The Unsung Principles of Dynamics

Christopher R. Dishop[1], Jeffrey Olenick[1], & Richard. P DeShon[1]

[1] Michigan State University

Author Note

. . . .

Correspondence concerning this article should be addressed to Christopher R. Dishop, 316 Physics Rd, Psychology Building Room 348, East Lansing, MI 48823. E-mail: dishopch@msu.edu

Abstract

Begin here...

Keywords: ....

Word count: 95

The Unsung Principles of Dynamics

We – organizational psychologists – are increasingly interested in dynamics and process phenomena. Longitudinal studies are becoming more prevalent in our literature and the number of time points they employ appears to be growing. The empirical literature uses the terms "dynamics" and "dynamical" at exponentially larger rates in recent years (DeShon, 2012). A majority of published methods literature now focuses on longitudinal data analysis (Aguinis, Pierce, Bosco, & Muslin, 2009), and there are a number of great reviews on dynamic models (Wang, Zhou, & Zhang, 2016) and issues of time (Beal, 2015; Shipp & Cole, 2015). Moreover, this interest covers many content areas, including self-regulation, leadership, and team performance (Hardy, Day, & Steele, 2018; Schaubroeck, Lam, & Peng, 2016).

We have noticed a pattern in how people think about and describe dynamics in empirical studies. Researchers tend to study and convey their dynamic process of interest with respect to a statistical model or class of models. For example, researchers that are familiar with growth models will talk about the importance of growth in a variable or how within-person trajectories have been ignored in prior research, they will then estimate a growth curve, and ultimately convey something about trends or growth over time and how this has added a new dynamic perspective to our understanding. "Growth model thinking," as well as other recent ways of discussing how things happen over time, have produced wonderful insights into important processes in organizational science, and we see them as initial steps toward dynamics.

When researchers couch their thinking in a model, however, some concepts naturally go unnoticed. We are accumulating tremendous knowledge about our core variables and processes by opening the door of dynamics, but there are even more principles that have yet to be exposed in our literature – we have not yet stepped fully through the door. In this paper we discuss a variety of dynamics principles; some are concepts that will reorient how researchers think about dynamics, and others are statistical properties that, if ignored, could result in biased inferences.

Below, we first discuss two broad classes of "thinking with respect to a statistical model" that have done the hard work – they are sets of empirical studies taking initial steps towards dynamics. The first we call "growth," and the second "relationships," and we discuss example studies in each to briefly show our field's interest in dynamics and how some researchers approach it. These first two sections are not exhaustive, we are simply sampling a few of the common ways researchers currently think about dynamics to motivate the core of the paper. There, we unpack a variety of dynamics principles that must be incorporated as we enter this domain.

Stepping Toward Dynamics – Growth

It is becoming increasingly popular to examine whether something goes up or down over time – its trend or growth pattern. Some also call this notion "change."

Hülsheger (2016) examines fatigue trends. He motivates his study by stating that his examination of the "the continuous ebb and flow of fatigue over the course of the day and about the factors that influence this temporal ebb and flow" responds to calls to "empirically address the dynamic process of recovery and thereby helps refine recovery theory" (p. 906). For 5 consecutive workdays he employes fatigue surveys – one in the morning, another at the first work break, a third at the end of work, and the last in the evening – among a sample of Dutch employees. All surveys measure fatigue, and the morning survey also assessses sleep quality whereas the fourth measures psychological detachment. He estimates growth curves for fatigue across his sample and correlates sleep quality and psychological detachment with both the fatigue intercept and slope, respectively.

Dunford, Shipp, Boss, Angermeier, and Boss (2012) examine burnout trajectories over two years. They motivate their study by stating that, “theoretically, much of the burnout literature suggests that burnout should be progressive and dynamic, yet most empirical research has focused on explaining and testing the antecedents of static levels of burnout,” therefore “knowing for whom burnout changes and when this pattern of change occurs leads to a more realistic view of the dynamism of human experience and better managerial prescriptions for addressing burnout” (p. 637). Over two years they assess healthcare workers with five measurements, each separated by six months. All surveys measure burnout (all dimensions), and the researchers also collect between person assessments of job transitions (a categorical variable indicating whether an employee is a newcomer, recently underwent an internal job change, or remained at the same position throughout). They estimate a sequence of growth curves and examine linear and quadratic slope terms for all three burnout dimensions. They also covary job transition type with the intercept and slope terms.

