1 Principles for Describing or Explaining Process

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Abstract

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<center>Principles for Describing or Explaining Process</center>

11 We – organizational psychologists – are increasingly interested in process and dynamic

13 phenomena. Longitudinal studies are becoming more prevalent in our literature and the

14 number of time points they employ appears to be growing. The empirical literature uses the

15 term "dynamics" at exponentially larger rates in recent years (DeShon, 2012). A majority of

16 published methods literature now focuses on longitudinal data analysis (Aguinis, Pierce,

17 Bosco, & Muslin, 2009), and there are many great reviews on the conceptual and

18 methodological issues related to dynamic and within-person models (Beal, 2015; Shipp &

19 Cole, 2015; Wang, Zhou, & Zhang, 2016). Moreover, this interest covers many content areas,

20 including self-regulation, leadership, and team performance (Hardy, Day, & Steele, 2018;

21 Schaubroeck, Lam, & Peng, 2016).

22 Given our interest in "process" phenomena, what distinguishes a process from a

23 non-process study? What are some fundamentals for people wanting to study process?

24 Consider the following studies and, while reading, ask yourself which you feel appropriately

25 represents process. Imagine that we are interested in weight gain among US males who are

26 50 years or older, and to investigate it we conduct three longitudinal studies. **Option A**. In

27 the first, we find and report that the average male gains one pound every year for the rest of

28 his life. In the second, we find and report a positive relationship between male weight and

29 caloric intake across time, and suggest that caloric intake has an effect on weight. In the

30 third, we propose that weight on any day is determined by its value from the day before and

31 the difference between today's caloric intake and expenditure.

32 **Option B**. In the first, we model weight over time, find a significant, positive trend,

33 and suggest that the average male gains one pound every year for the rest of his life. In the

34 second, we model weight and the number of consumed calories over time, find a significant,

35 positive relationship between them, and suggest an effect of caloric intake and weight. In the

third, we model initial weight, weight, and the number of consumed and expended calories over time and suggest that weight is a function of prior weight and difference between caloric intake and expenditure.

Which of these is a process study? Where is the line between explaining a process versus describing its manifest properties? What are the different ways that we can represent it? In this paper we call attention to these questions and provide a number of principles to help researchers convey some components of process. We are agnostic as to which of the studies above is a "true" process study – we feel that, at the current state of our literature, it is more important to raise attention to the issue and initiate discussion and debate over the coming years. All three studies have meaningful pieces to convey, what we want to do here is give researchers the tools to talk about each aspect. We do so in two parts.

In the first section we contrast process with other, "over time" concepts. There are loose and formal ways to use terms and notions about behavior over time, and we point out the differences to locate process within that concept map. We then provide a definition drawn from Pettigrew (1992) and Pettigrew (1997) that orients the rest of the paper.

In the second section we discuss principles for either describing or explaining processes. The principles come from a number of areas, including mathematics, systems theory, dynamics, and computational modeling, and they are all ways to represent and describe relationships over time at different levels of abstraction. For example, we could use a difference equation to explain the trajectory of one variable, or we could use terms like trend or cycles that describe its manifest behavior but through a different lens. We want to point researchers to principles that they can use to represent or convey variables/behavior over time – regardless of whether they are truly causal or non causal explanations.

(**Not clean paragraph** - may not even need it). We provide several contributions in doing so. First, we believe our discussion will help researchers augment their current

approach to explaining process. It can be helpful to be exposed to different approaches, provide ideas etc., and we hope our paper provides new ideas to seasoned researchers in this area. Second, although there is a substantial amount of literature on mathematical process principles and dynamics, it is sophisticated and technical. Much of this work is not easily accessible to researchers with the usual methodological and statistical background obtained from doctoral level training in OP/OB; we want to help distill it. Finally, we discuss ways to study process for researchers who may not want to want to develop sophisticated math or computational models. Some people claim that math is the only option. For example, Pearl (2009) states that any explanation "worthy of the title theory must be able to represent causal questions in some mathematical language" (p. 102). There is also some pressure to produce computational theories. For example, VANCOUVER COMP MODELS ARE BETTER; AND KOZLOWSKI COMP FRAMEWORKS ARE BETTER. But there are not many comp modelers in organizational psychology (vancouver orm); and the social sciences do not emphasize mathematics as much as some of the more physical sciences (vancouver orm). Moreoever, Renee Thom points out that sometimes qualitative representations produce more error than their quantitative counterparts but nonetheless are better clues to the underlying process. We do not claim that one approach is better or worse than another; we simply want to describe process principles from different domains to give researchers alternative ways of talking about, specifying, and representing process behavior.

Process

Before jumping to a definition of process it is helpful to consider other, related concepts.

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.

Longitudinal.   Longitudinal is a broad term that is usually paired with one additional term to refer to an investigation's method, data, or aim. A study that uses a longitudinal *method* is different from a cross-sectional design due to the number of observations, such that longitudinal designs employ repeated observations, whereas cross-sectional studies do not. Longitudinal *data* are repeated observations on multiple units, whereas panel or time series data – the common data structure in economics – are repeated observations on one unit.

