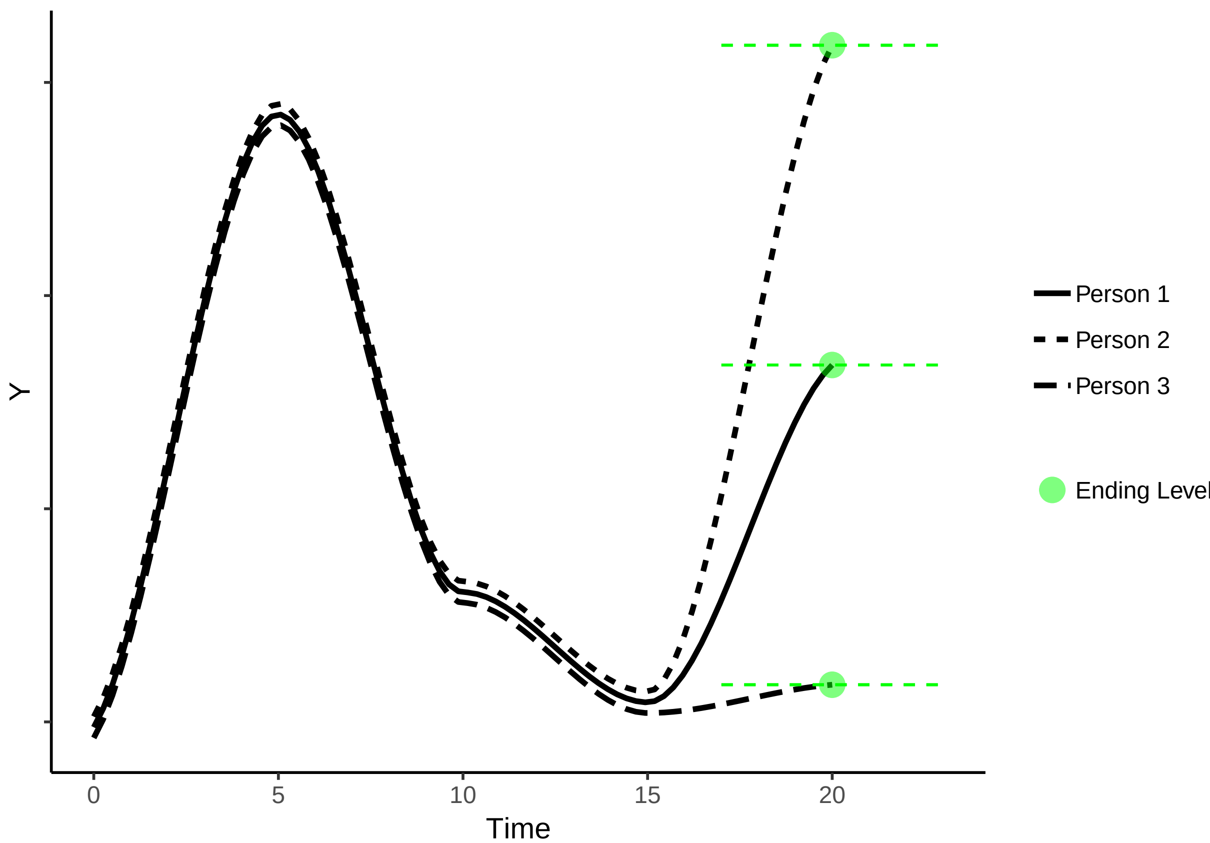

Figure 2. Trajectories with variability in ending level across units.