Summary

These authors are clearly interested in dynamics, and in this framework they examine within-person trajectories, whether those trajectories exhibit trends (growth), and correlate other variables with those trends.

Stepping Toward Dynamics – Relationships

Another popular approach is to examine relationships across time rather than trends or covariates of trend.

Gabriel, Koopman, Rosen, and Johnson (2018) study the association among helping acts, depletion, and self-serving political acts. They motivate their study by highlighting the limitations of between-person research and then stating that “a more appropriate empirical test of this process requires an intraindividual lens that allows researchers to consider how

OCBs, resources, and subsequent behaviors vary daily. That is, not assessing the dynamic relations between helping behaviors and related constructs potentially misaligns the theoretical underpinnings of the construct and the level of analysis used to assess their relationships (i.e., taking dynamic processes and assessing them with static, 'in general' assessments of constructs; Klein & Kozlowski, 2000)" (p. 2). For ten work days they collect surveys twice a day (morning and afternoon). Both the morning and afternoon surveys assess helping acts, depletion, and political acts. They regress afternoon depletion on afternoon helping acts and morning depletion. They regress afternoon political acts on afternoon depletion and morning political acts. They regress afternoon helping acts on afternoon depletion and morning helping acts.

Johnson, Lanaj, and Barnes (2014) study the relationship between justice behaviors, depletion, and OCBs – they argue that exhibiting procedural justice behaviors is depleting and can negatively influence OCBs. They motivate their study by stating that our current justice knowledge comes from "cross-sectional studies examining between-person differences," but "there is a need for longitudinal, daily investigations of justice experiences that take a dynamic person-centric view" (p. 1). Ultimately they argue that their research design enabled them to "examine dynamic, within-person effects" and test a model "via a more granular approach to time" (p. 11). Their participants responded to surveys twice a day for 10 working days (morning and afternoon). The morning survey measured sleep quantity, whereas the afternoon survey measured justice behaviors, depletion, and OCBs. They regress afternoon depletion on the morning sleep quantity, the prior day's afternoon justice behavior, and the prior day's afternoon depletion.

Rosen, Koopman, Gabriel, and Johnson (2016) explore the relationship between incivility and self-control. They motivate their research by stating that "although examinations of incivility have gained momentum in organizational research, theory and empirical tests involving dynamic, within-person processes associated with this negative interpersonal behavior are limited" (p. 1). They also argue that "previous studies focused almost exclusively on chronic forms of incivility that occur on average during unspecified periods of time, which overlooks the dynamic and temporal nature of incivility and its effects. Consistent with ego depletion theory, we consider a dynamic process that explains why employees become more uncivil." (p. 2). Their participants respond to three surveys a day (morning, afternoon, and evening) for 10 workdays. The morning survey assesses self-control, the afternoon survey assesses self-control, experienced incivlity, and instigated incivility, and the evening survey measures experienced incivility and instigated incivility. They regress afternoon self-control on afternoon incivility and morning self-control. Another model regresses evening incivility on afternoon self-control.

Koopman, Lanaj, and Scott (2016) examine the costs and benefits of OCBs on behalf of the actor – specifically how OCBs relate to positive affect and work goal progress. They motivate their study by stating that they "respond to calls in the literature to examine the consequences of OCB on a more dynamic basis" (p. 415). Their respondents fill out three surveys (morning, afternoon, and evening) for ten workdays. The morning survey assesses OCBs, positive affect, and work goal progress. The afternoon survey measures work goal progress, and the evening survey assesses outcome variables irrelevant to the discussion here. They examine the relationship between OCBs and positive affect by regressing afternoon positive affect on morning OCB and morning work goal progress. They examine the relationship between OCBs and work goal progress by regressing afternoon work goal progress on morning OCB and morning work goal progress.

Summary

These authors are also interested in dynamics. All test for within-person variance and motivate their studies by stating that "the good stuff" resides in the within-person relationships. They examine concurrent or lagged relationships across their variables over time, and they are able to collect many observations due to their frequent sampling.

Dynamics

Both frameworks above get things moving toward dynamics. They bring up great notions like within-person trajectories and lag relationships, but there are many more principles left to appreciate and we want to expose our field to them so that researchers have an even greater number of tools to explore this domain. Moreover, there are a number of statistical properties that arise in dynamic modeling that have received almost no attention but can produce inferential errors if left unchecked.

