The Unsung Principles of Dynamics

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Abstract

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Think about how common it is to find phrases about dynamics scattered throughout an introduction to an article, phrases like "we are going to address the dynamics," "taking a dynamic perspective," "prior research has not appreciated the dynamics," "we consider the phenomenon as dynamic," or "we examine it on a dynamic basis." What do these mean? How do researchers take a dynamic perspective?

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 by collecting longitudinal data, focusing on how things happen over time, and opening the door of dynamics, but there are dynamic 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, result in biased inferences. Ultimately we are bringing attention to principles that should be incorporated if we are truly interested in a "dynamic perspective."

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 the dynamic principles.

Stepping Toward Dynamics – Growth

One of the first steps our field is taking toward appreciating dynamics is by examining whether something goes up or down over time – examining trend or "growth" patterns.

Hülsheger (2016) explores 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 assesses fatigue with self-report 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 fatigue growth curves 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 to "getting dynamic" 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 state 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, and they regress afternoon political acts on afternoon depletion and morning political acts.

Johnson, Lanaj, and Barnes (2014) study relationships 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.

Opening the Door to Dynamics

Both frameworks above get things moving toward dynamics. They consider great notions like within-person trajectories, patterns over time, and lag relationships, and they are clearly exploring domains where prior research was limited. What we want to do is expose researchers to principles outside of the toolkit they are currently familiar with, outside of frameworks that are couched in statistical models like growth curves and relationship patterns with random coefficient models. There are a host of dynamic principles to cover. Some are concepts, ways of thinking that are necessary to appreciate as researchers and theorists explore dynamic phenomona. Others are statistical properties that arise when researchers apply models to longitudinal data structures – they are statistical issues that produce inferential errors if left unchecked, and they are important across all types of longitudinal models.

Dynamics

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

These first principles are concepts – they are 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 instantaneously 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 am now more fatigued and on my third assignment I perform poorly. After performing poorly I do 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. The room to room dynamic influences have short lags, whereas the influence of the outside temperature on any specific room has a much longer lag.

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. Communication may fluctuate day to day, and it may even increase steadily as an employee transitions into a new role, but it is unlikely that it will continue to increase or decrease without bound forever.

Initial Conditions. The last concept is that initial conditions may or may not influence the overall dynamics. An employee's climate perceptions may vary over time, and they are reciprocally related to a number of important states. But the dynamics of his climate perceptions may depend on his first encounters with the company – his initial perceptions. Perhaps his initial perceptions were positive and over time showed reciprocal patterns with performance, dyadic social exchanges, burnout, and leadership perceptions. A researcher paying attention to initial conditions would examine if those same reciprocal patterns emerge under different starting conditions, like a bad first encounter.

An empirical example is in Liebovitch, Vallacher, and Michaels (2010) explanation and model of conflict and cooperation between two actors. Their explanation takes into account several states for a two-person situation, including (1) each individual's general affective state, (2) feedback from one person to the other, and (3) each individual's general tendency to change based on the feedback. They explain and argue that the patterns of conflict and cooperation that two individuals demonstrate over time differ dramatically if both individuals start with the same affective tone (positive and positive or negative and negative) versus opposing tones.

Describing Trajectories. In this paper we are introducing concepts and statistical properties that merit attention as we approach dynamics. We want to close this section by pointing readers to a wonderful paper by Monge (1990) that provides basic vocabulary for describing trajectories. He discusses terms like trend, periodicity, and cycles – lexicon for patterns over time rather than key concepts that are emphasized here. We feel that his paper 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 above, (b) introduce new dynamic principles, and (c) make it easier to talk about some of the more complicated statistical properties of dynamic modeling that we turn to in the final section.

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, four at time two, four at time three, and so on. This type of equation is called a difference equation, and it is a foundation in dynamics.

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 extreme oscillations 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.

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

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.

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

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 and all of their IVs are not random walks or white noise processes. This step is currently absent in our literature but, again, is the essential starting place in econometrics.

Insert Figure 2 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 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 either Bob or Rachel, 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 represents aggregate, stable individual differences. Rachel's fatigue over time may look different from Bob's fatigue over time due to unmeasured individual differences and states. These unacknowledged effects are responsible for individual differences on fatigue so they need to be incorporated in statistical models. We acknowledge them by incoporating unobserved heterogeneity, again it is a term that is meant to represent all of the unmeasured things that make Rachel's trajectory different from Bob's trajectory.

In dynamic modeling unobserved heterogeneity must be handled appropriately: 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.

Dynamic 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 - A Dynamic Perspective

We opened this paper by talking about how researchers are beginning to approach dynamics. We pointed to two frameworks – growth and relationships – as example empirical research doing the hard work of getting our thinking beyond static, cross-sectional relationships. They were appropriate first steps toward dynamics given our field's history with random coefficient models and recent introduction to growth curve modeling, but there are many principles of dynamics outside the context of a specific longitudinal model – we broached them here. Taking a dynamic perspective means focusing on memory, constraints, timescales, reciprocal influence, initial conditions, and exploring an array of satistical properties like serial correlation and stationarity.