The other distinction surrounding longitudinal studies is what researchers hope to discover by using them. Ployhart and Vandenberg (2010) state that "longitudinal research emphasizes the study of change and contains at minimum three repeated observations on at least one of the substantive constructs of interest" (p. 97). Similarly, Baltes and Nesselroade (1979) note, "the study of phenomena in their time-related constancy and change is the aim of a longitudinal methodology" (p. 6). Both of these definitions reveal the recent tendency to focus on change in longitudinal studies. For example, a longitudinal investigation could observe increasing or decreasing trajectories (or other forms of change) across time. This

change emphasis is likely due to the increasing knowledge and application of growth models, where change is the main interest.

Process. We presented the notions above to help pinpoint what process refers to. Dynamic systems have memory, where current states are driven to future states by transition rules and external inputs. Longitudinal studies collect data on multiple units across time, and some suggest that they ought to emphasize change. Process is about sequences of events with or without memory and with or without change. Pettigrey (1997) provides a formal definition: process is "a sequence of individual and collective events, actions, and activities unfolding over time in context" (p. 2).

This definition is consistent with sentiments found in Ilgen and Hulin (2000). These authors indirectly define process by describing their dissatisfaction with static research. They compare (some) OP/OB research to individual snapshots of behavior that – even if compiled and aggregated to form a longitudinal study – only reveal fleeting glances of the flow of the system. "Frozen moments do not capture. . . a process, nor do statistical interactions make a sequence" (71). Process, then, seems to entail sequences of events that, as stated above, must be couched in context.

Another point we want to reiterate is how words like "dynamics," "change," and "process" tend to be coupled. It is common to pair two or more of these terms with a phrase like "the dynamic process." But each of these words has a precise meaning. Dynamics is used for systems or variables with memory. Growth describes the systematic increase or decrease of a variable or system over time. Change has been used in two ways. It is sometimes used synonymously with growth: systematic increase or decrease. At other times, researchers partial prior observations of their dependent variable and in a regression model to emphasize the effect of an IV on the change in the DV (e.g., Johnson, Lanaj, & Barnes, 2014). In this second way, change does not mean "growth" but instead, "how a variable is different from the last point in time."

Process is distinct from each of these terms, and it does not need to be paired with any. Processes can grow, or they can not grow; they can change or not change; they can contain dynamics or no dynamics. Stated differently, "no change" in not synonymous with "not process." We can still find process in behavior that does not change over time.

Having discussed the differences between terms like process, longitudinal, and dynamics, we now unpack the principles. All of these are ways to represent process behavior – to talk about how things unfold over time. Some are explanatory, whereas others simply describe manifest behavior while remaining agnostic to the undiscovered true underlying mechanism, but all help convey process behavior.

Systems Theory Principles

We start with principles from systems theory – a gentle place to begin given that some of the terms will overlap with the growth modeling literature.

Stocks and Flows

One common approach to explaining how things happen over time is to identify stocks and flows. Meadows (2008) defines both with the following:

> A stock is a store, a quantity, an accumulation of material or information that has built up over time. It may be the water in a bathtub, a population, the books in a bookstore, the wood in a tree, the money in a bank, your own self confidence. A stock does not have to be physical. Your reserve of good will toward others or your supply of hope that the world can be better are both stocks.

> Stocks change over time through the actions of flows. Flows are filling and draining, births and deaths, purchases and sales, growth and decay, deposits and

160   withdrawals, successes and failures. A stock, then, is the present memory of the

161   history of changing flows within the system (18).

162 That last sentence is what makes a stock imply behavior over time. We speak about stocks

163 by both referring to what they contain right now but also how they have developed and

164 where they are likely to go. Also note that stocks do not have to change.

165   The behavior of a stock – whether it rises, falls, or remains the same – depends on the

166 nature of flows. We can learn about stock behavior by subtracting outflows from inflows.

167 Doing so leads to three general principles about stocks. They will (Cronin, Gonzalez, &

168 Sterman, 2009): (1) rise when inflows exceed outflows, (2) fall when outflows exceed inflows,

169 and (3) remain the same when inflows equal outflows. In other words, stocks change with

170 respect to the summative properties of their flows. Stocks also set the pace for the

171 cumulative rhythm of the system. Even when flows are changing rapidly, the stock may

172 change slowly because accumulation occurred over a long period of time.

173   Figure 1 plots a simple stock and flow system over 20 time periods.

174   ————————

175   Insert Figure 1 Here

176   ————————

177 Beginning at the first time point, inflows are equal to outflows and the stock therefore sits at

178 zero. Over the first ten time points, however, outflows remain the same whereas inflows

179 increase. With inflows exceeding outflows the stock also increases up until time point ten. At

180 this time, inflows drop back down to five whereas outflows increase – leading to a large

181 reduction in the stock. As outflows continue to rise over time – with no counterbalancing

182 movement from the inflow – the stock ultimately decreases.

183   Systems theory uses stocks and flows as general labels for each of the things in the

184   system. Above, we described the behavior of the stocks and flows with simple terms –

185   increasing, decreasing, or constant. Systems theory also provides a more systematic way of

186   describing trajectories and explaining behavior over time. These are unpacked in an excellent

187   paper by Monge (1990), and the framework includes trend, magnitude, rate of change, and

188   periodicity. These are shown respectively in figure 2.