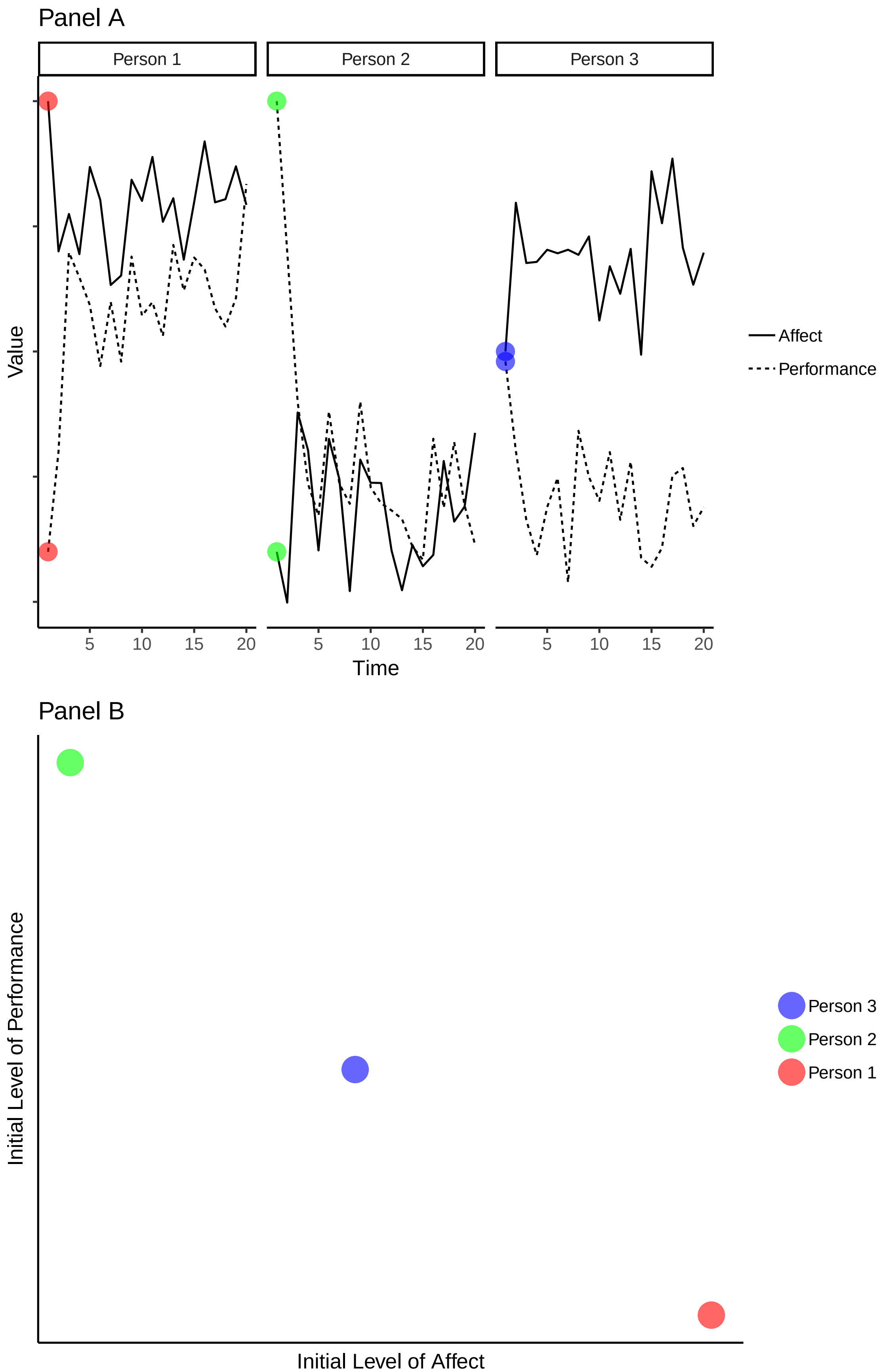

Figure 3. Correlating starting levels, or relating initial affect to initial performance.