Dynamics refers to a specific branch of mathematics/mechanics, 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. Below, we unpack a number of important principles couched in this simple idea.

Concepts and Conventions

The first set of principles are concepts. Ways of thinking.

States. In organizational science we typically use the term "variable" to describe a measured construct, and our lens is usually across people. Burnout, depletion, fatigue, OCBs, performance, job satisfaction – these are all variables; they are quantities with values that fluctuate across people. When we instead focus on how values fluctuate across time we call them "states." Performance as a variable, therefore, focuses on the set of values across people, whereas performance as a state focuses on its values across time.

The convention to label states is to use what is called a state vector. A state vector for depletion, fatigue, and performance would be: $(depletion, fatigue, burnout)$ and its mathematical equivalent is, (x_1, x_2, x_3) or $(x_1 ... x_n)$. We will use this notation later after introducing more concepts.

Memory and Self-similarity. Arguably the most fundamental concept in dynamics is that states often have memory – they are self-similar across time. Performance may vary or fluctuate over time, but it retains self-similarity from one moment to the next. Job satisfaction now is some function of what it was just prior to now. My conscientiousness tomorrow will have carry over from what it was today, as will the number of people I communicate with. Researchers of course may argue that some states have no memory, but the point here is that states tend to retain something about what they are from moment to moment.

Constraints. When a state has memory or self-similarity it can still fluctuate or change over time – to say that Rachel's job satisfaction will predict itself over time does not mean that we expect her job satisfaction to be identical every day. Instead, it will fluctuate or vary but under the constraints of where it was in the past. Imagine we argue that job satisfaction has no memory. If we grant that statement, then Rachel's job satisfaction from moment to moment is unconstrained and it can swing (potentially) to positive or negative infinity based the states that cause it. But if it does have memory then it is constrained, it cannot swing explosively. When she experiences something negative at work – like ridicule – her job satisfaction will certainly decrease in the moment, but what is her job satisfaction decreasing from? The answer is its prior level – the negative experience is pushing against her prior level of job satisfaction, job satisfaction is not created from scratch just after ridicule. States vary over time, but where they go is constrained by their history.

It is also helpful to consider what would happen if we vary the strength of Rachel's job satisfaction memory. First imagine that her job satisfaction is only weakly self-similar. Now when she experiences ridicule we would expect her job satisfaction to fluctuate to a large extent, whereas when her job satisfaction is self-similar we would expect the fluctuation to be smaller.

Lags. Memory is not limited to a single variable. Job satisfaction may also be influenced by the prior history of other states, like depletion or fatigue. Imagine that we believe that fatigue has a lag effect on performance. This means that we expect some amount of time to pass before fatigue influences performance. Said another way, the influence of fatigue on performance does not happen immediately. Despite collecting longitudinal data many researchers still examine concurrent relationships by regressing DVs on IVs at the same moment. That is, they regress performance at time four on fatigue at time four and performance at time six on fatigue at time six, despite having the possibility to explore lag effects. What these concurrent models imply is that the researcher expects fatigue to immediately influence performance. With some states immediate cause makes sense, but as our "over time" thinking progresses there will be many opportunities to explore lags.

Reciprocal Influence. Many research questions can be boiled down to trying to find antecedents and outcomes, but when we focus on dynamics and start thinking about memory, constraints, and lags across multiple states we focus less on “true causes” or antecendents and more on reciprocal influence. This kind of thinking often takes the form, “and then this happens.” Consider the (example) reciprocal relationships between performance, superior support, and fatigue. I performed my assignment well so my boss sent me a nice email letting me know that she appreciated my work. I subsequently increased my performance and again performed well on my second assignment. Having increased my performance, however, I was now more fatigued and on my third assignment I performed poorly. After performing poorly I did not receive the congratulatory email. In this simple example, performance, fatigue, and superior support fluctuate across time. We are not necessarily interested in finding the “true” cause, direction of effects, or the exact coefficient between one state and another, but we are interested in the pattern of reciprocal relationships across time.