189   ———————

190   Insert Figure 2 Here

191   ———————

Trend

192

193   Dividing figure 2 into two portions – the top and bottom – reveals differences in trend.

194   All of the panels on the top of the figure have trend, whereas those on the bottom do not.

195   Trend is the systematic increase or decrease of a variable over time.

Magnitude

196

197   Magnitude is the level, value, or amount of the variable at each time point – the

198   number on the y axis at each respective point in time. For example, in panel C of figure two

199   the magnitude is low at times 1, 2, and 3, but is high at later points in time. Additionally,

200   panel E and F have the same magnitude if we average their values over time, but panel E

201   contains both high and low magnitude, whereas the magnitude for the trajectory in panel F

202   remains relatively constant.

Rate of Change

Monge (1990) refers to rate of change as "How fast the magnitude increases or decreases per one unit of time." Panels *G* and *H* reveal differences in rates of change.

Periodicity

Periodicity is the amount of time before a pattern repeats itself, and it is equivalent to the term cycle. The most important piece about periodicity is that it must be couched with "controlling for trend." Notice that panel *A* is periodic because, after controlling for trend, there are repeated patterns over time.

Two Variables

It is of course possible to combine these notions when researchers are studying processes with more than one variable. For example, a researcher might describe the magnitude in their presumed dependent variable with respect to the magnitude of their independent variable, or the rates of change across the system of variables. When we turn to the behavior and relationships among two or more variables – i.e., a system of variables – a few additional principles are available.

Lags

How long does it take for the presumed independent variable to produce an effect on the outcome? This is the notion of lag.

Permanence

Once the effect happens, how long does it last? That is, if the independent variable causes the dependent variable to change to a new value, does the dependent value remain at that new value indefinitely?

Feedback Loops

Systems theory researchers often convey process by using feedback loops. Feedback loops describe processes where a variable eventually relates back to itself.

There are two common ways to describe the behavior of a focal variable within a feedback loop. When feedback causes the variable to move in the opposite direction than it initially moved, this is known as negative feedback, deviation counteraction, or a balancing feedback loop (Meadows, 2008; Monge, 1990). Here, an initial increase in x leads to subsequent changes in the system that, through time, eventually cause x to decrease. Now that x has gone down, more changes happen in the system that, through time, eventually cause x to increase.

When feedback, instead, causes the variable to move in the same direction that it initially moved, this is known as postive feedback, deviation ampliciation, or a reinforcing feedback loop (Meadows, 2008; Monge, 1990). Here, changes in x in one direction lead to eventual changes in x in the same direction and thus produce exponential, explosive, or amplifying behavior. Of course, we can also identify whether there is positive or negative feedback for every variable in the system.

Examples

People from our literature using these terms and principles to explain something. Study 1 measured X and Y and described trend. Study 2 measured X and Y and talked about cycles. Study 3 measured X and Y and reported lags.

Summary

These systems theory notions are valuable tools to explain and describe process. Note that we did not cover everything to keep the reading concise and consistent. For example, (**???**) also covers discontinuous systems, so please refer to his excellent paper for an even deeper discussion. Now we turn to mathematics and dynamics and describe principles from these domains that are used to explain or describe process.

Mathematics and Dynamics Principles

Difference Equations

In mathematics, a basic representation of a process over time is a difference equation:

$$y_t = y_{t-1} \tag{1}$$

where y_t represents y now and y_{t-1} is the variable at the prior time point. Here, the value of y is the same at each t, and the emergent behavior would be a flat line across time. In systems theory terms, there would be no trend.

Although equation 1 seems simple, it introduces a fundamental concept in dynamics: memory. The variable now depends on where it was in the past. It is constrained, there are

259 boundaries on where it can go.

260   As we add terms to this basic difference equation the behavior of the variable becomes

261 more complex. Adding a forcing constant, c in equation 1 produces positive or negative

262 trend depending on whether c is, respectively, positive or negative. For example, the

263 following equation:

$$y_t = y_{t-1} + c$$
$$c = -4$$
$$(2)$$

264 produces a line that decreases by four units at each time point.

265   The next level of complexity comes from autoregressive terms, which represent the

266 extent to which the variable relates to itself over time. Here,

$$y_t = ay_{t-1}$$
$$a = 0.5$$
$$(3)$$

267 the variable is described over time but it does not retain the same value at each t. Instead,

268 the variable is *similar* over time and the autoregressive term, a, describes the extent of that

269 similarity. In equation 3, a is 0.5, meaning that the relationship between the variable now

270 and itself at the next time point will be 0.5.

271   There are fundamental behaviors of dynamic variables based on their autoregressive

272 terms, and these are shown in figure 3. The top row of figure 3 shows the trajectory of

273 variables with autoregressive terms that are greater than one in absolute value. These large

274 terms produce explosive behavior – exponential growth when a is positive and oscillating

275 chaos when a is negative. When the autoregressive term falls between zero and one in

absolute value, conversely, the variable converges to equilibrium – shown in the bottom two panels. Either the variable oscillates at a decreasing rate until it reaches equilibrium (when a is negative) or it converges there smoothly (when a is positive).