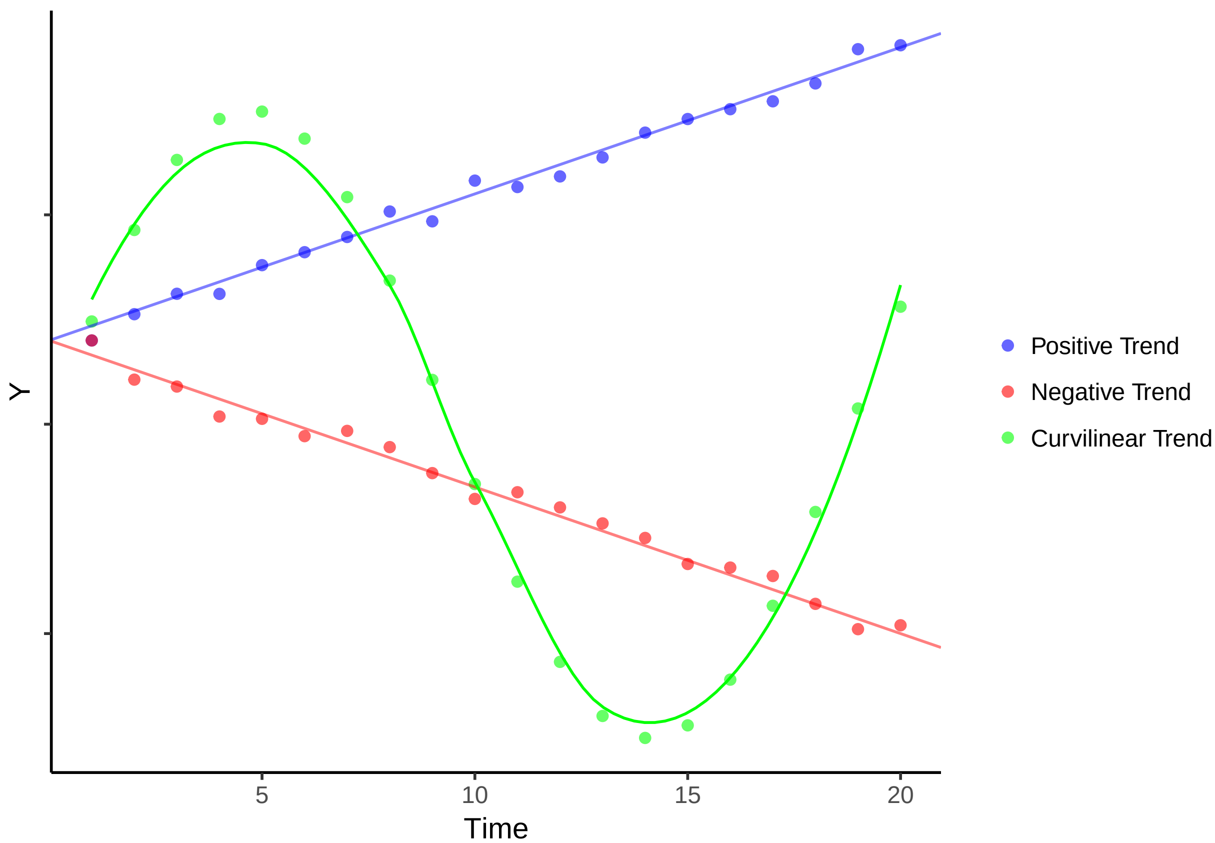

Figure 4. Trend across time.