Time Scales. Researchers can gain valuable insights by considering the timescales of dynamics. Consider the temperature of a building and each of its interior rooms. The quick dynamics occur from room to room. Air molecules pass between them until they are all roughly the same temperature. But the weather outside also influences the temperature of the building as a whole – it just takes longer to occur. When the sun comes up it does not immediately change the room-to-room dynamics.

Boundary Space. When researchers estimate a growth curve and argue for a positive linear trend what they are implying is that the trajectory increases forever. Job satisfaction continually increases; OCBs go down forever. In dynamic systems with reciprocal influence and constraints there are boundaries on where processes can go.

Describing Trajectories. We want to close this section by pointing readers to a wonderful paper by Monge (1990) that provides vocabulary for describing trajectories. In this paper we are introducing concepts and statistical properties that will need to be accounted for as we approach dynamics. Monge’s paper will provide readers with terms to describe trajectories over time, and we feel that it should be required reading for anyone interested in dynamics.

Mathematics and Statistics

We are now going to translate some of the concepts into math. Doing so will (a) reiterate the principles and (b) make it easier to talk about some of the more complicated statistical properties.

Basic Concepts In Equations. Remember that in dynamics we are focused on memory, self-similarity, and constraints as states move across time. Imagine that we are interested in performance over time. What we are going to do here is begin to capture those ideas with equations. First, consider performance across time:

$$\text{Performance}_t = \text{Performance}_{t-1} \tag{1}$$

where performance at time t is exactly identical to what it was at $t-1$. This equation says that performance does not fluctuate, change, move, or grow across time – there is zero trend. Performance is, say, four at time one, and four at time two, and four at time three, and so on. This type of equation is called a difference equation, and it is the foundation of dynamic analysis.

Although this first equation seems disceptively simple, we have already captured memory. Performance, in this case, is perfectly self-similar. What if performance is similar, but not perfectly self-similar across time? To capture this idea we need a new term:

$$\text{Performance}_t = a\text{Performance}_{t-1} \tag{2}$$

where a is the extent to which performance is self-similar and all other terms are defined above. a is a coeffient relating performance now to performance at the next moment, and when you estimate that term in a statistical model it is called an autoregressive term. When the autoregressive term is large performance is highly self-similar, whereas when a is close to zero performance has less self-similarity.

Fundamental Autoregressive Behaviors. There are fundamental behaviors of dynamic states based on their autoregressive terms, and these are shown in figure 1. The top row of figure 1 shows the trajectory of states with autoregressive terms that are greater than one in absolute value. These large terms produce explosive behavior – exponential growth when a is positive and oscillating chaos when a is negative. When the autoregressive term falls between zero and one in absolute value, conversely, the state converges to equilibrium – shown in the bottom two panels. Either the state oscillates at a decreasing rate until it reaches equilibrium (when a is negative) or it converges there smoothly (when a is positive). Again, these behaviors hold for all states with the given autoregressive terms.

Insert Figure 1 Here

Equilibrium. Notice that we introduced a new term in our description above: equilibrium. Equilibrium describes the state of a variable that no longer changes unless disturbed by an outside force. It can also be used to describe multiple variable systems – where equilibrium again means that the state remains constant unless disturbed by an outside force, but here state refers to the the entire system (i.e., all of the variables). In *static* equalibriums, the system has reached a point of stability with no change, whereas *dynamic* equilibrium refers to systems with changes and fluctuations but no net change. That is, the variables fluctuate across time in periodic ways but the general state of the system does not diverge so as to change the behavior of the entire system.

Predator-prey relationships are a typical example of a system in dynamic equilibrium. For example, consider a predator-prey relationship between bobcats and rabbits. As the rabbit population increases, the amount of available food for the bobcats goes up. Over time, this raises the population of the bobcats as well. Now with a greater bobcat population, the rabbit population decreases because more are being killed. Over time, this reduction in food opportunity decreases the bobcat population. This back and forth oscillating pattern between states describes a dynamic equilibrium. The states change and there may be random disturbances to the system across time, but the net dynamics of the system remain stable – and therefore this situation is still called "equilibrium."