———————

Insert Figure 3 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 variables describes a dynamic equilibrium. The variables change and there may be

299 random disturbances to the system across time, but the net dynamics of the system remain

300 stable – and therefore this situation is still called "equilibrium."

Stochastics

302   Our route so far has been deterministic – the mathematical representations do not

303 contain error. When we want to convey a process with error we can consider a host of

304 additional principles. Stochastics, stated simply, refers to processes with error. Consider our

305 simple difference equation from above, adding an error component produces:

$$y_t = ay_{t-1} + c + e_t \tag{4}$$

306 where all terms are defined above but e_t represents an error term that is incorporated into y

307 at each time point. Errors cause y to be higher or lower at specific points in time than we

308 would have expected given a deterministic process. For example, at time t the error might

309 push y to a higher value, and at $t+1$ to a lower value. Errors are therefore said to be

310 random because we cannot predict their value at any specific t. In aggregation (i.e., averaged

311 across time), however, positive errors cancel negative errors, and large errors are less likely

312 than small errors. Any time we have an accumulation of random error we get a normal

313 distribution (McElreath, 2016). In stochastic systems, therefore, the errors are said to be

314 distributed $N(0, 1)$ – that is, random and unpredictable at any specific t but distributed with

315 certain constraints across time.

316   It can also be helpful to think about what error is not. Anything that is systematic,

317 predictable, or common (using those in layman's terms) cannot be error – leaving error to be

318 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 c and a to zero in equation 4 produces a white noise process.

$$y_t = ay_{t-1} + c + e_t$$
$$a = 0 \tag{5}$$
$$c = 0$$

Here, all we have is error over time. Panel "A" of figure 4 shows the behavior of a white noise process over time. Random walks are similar, but a is now equal to one.

$$y_t = ay_{t-1} + c + e_t$$
$$a = 1 \tag{6}$$
$$c = 0$$

This representation is also an error process, but there is self-similarity across time. Panel "B" of figure 4 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.

System of Equations

Our discussion so far has focused on one variable. Before moving to two or more variables we want to pause and highlight how much researchers can explore with single variables. It is of course interesting and fun to ask how two or more variables are related, or posit a complex sequence among a set of variables. But understanding whether or not one variable 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 variable. Before, we demonstrated a simple difference equation for y. In a multivariate system with two variables, x and y, we need one equation for each:

$$y_t = ay_{t-1} + e_t \tag{7}$$

$$x_t = ax_{t-1} + e_t \tag{8}$$

where both equations posit that their variable 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 variables with more terms.

First, consider a system where x concurrently causes y. A more appropriate way to say this would be that x_t causes y_t:

$$y_t = ay_{t-1} + bx_t + e_t \tag{9}$$

$$x_t = ax_{t-1} + e_t \tag{10}$$

353 where all terms are defined above but now the equation for y also includes x_t, the value of x

354 and time t, and b, the coefficient relating x to y. This set of equations says that x is simply a

355 product of itself over time (with error), whereas y is a function of itself and also x at the

356 immediate time point.

357   What if there is a lag between when x causes y? That is, perhaps we posit that x does

358 not immediately cause y but instead causes y after some period of time. If the lag effect were

359 2, that would mean that x_t causes y_{t+2}, and to express the "lag 2 effect" mathematically we

360 would use the following.

$$y_t = ay_{t-1} + bx_{t-2} + e_t \tag{11}$$

361

$$x_t = ax_{t-1} + e_t \tag{12}$$

362 Here, all terms are nearly identical to what we saw above but now there is a lag-two effect

363 from x to y. y is now a function of both its immediately prior self and the value of x from

364 two time points ago.

365   What if we want to convey feedback, or a reciprocal relationship between x and y?

366 That is, now we posit that both x causes y and y causes x. To do so we update our

367 equations with a simple change:

$$y_t = ay_{t-1} + bx_{t-2} + e_t \tag{13}$$

368

$$x_t = ax_{t-1} + by_{t-2} + e_t \tag{14}$$

369 where all terms are defined above but now x and y are reciprocally related. Both are

370 determined by themselves at the immediately prior time point and the other variable two

371 time points in the past. x happens, and two moments later this influences y, and two

moments later this influences x, and so on throughout time. All the while, both variables

retain self-similarity – they change 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. If we were to plug values into the coefficients and variables we would produce

trajectories over time, and to describe those trajectories we could then use terms like "trend,"

"periodicity," or "feedback" like we saw in the systems theory section.

Examples

People from our literature using these principles to explain something. Study 1 argued

for random walk behavior in X. Study 2 measured X and Y and posited an equation.

Summary

Computational Principles

Above, we unpacked representations most people are familiar with: verbal descriptions,

plots, and math. There has recently been a push to use computational models – where the

goal is still to convey process but in computer code. In this section we discuss several

principles that researchers can use when they are explaining a process and expect that

explanation to eventually be evaluated with a computational model. We are not going to

show code or a set of scripts or "if statements" (although doing so would be a valuable paper

on its own). Instead, the principles below are pieces that should be incoporated into an

explanation if the researcher hopes to eventually evaluate it in a computer simulation. This

section will also be different from the sections above because we will use a running example throughout, and the example comes from Simon (1956).