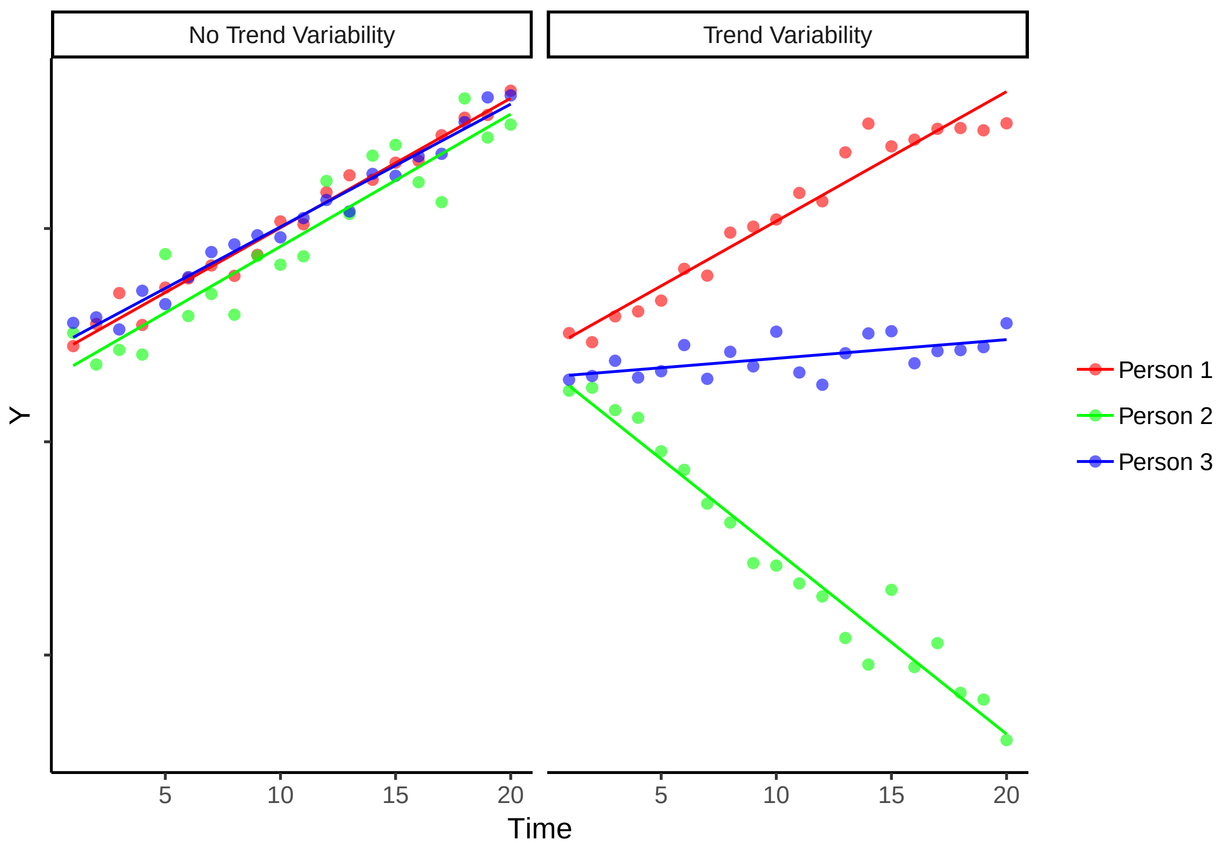

Figure 5. Differences in trend variability across units.