Stochastics. Our route so far has been deterministic – the mathematical representations do not contain error. When we want to convey a process with error we can consider a host of additional principles. Stochastics, stated simply, refers to processes with error. Consider our simple difference equation from above, adding an error component produces:

$$\text{Performance}_t = a\text{Performance}_{t-1} + e_t \tag{3}$$

where all terms are defined above but e_t represents an error term that is incorporated into performance at each time point. Errors cause performance to be higher or lower at specific points in time than we would have expected given a deterministic process. For example, at time t the error might push performance to a higher value, and at $t+1$ to a lower value. Errors are therefore said to be random because we cannot predict their value at any specific t. In aggregation (i.e., averaged across time), however, positive errors cancel negative errors, and large errors are less likely than small errors. Any time we have an accumulation of random error we get a normal distribution (McElreath, 2016). In stochastic systems, therefore, the errors are said to be distributed $N(0, 1)$ – that is, random and unpredictable at any specific t but distributed with certain constraints across time.

It can also be helpful to think about what error is not. Anything that is systematic, predictable, or common (using those in layman's terms) cannot be error – leaving error to be the random "left overs." An aggregation of randomness is a normal distribution.

White Noise and Random Walks. There are two fundamental stochastic processes: white noise and random walks. White noise is a process that only has error. Setting a to zero in equation 3 produces a white noise process.

$$\begin{gathered}\text{Performance}_t = a\text{Performance}_{t-1} + e_t \\ a = 0\end{gathered} \tag{4}$$

Here, all we have is error over time. Panel "A" of figure 2 shows the behavior of a white noise process over time. Random walks are similar, but a is now equal to one.

$$\begin{gathered}\text{Performance}_t = a\text{Performance}_{t-1} + e_t \\ a = 1\end{gathered} \tag{5}$$

This representation is also an error process, but there is self-similarity across time. Panel "B" of figure 2 presents a random walk. Although random walks can sometimes appear to be moving in a systematic direction, ultimately their behavior is unpreditable: they could go up or down at any moment.

Random walks and white noise are error processes over time. White noise processes fluctuate randomly, whereas random walks fluctuate randomly while retaining some self-similarity through time. These two principles are the null hypotheses of time-series analysis in econometrics – where the first task in a longitudinal study is to demonstrate that you are investigating something that is not a random walk or white noise.

Using our performance equation example, that would mean that if a researcher wanted to show the effect of IVs on performance across time they would first need to demonstrate that performance is not a random walk or white noise process. This step is currently absent in our literature but, again, is the essential starting place in econometrics.

Insert Figure 1 Here

System of Equations. Our discussion so far has focused on performance, a single state. Remember that in dynamics we are also interested in reciprocal influence, but before moving to two or more state equations we want to pause and highlight how much researchers can explore with single states. It is of course interesting and fun to ask how two or more states are related, or posit a complex sequence among a set of states. But understanding whether or not one state exhibits white noise or random walk behavior across time is a valuable study in itself. We feel that our field could substantially benefit from spending more time plotting and analyzing the individual trajctories of every measured variable in a study.

With multivariate systems we need multiple equations – one for each state. Before, we demonstrated a simple difference equation for performance. In a multivariate system with two states, performance and effort, we need one equation for each.

$$\text{Performance}_t = a\text{Performance}_{t-1} + e_t \tag{6}$$

$$\text{Effort}_t = a\text{Effort}_{t-1} + e_t \tag{7}$$

Here, both equations posit that their state is a function of its prior self to the extent of the autoregressive term (a). Notice that there are no cross-relationships, we are simply representing a system with two independent variables across time. It is of course also possible to introduce relationships among the different states with more terms.

First, consider a system where effort concurrently causes performance. Another way to say this is that effort$_t$ causes performance$_t$:

$$\text{Performance}_t = a\text{Performance}_{t-1} + b\text{Effort}_t + e_t \tag{8}$$

$$\text{Effort}_t = a\text{Effort}_{t-1} + e_t \tag{9}$$

where all terms are defined above but now the equation for performance also includes Effort$_t$ – which is the value of effort at time t – and b, the coefficient relating effort to performance. This set of equations says that effort is simply a product of itself over time (with error), whereas performance is a function of itself and also effort at the immediate time point.

What if there is a lag between when effort causes performance? That is, perhaps we posit that effort does not immediately cause performance but instead causes performance after some period of time. If the lag effect were 2, that would mean that Effort$_t$ causes Performance$_{t+2}$, and to express the "lag 2 effect" mathematically we would use the following.

$$\text{Performance}_t = a\text{Performance}_{t-1} + b\text{Effort}_{t-2} + e_t \tag{10}$$

$$\text{Effort}_t = a\text{Effort}_{t-1} + e_t \tag{11}$$

Here, all terms are nearly identical to what we saw above but now there is a lag-two effect from effort to performance. Performance is now a function of both its immediately prior self and the value of effort from two time points ago.