While developing his notion of satisficing Simon wrote a paper exploring simple rules that could yield adaptive behavior. His paper was not framed as a "computational model," but his writing is a great example of how authors can write verbal explanations that lend themselves to computer simulations. Writing equations is of course preferred, but the concepts below are tools/criteria for researchers without a strong mathematical background.

Key States

Simon's (1956) paper is about how agents move through an environment and choose among multiple goals – it is about multiple goal self-regulation. He begins by arguing that agents choose among multiple goals to satisfy needs, and need satisfaction is the core driver of behavior. There are of course other causes, but everything is done with respect to the need requirements. The two needs he includes are food and water.

Simon begins his explanation with needs, and although there are other causes of behavior he makes the assumption that needs are the lowest level of abstraction required to explain his model. They can be thought of as the "foundation" variables to build from. Researchers should be clear about the core variables that drive all other behavior in their models. Variables are called "states" when we talk about them over time, so the first principle is to adequately identify and describe the key states.

State Dynamics

Once we identify the states we need to describe their behavior over time. Again, Simon's (1956) key states are food and water, and he then goes on to describe how they

⁴¹⁶ unfold as time progresses. He posits that an agent's food and water states decrease over time

⁴¹⁷ because his or her body requires energy. The body is constantly using food and water in its

⁴¹⁸ stores, so as time passes the key states naturally decrease.

Actions

⁴²⁰ The key states are the assumed "proximate" causes of behavior, and we have now

⁴²¹ explained how they unfold over time. Next, we need to explain the list of possible behaviors

⁴²² that the causes lead to. In other words, we need actions that result given the set of states

⁴²³ and their current dynamics. In Simon's model he lists three agent actions: resting, exploring,

⁴²⁴ and goal striving. These actions satisfy the internal state dynamics. How so? That is the

⁴²⁵ next criteria.

Action Selection

⁴²⁷ Assuming a set of actions, how does the agent select among them? Action selection is

⁴²⁸ the principle for explaining how one of the actions actually occurs given the states and their

⁴²⁹ dynamics. Simon argues that if the food and water states are above threshold then the agent

⁴³⁰ rests. That is, he suggests that the food and water states act like stores (although they

⁴³¹ constantly decrease) and only produce action when some negative discrepancy exists. When

⁴³² one of the states dips below threshold the agent explores its environment. During

⁴³³ exploration the agent randomly runs into objects, and if he or she encounters a single object

⁴³⁴ relevant to one of the needs the agent acquires it. If instead the agent encounters two or

⁴³⁵ more need-relevant objects he or she makes a decision based on the ratio of effort required to

⁴³⁶ get the object versus the size of the state discrepancy. In summary, action selection is about

⁴³⁷ how behavior occurs given the states and their dynamics, whereas actions are simply the

⁴³⁸ names of the behaviors themselves.

Environment

⁴³⁹

⁴⁴⁰   Finally, computer simulations require a structure or environment for agents to operate

⁴⁴¹ within. The environment could be a lattice, a well-mixed population, or any number of

⁴⁴² network arrangements, but the core idea is that context shapes what ultimately happens.

⁴⁴³ Simon explains his simple rules model within a grid that contains spatially distributed

⁴⁴⁴ sources of food and water. The size of the food and water stocks are determined by the

⁴⁴⁵ availability of the resources in the environment. Water is easier to come by than food and so

⁴⁴⁶ food requirements are greater.

⁴⁴⁷ **Summary**

<div align="center">

Discussion

</div>

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⁴⁴⁹   Having presented the principles and terms like process, longitudinal, and dynamics, we

⁴⁵⁰ close with our opinion about how the term "process" should be used. In our view, only

⁴⁵¹ explanations about the proposed "true" mechanism should be called "process." If a

⁴⁵² researcher, instead, simply observes and describes manifest behavior like trend or correlates

⁴⁵³ of trend then they are not explaining process – but it is still a useful study!

⁴⁵⁴ **References**

⁴⁵⁵ Aguinis, H., Pierce, C. A., Bosco, F. A., & Muslin, I. S. (2009). First decade of

⁴⁵⁶   Organizational Research Methods: Trends in design, measurement, and data-analysis

⁴⁵⁷   topics. *Organizational Research Methods*, *12*(1), 69–112.

⁴⁵⁸ Baltes, P. B., & Nesselroade, J. R. (1979). *Longitudinal research in the study of behavior and*

⁴⁵⁹   *development.* Academic Press New York, NY.

⁴⁶⁰ Beal, D. J. (2015). ESM 2.0: State of the art and future potential of experience sampling

⁴⁶¹   methods in organizational research. *Annu. Rev. Organ. Psychol. Organ. Behav.*,

⁴⁶²   *2*(1), 383–407.

⁴⁶³ Cronin, M. A., Gonzalez, C., & Sterman, J. D. (2009). Why don't well-educated adults

⁴⁶⁴   understand accumulation? A challenge to researchers, educators, and citizens.