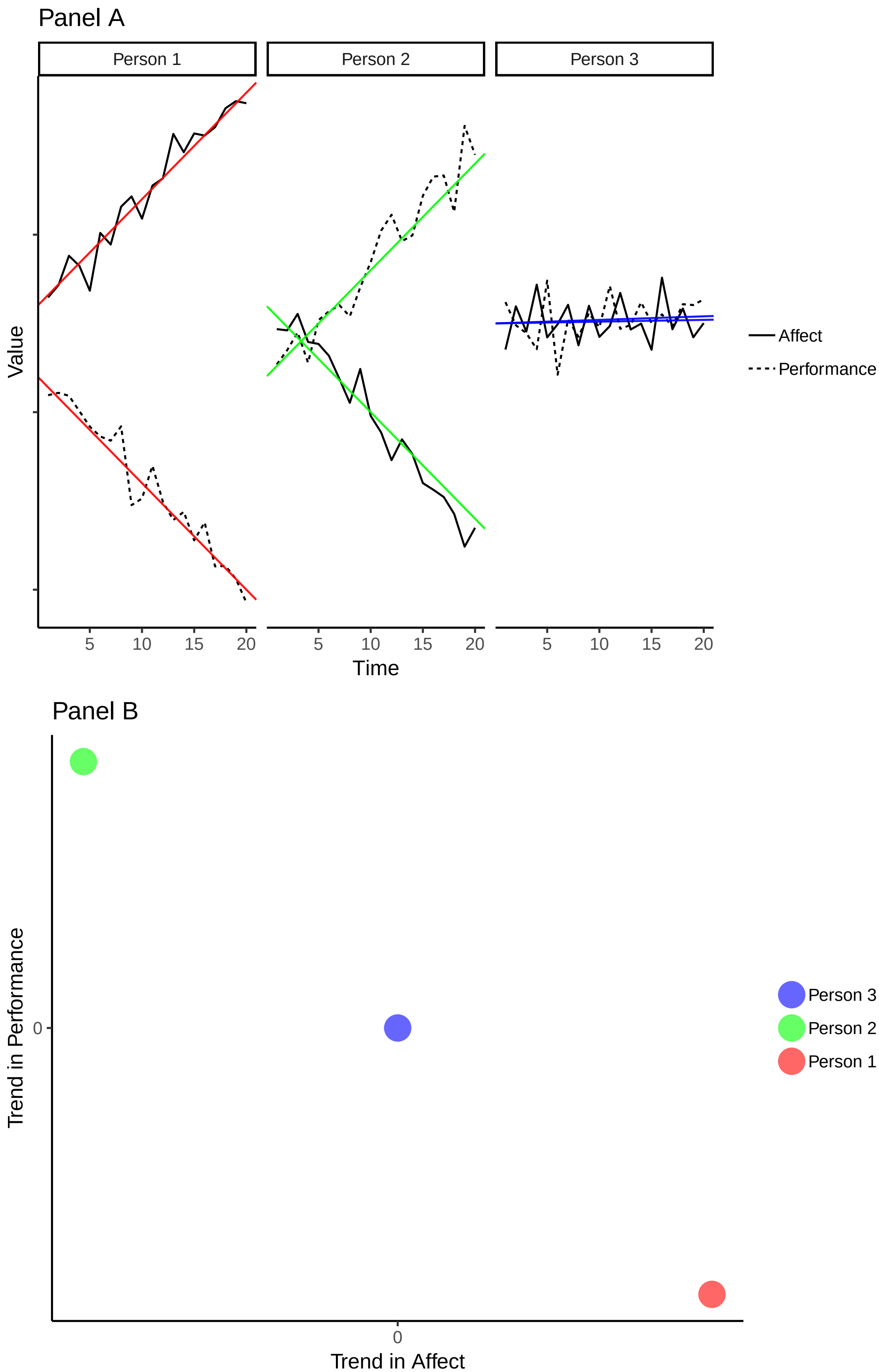

Figure 6. Correlating slopes, or relating the affect to performance trend.