What if we want to convey feedback, or a reciprocal relationship between effort and performance? That is, now we posit that both effort causes performance and performance causes effort. To do so we update our equations with a simple change:

$$\text{Performance}_t = a\text{Performance}_{t-1} + b\text{Effort}_{t-2} + e_t \tag{12}$$

$$\text{Effort}_t = a\text{Effort}_{t-1} + b\text{Performance}_{t-2} + e_t \tag{13}$$

where all terms are defined above but now effort and performance are reciprocally related. Both are determined by themselves at the immediately prior time point and the other state two time points in the past. Effort happens, and two moments later this influences performance, and two moments later this goes back to influence effort, and so on throughout time. All the while, both states retain self-similarity – they fluctuate and develop but only under the constraints afforded by the autoregressive terms.

We can make the equations more complicated by continuing to add variables or longer/shorter lag effects, but the beauty of math is its freedom to capture whatever the researcher desires. These equations are language tools to help researchers convey a process over time.

Dynamic Modeling

We have introduced some fundemental concepts for dynamics. Memory, constraints, random walks, equilibrium – these are core ideas for researchers to grapple with as they consider dynamic phenomenon. When researchers then collect longitudinal data and estimate models (with these ideas in mind) there are a host of challenges that must be considered. In this section we are going to describe two: stationarity and dynamic panel bias.

Stationarity. Stationarity is about the stability of the properties of a process. Rachel's performance score across time is called a time-series – it is the trajectory of performance for a single unit (Rachel) over time. That trajectory has properties: it has a mean and a variance. If the mean is unstable then Rachel's performance either grows or decreases unconditionally over time. If instead the mean is stable, then Rachel's performance across time fluctuates but within the constraints of its memory and bounds on the system. Almost all models used to estimate coefficients in the organizational literature are stationary models that assume the data they are modeling are realizations of a stationary process. That is, they assume that the process they are trying to estimate paramters for have properties at time t that are the same as the properties at time $t + 1$.

In simple terms, a stationary process has stable properties across time – data that demonstrate trend, growth, or random walk behavior are (almost certainly) non-stationary. Here is the hard part: two independent time-series will appear related if both are non-stationary (kukljan; braun; granger). That is, if we measure Rachel's performance and it is consistent with a random walk and we also measure rainfall at Rachel's mother's house across the state and it demonstrates increasing trend for the day, even though these two things are completely unrelated we will more than likely find a relationship between them in a regression-based analysis like those presented at the start of this paper. There are many other papers that describe how to test for stationarity (e.g., CITES), all we are trying to do here is convey how important this notion is. Our literature is not paying attention to random walks, we are not checking for memory, or seriel correlation, or stationarity; we should be.

Dynamic Panel Bias. Another challenge for dynamic modeling is a congregation of effects known as dynamic panel bias. First, in dynamics we pay attention to memory, and our equations above took the form:

$$y_t = ay_{t-1} + e_t \tag{14}$$

where the only change is that we replaced performance with a generic y. Again, these equations appropriately represent underlying systems with memory, but when a researcher estimates a statistical model and includes a lagged DV the errors become correlated with the predictors and the well-known independence of errors assumption is violated. This issue therefore has to do with estimating relationships for a single unit when we want to incoporate lagged DVs.

The second issue arises when we are interested in relationships with a multiple-unit sample across time. Almost all organizational studies are multiple-unit, they collect data on more than one participant. If the people in the sample are not perfectly exchangeable – which means that I can learn the same thing about performance and fatigue by studying Bob as I did with Rachel, I gain no information by studying one over the other, or I lose no information by restricting my analysis to one of them – then the parameter estimates are influenced by what is known as unobserved heterogeneity. Unobserved heterogeneity are aggregate, stable individual differences. They are all of the unmeasured things that make Rachel's trajectory different from Bob's trajectory. Every study misses some variables, those stable effect that those variables in aggregate have on each unique person is unobserved heterogeneity. In dynamic models unobserved heterogeneity must be modeled correctly: if is is modeled as independent but in fact correlates with the model predictors then ommitted variables bias is introduced into the estimates, and if unobserved heterogeneity is ignored then seriel correlation will be introduced into the errors.