⁴⁶⁵   *Organizational Behavior and Human Decision Processes*, *108*(1), 116–130.

⁴⁶⁶ DeShon, R. P. (2012). Multivariate dynamics in organizational science. *The Oxford*

⁴⁶⁷   *Handbook of Organizational Psychology*, *1*, 117–142.

⁴⁶⁸ Hardy, J. H., Day, E. A., & Steele, L. M. (2018). Interrelationships Among Self-Regulated

⁴⁶⁹   Learning Processes: Toward a Dynamic Process-Based Model of Self-Regulated

⁴⁷⁰   Learning. *Journal of Management*, 0149206318780440. doi:10.1177/0149206318780440

⁴⁷¹ Ilgen, D. R., & Hulin, C. L. (2000). *Computational modeling of behavior in organizations:*

⁴⁷²   *The third scientific discipline.* American Psychological Association.

⁴⁷³ Johnson, R. E., Lanaj, K., & Barnes, C. M. (2014). The good and bad of being fair: Effects

⁴⁷⁴   of procedural and interpersonal justice behaviors on regulatory resources. *Journal of*

⁴⁷⁵   *Applied Psychology*, *99*(4), 635.

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

Meadows, D. H. (2008). *Thinking in systems: A primer.* chelsea green publishing.

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

Pettigrew, A. M. (1992). The character and significance of strategy process research. *Strategic Management Journal, 13*(S2), 5–16.

Pettigrew, A. M. (1997). What is a processual analysis? *Scandinavian Journal of Management, 13*(4), 337–348. doi:10.1016/S0956-5221(97)00020-1

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

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.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review, 63*(2), 129.