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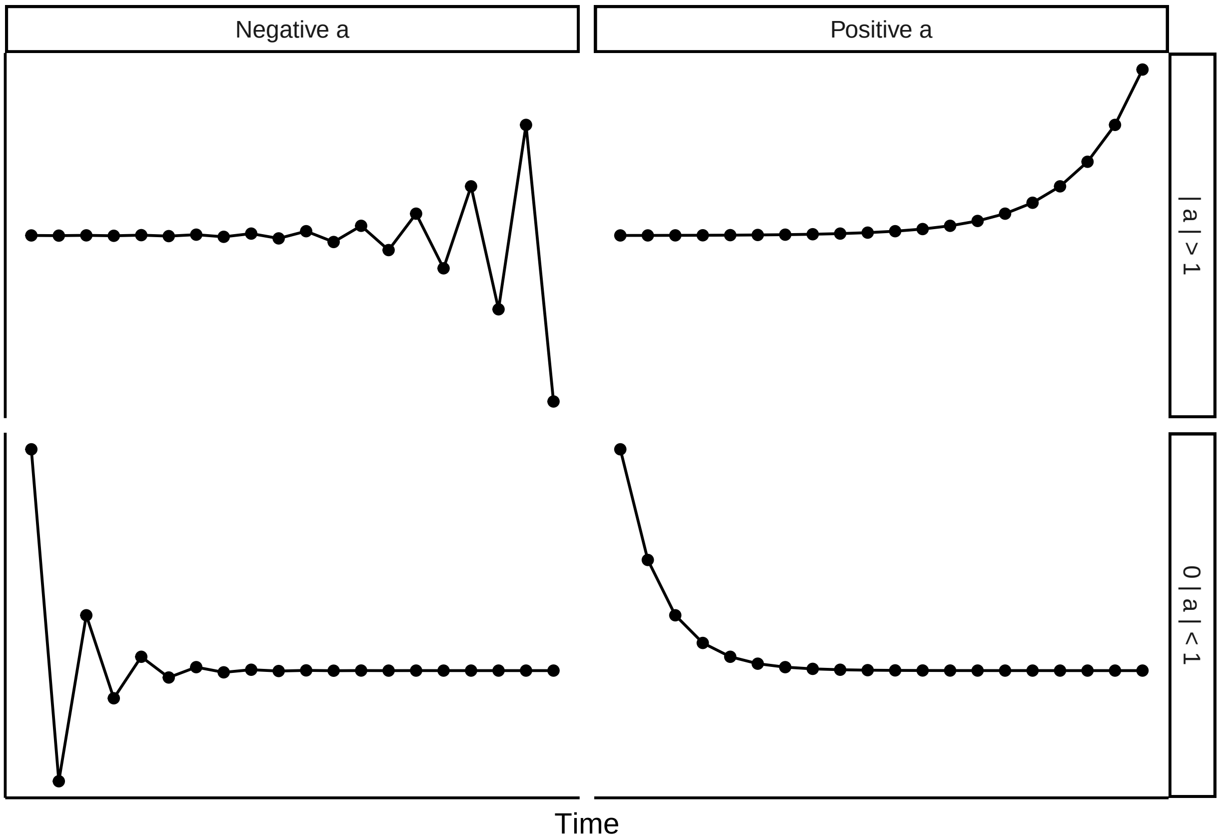

Figure 1. dynamic equilibrium fig

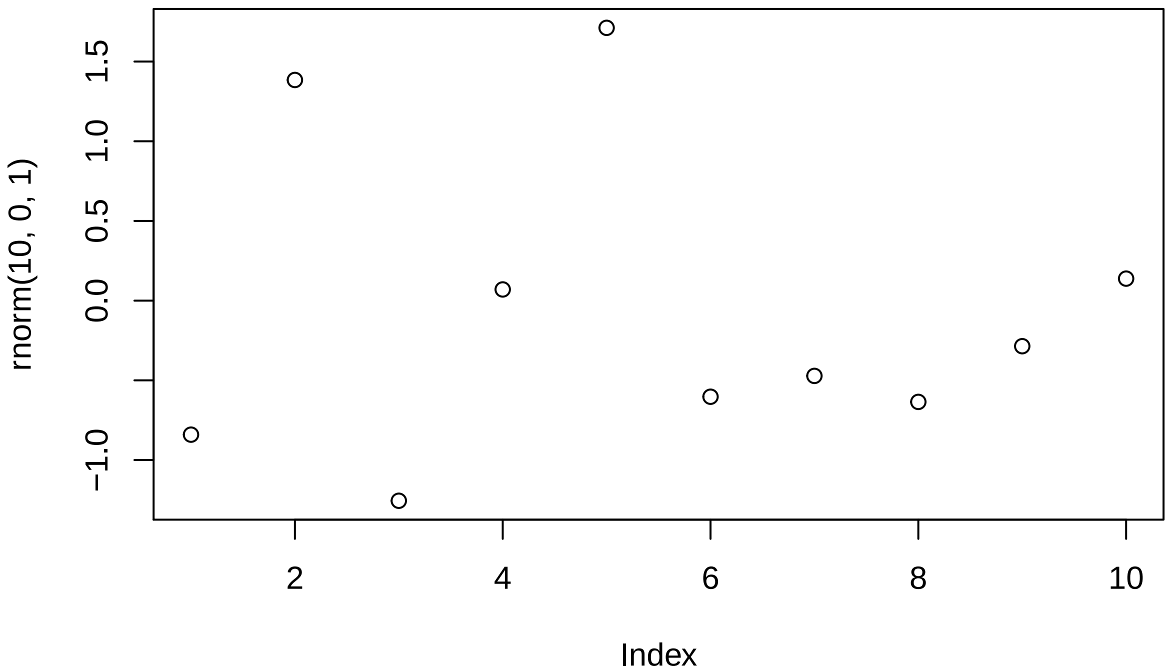

Figure 2. this one will be a white noise process and a random walk