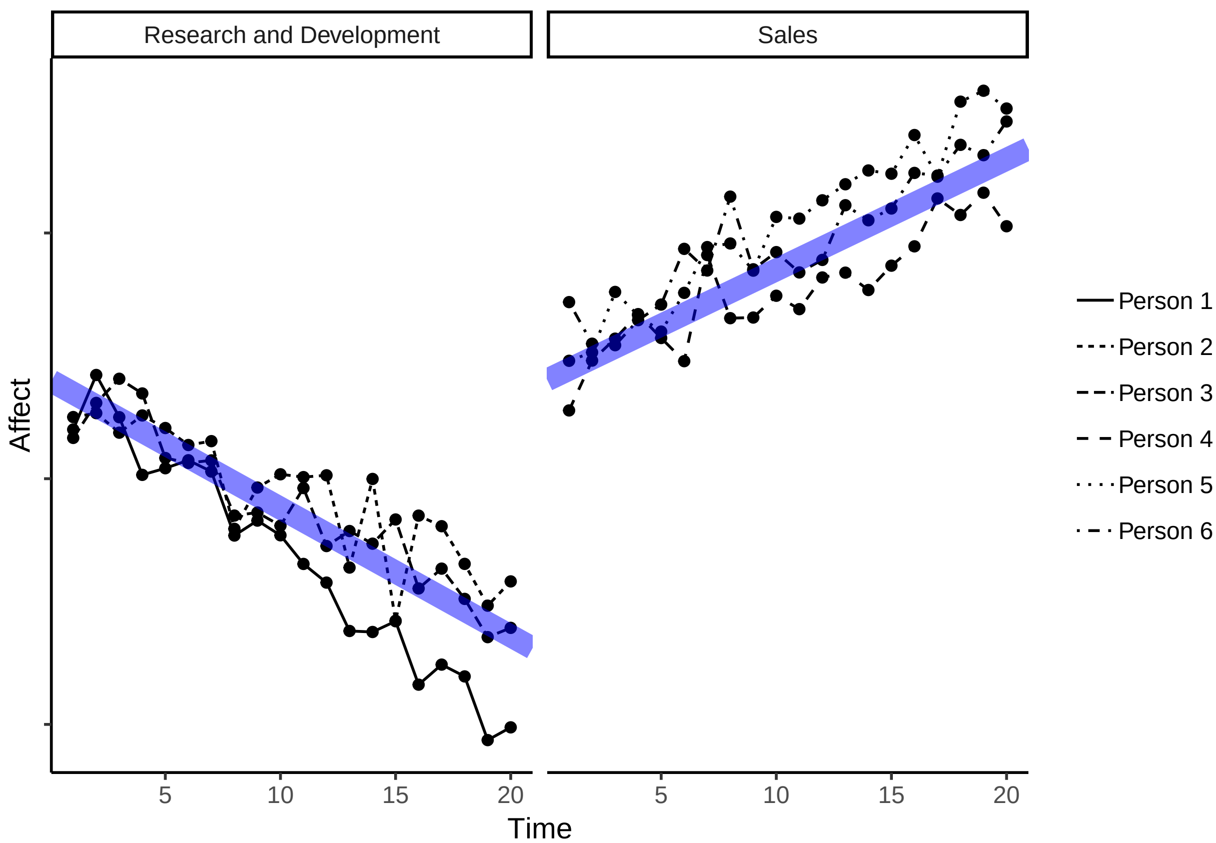

Figure 7. Job type as a covariate of affect trend.