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

499   Wang, M., Zhou, L., & Zhang, Z. (2016). Dynamic modeling. *Annual Review of*

500   *Organizational Psychology and Organizational Behavior*, *3*(1), 241–266.
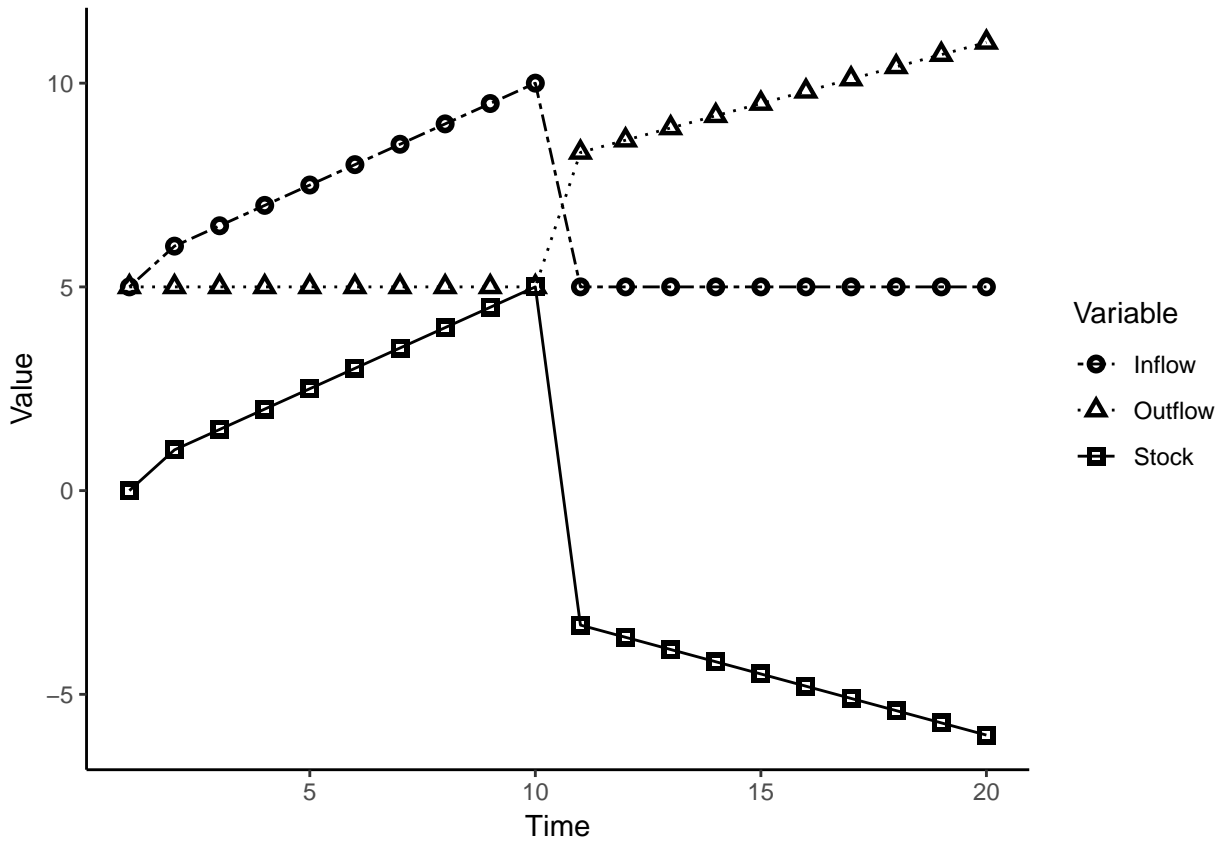
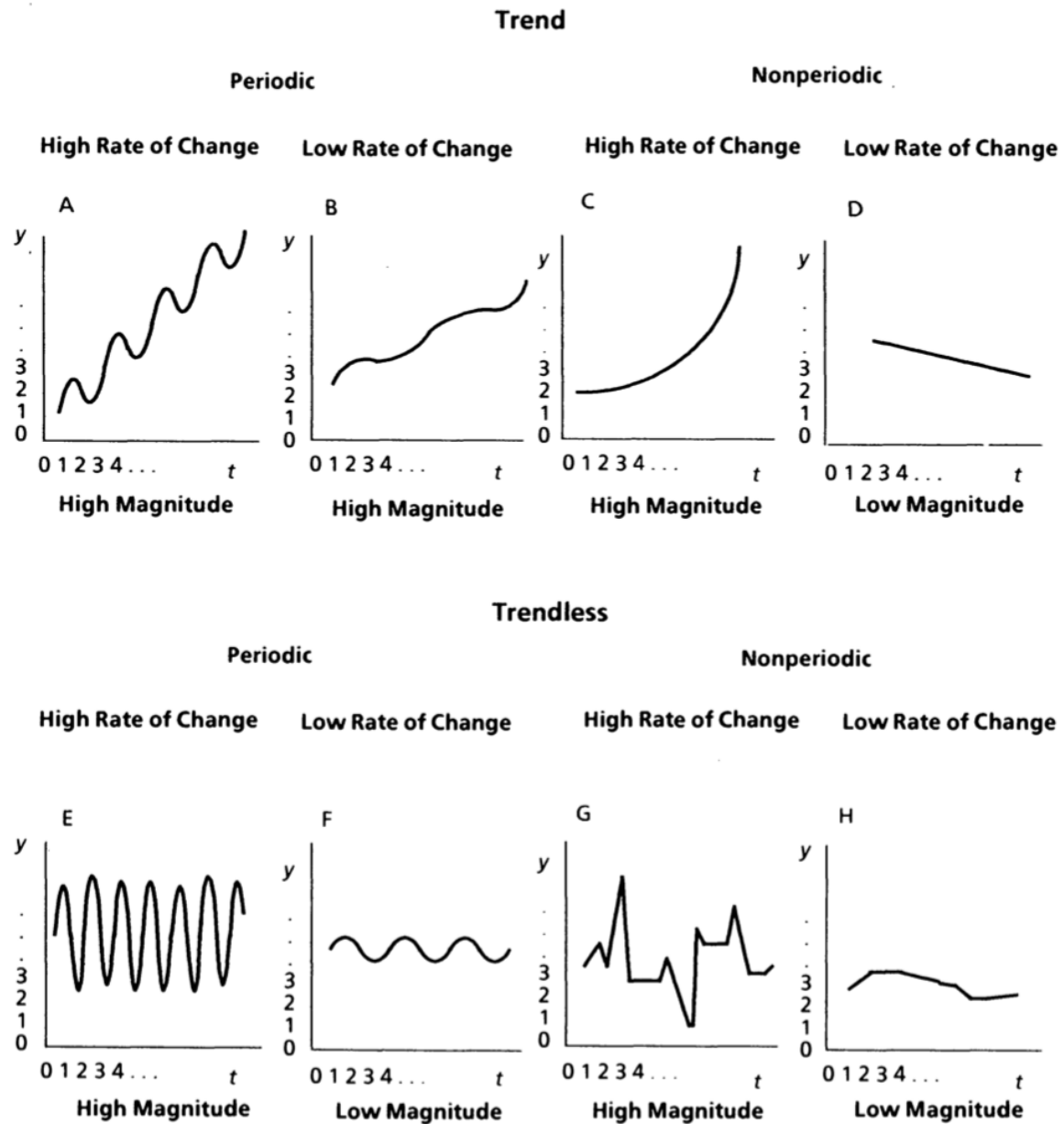501   doi:10.1146/annurev-orgpsych-041015-062553