Dyanamic panel bias is the combined effect of these two biases. Lagged DVs help us convey a dynamic process but they create estimation problems, and unobserved heterogeneity must be accounted for. Hierarchical linear models (or random-coefficient, multi level, random effects) do not handle these biases appropriately (CITES).

Discussion

CLOSE WITH THE DIFFERNCE BETWEEN A STATIC AND DYNAMIC EQUATION. All we did was change the lags, but the differences between how the two equations see the world is gigantic. One is about concurrent relationships in cross sections of time. The other is dynamic – how relationships span and evolve across time.

References

Aguinis, H., Pierce, C. A., Bosco, F. A., & Muslin, I. S. (2009). First decade of Organizational Research Methods: Trends in design, measurement, and data-analysis topics. *Organizational Research Methods*, *12*(1), 69–112.

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.

DeShon, R. P. (2012). Multivariate dynamics in organizational science. *The Oxford Handbook of Organizational Psychology*, *1*, 117–142.

Dunford, B. B., Shipp, A. J., Boss, R. W., Angermeier, I., & Boss, A. D. (2012). Is burnout static or dynamic? A career transition perspective of employee burnout trajectories. *Journal of Applied Psychology*, *97*(3), 637–650. doi:http://dx.doi.org.proxy2.cl.msu.edu/10.1037/a0027060

Gabriel, A. S., Koopman, J., Rosen, C. C., & Johnson, R. E. (2018). Helping others or helping oneself? An episodic examination of the behavioral consequences of helping at work. *Personnel Psychology*, *71*(1), 85–107.

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

Hülsheger, U. R. (2016). From dawn till dusk: Shedding light on the recovery process by investigating daily change patterns in fatigue. *Journal of Applied Psychology*, *101*(6), 905–914. doi:http://dx.doi.org.proxy2.cl.msu.edu/10.1037/apl0000104

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.

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

McElreath, R. (2016). *Statistical Rethinking: A Bayesian Course with Examples in R and Stan* (Vol. 122). CRC Press.

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

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.

Schaubroeck, J. M., Lam, S. S., & Peng, A. C. (2016). Can peers' ethical and transformational leadership improve coworkers' service quality? A latent growth analysis. *Organizational Behavior and Human Decision Processes*, *133*, 45–58.

Shipp, A. J., & Cole, M. S. (2015). Time in individual-level organizational studies: What is it, how is it used, and why isn't it exploited more often? *Annu. Rev. Organ. Psychol. Organ. Behav.*, *2*(1), 237–260.