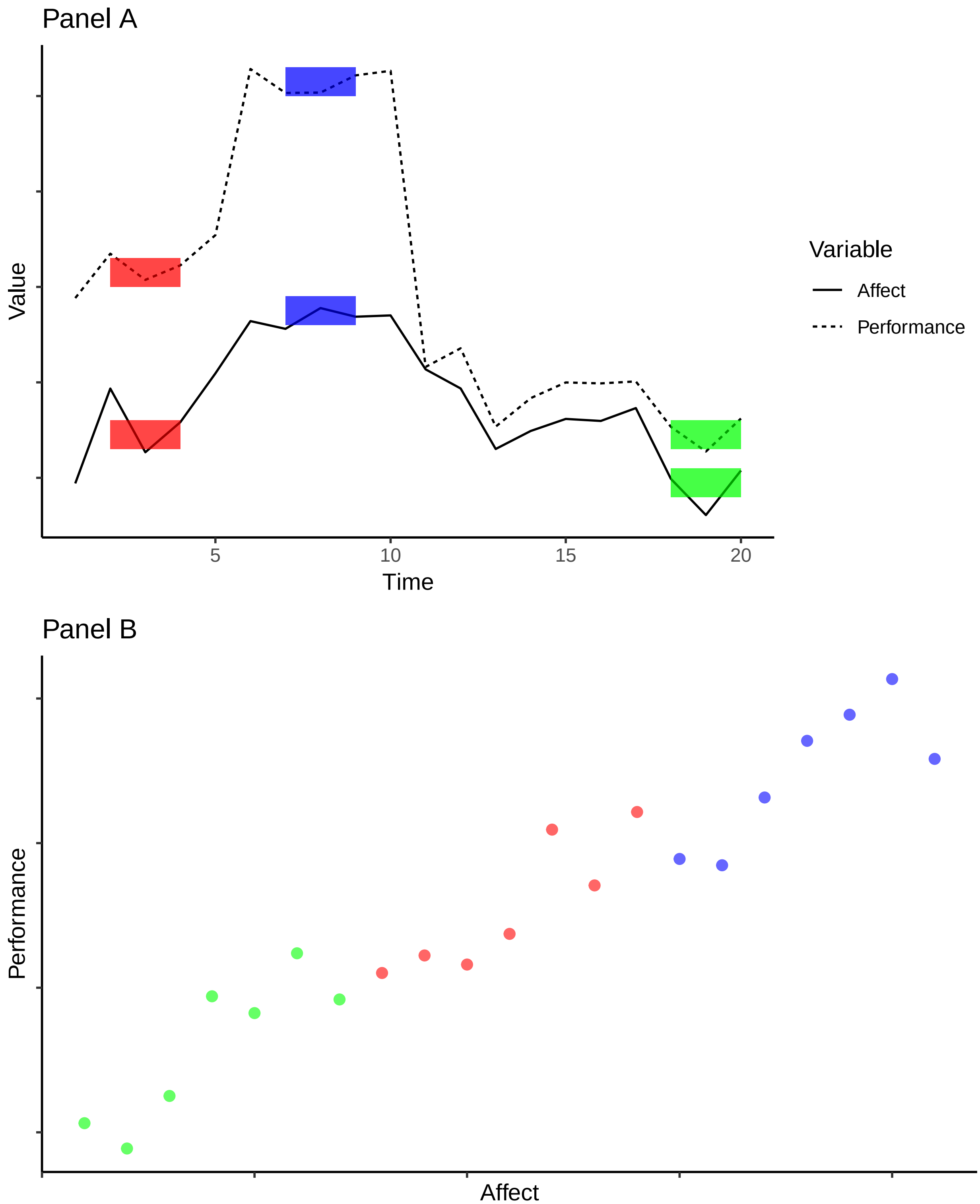

Figure 8. Relating affect to performance on one unit across time.