Figure 1. the ol stock system
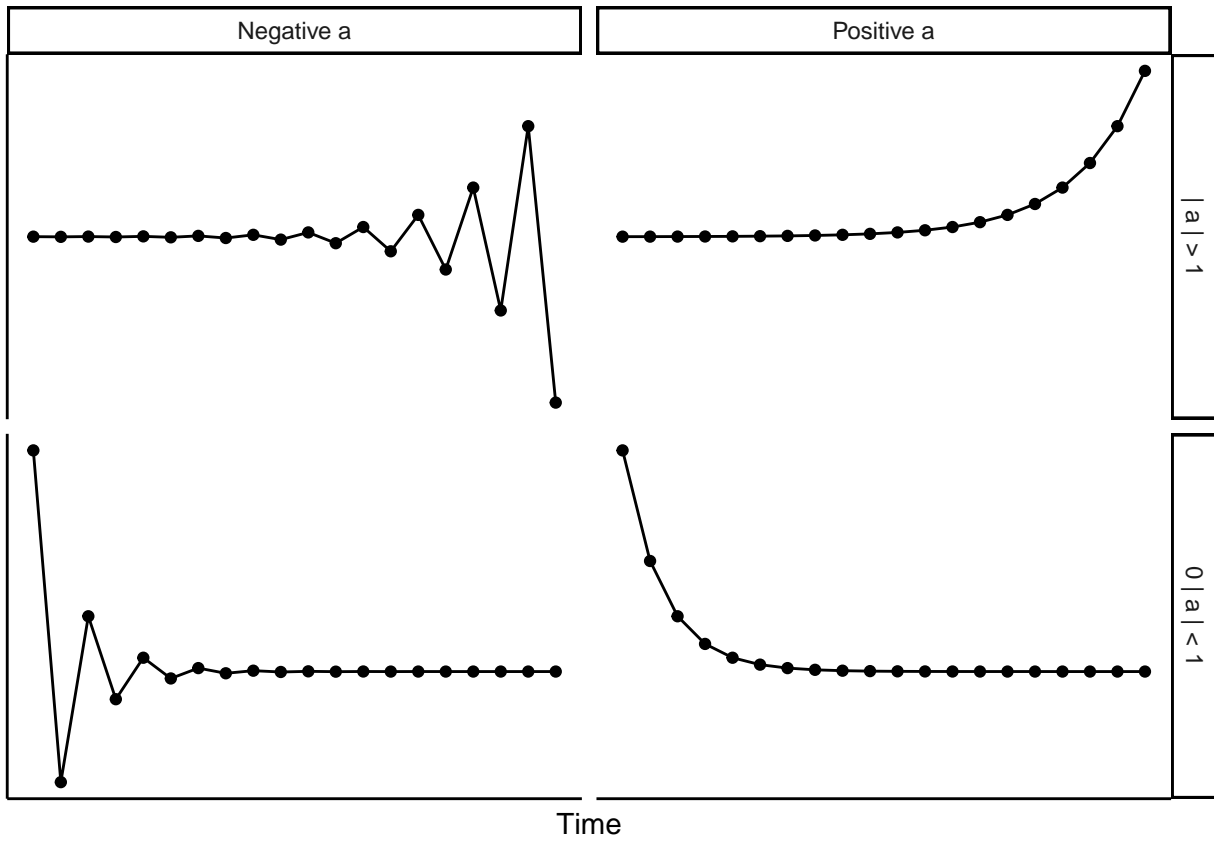
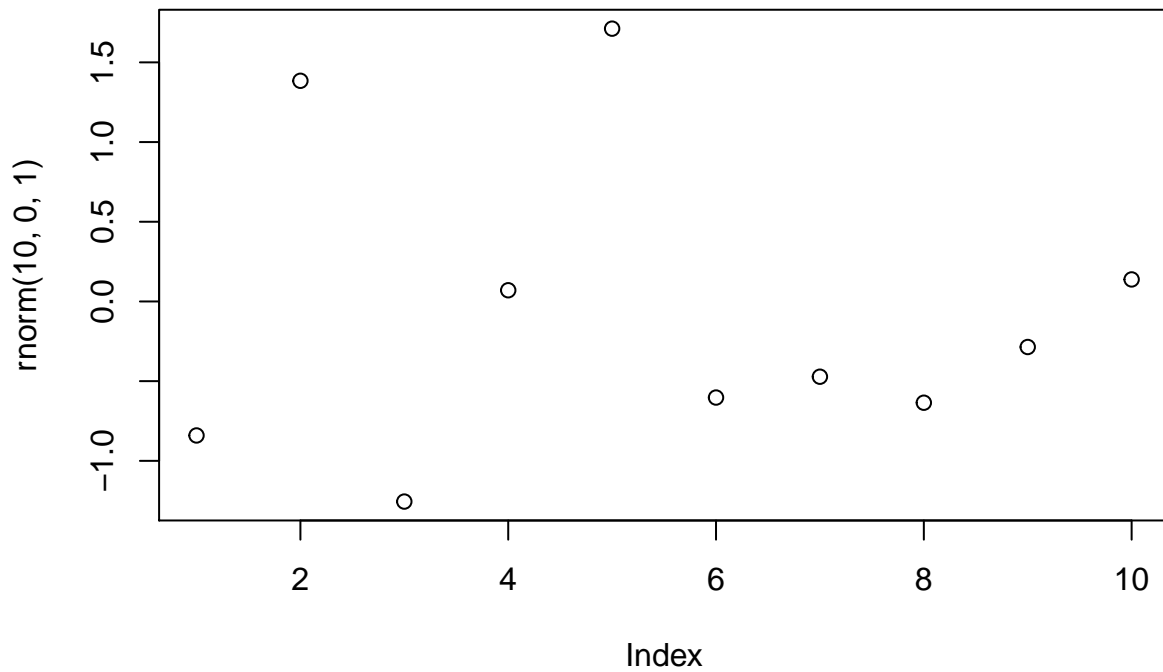*Figure 2.* monge image

Figure 3. dynamic equilibrium fig

Figure 4. this one will be a white noise process and a random walk