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

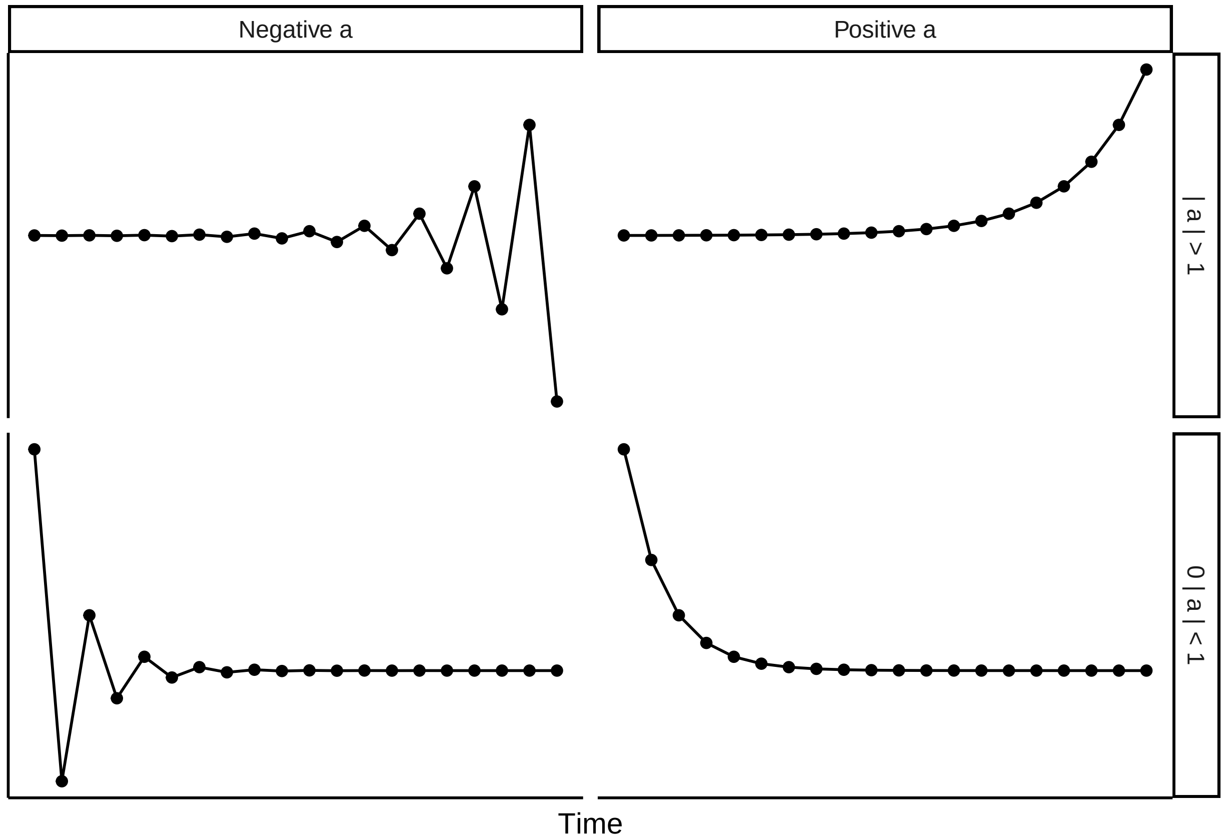

Figure 1. dynamic equilibrium fig

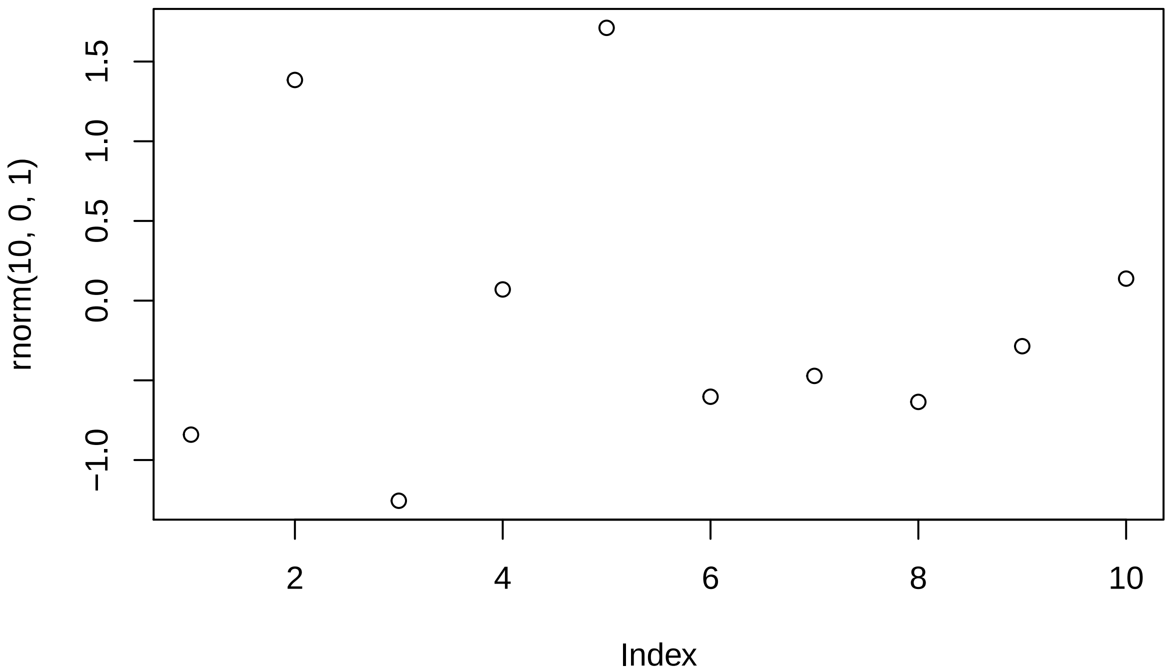

Figure 2. this one will be a white noise process and a random walk