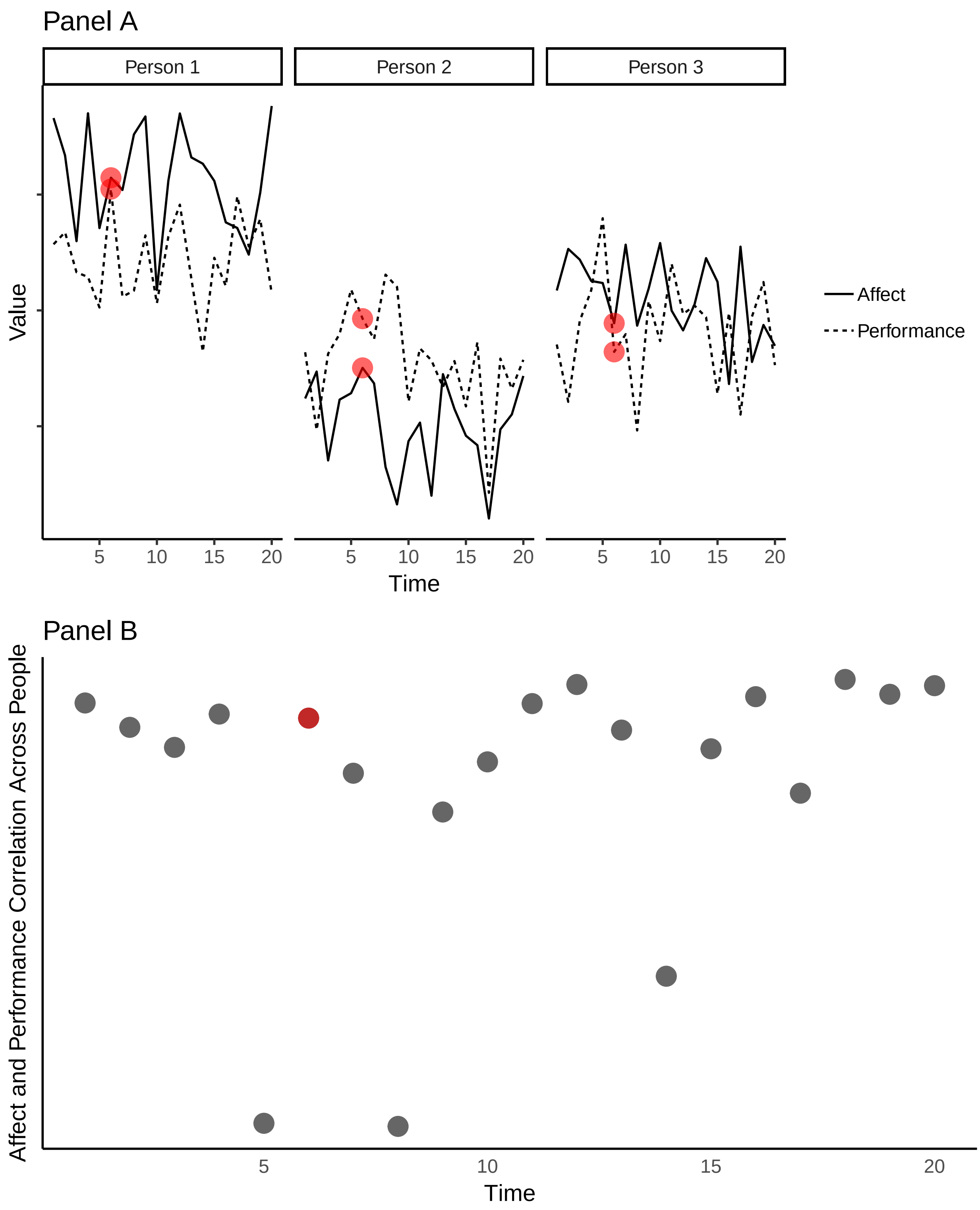

Figure 9. Relating affect to performance across units over time. A typical time-varying covariates model constrains the correlation to be equivalent across time. Here, the relationship is unconstrained at each time point.

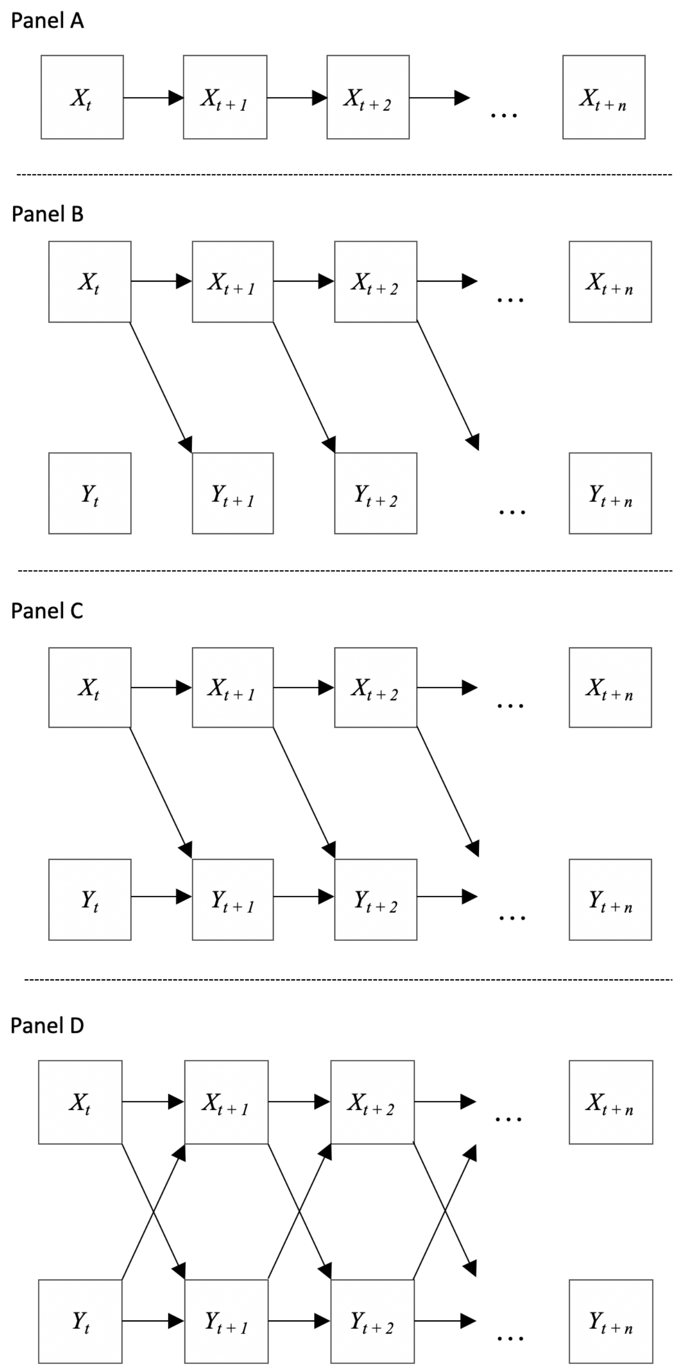

Figure 10. Univariate and bivariate dynamics adapted from DeShon (2012). Panel A shows self-similarity or autoregression in X across time. Panel B shows X predicting subsequent Y. Panel C shows X predicting subsequent change in Y. Panel D shows reciprocal dynamics between X and Y.