Thinking Longitudinal: A Framework for Scientific Inferences with Temporal Data

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Abstract

In this manuscript we explore how to think about patterns contained in longitudinal or panel data structures. Organizational scientists recognize that psychological phenomena and processes unfold over time and, to better understand them, organizational researchers increasingly work with longitudinal data and explore inferences within those data structures. Longitudinal inferences may focus on any number of fundamental patterns, including construct trajectories, relationships between constructs, or dynamics. Although the diversity of longitudinal inferences provides a wide foundation for garnering knowledge in any given area, it also makes it difficult for researchers to know the set of inferences they may explore with longitudinal data, which statistical models to use given their questions, and how to situate their specific inquiries within the broader set of longitudinal inferences. Moreover, the diversity of statistical models that can be applied to longitudinal data requires that researchers understand how one inference category differs from another.

Keywords: longitudinal inferences, between-unit, growth, trends, dynamics, relationships over time, processes

Thinking Longitudinal: A Framework for Scientific Inferences with Temporal Data

Imagine a close colleague that frequently agrees to volunteer for additional work when asked to do so. What causes her to act this way? Our intuition says that the cause must be something unique about her, a motive, personality trait, disposition, or her momentary enthusiasm. So it is with our research: the literature on correlates of why someone responds with help has focused almost exclusively on individual characteristics, such as affect, motives, attributions, justice or leadership perceptions, personality, and vigor. But this emphasis contradicts what we know about random processes, namely that long-run streaks of behavior can be by byproducts of chance. Because chance explanations have not been ruled out, statements about the necessity for organizations to monitor, evaluate, and influence individual characteristics to improve employee helping may be overblown. Moreover, a manager who reads this literature and then assumes that individual characteristics cause helping is more likely to falsely attribute good character to her employees when she witnesses it, leading to performance evaluations and reward recommendations that are, perhaps, biased. The purpose of this paper is to find evidence of randomness in the requests that employees receive asking them for assistance. If we identify chance, then researchers, managers, and consultants must account for it if they truly want to know whether something unique about the individual, rather than something random about the situation, led to exceptional, long-run helping. In the organizational literature, helping or providing assistance to colleagues is referred to as organizational citizenship.

Organizational citizenship behaviors (OCBs), or cooperative acts such as assisting others, volunteering for additional work, or speaking highly of the company, are increasingly emphasized in the organizational sciences (HANDBOOK; dalal). Leaders put OCBs on equal footing to task performance when asked about the merits of different behaviors within their teams (Podsakoff, MacKenzie, & Podsakoff, 2018), and researchers have gone so far as to describe OCBs as the key social aspect driving organizational success (Bateman & Organ, 1983). Researchers, as well as consultants, managers, and employees, are interested in knowing why people differ on this behavior, and in particular why someone might have sustained, superior levels of OCBs over time.

Employees that exhibit sustained, high-levels of OCBs are labeled “extra-milers” or “good citizens” in the literature (Li, Zhao, Walter, Zhang, & Yu, 2015; Methot, Lepak, Shipp, & Boswell, 2017), and researchers have identified a number of predictors of this behavior – many of which are individual characteristics. These include prosocial motivation and personality (Grant, 2008; Penner, Midili, & Kegelmeyer, 1997), impression management motives (Grant & Mayer, 2009), one’s propensity to be concerned for others (Meglino & Korsgaard, 2004), job satisfaction, perceived fairness, and organizational commitment (Organ & Ryan, 1995), perceptions of trust (HANDBOOK; moorman, fit (HANDBOOK; kristof brown), leader fairness (HANDBOOK; piccolo), and interaction quality with colleagues (Bolino, Hsiung, Harvey, & LePine, 2015), how employees appraise pressures to perform and goals (Mitchell, Greenbaum, Vogel, Mawritz, & Keating, 2019), their level of engagement and mindfullness (Hafenbrack et al., 2019; Wang, Law, Zhang, Li, & Liang, 2019), and their perceptions of ostracism (Lance Ferris et al., 2019). Indeed, Bolino (1999) and Bolino, Turnley, and Bloodgood (2002) state that there is a consensus that OCBs stem from dispositions, motivation, and fairness perceptions.

Studies have also identified predictors of within-person OCB variance, but again many of these are individual characteristics. Antecedents include positive affect (Dalal, Lam, Weiss, Welch, & Hulin, 2009; Glomb, Bhave, Miner, & Wall, 2011), job satisfaction (Ilies, Scott, & Judge, 2006), social comparisons and beliefs in a just world (Spence, Ferris, Brown, & Heller, 2011), core self evaluations and future orientation (Wu & Parker, 2012), engagement (Christian, Eisenkraft, & Kapadia, 2015), and perceptions of justice or supervisor support (Matta, Sabey, Scott, Lin, & Koopman, 2020; Schreurs, Hetty van Emmerik, Günter, & Germeys, 2012).

We offer an alternative, perhaps simpler, model to explain sustained, superior levels of OCBs – one that does not rely on individual characteristics such as motives, attributions, personality, or fairness perceptions. The mechanism, instead, uses (a) opportunities, or signals that an act of assistance can be performed, and (b) chance accumulation, or the notion of randomly assembling components to an existing stock as an employee moves through time. To say that an employee randomly accumulates opportunities is to mean that he or she is confronted with requests, notifications, or prompts that signal to him or her that an act of help can be performed, and each of these successive cases then compiles into his or her existing pool. We show that whenever help requests follow a random accumulation process, then superior, sustained citizenship behaviors by one employee compared to others is not only a possibility but in some cases it is the most likely outcome – it is to be expected. Even when two people have the same level of trust toward others, empathy, or prosocial values, one may have continual, superior helping due to the underlying, random accumulation. Moreover, this result occurs even when the mechanism is identical for every employee. In other words, we show that vastly different observed citizenship does not depend on a unique causal diagram for every employee. The fundamental process – accumulation – is the same, but the manifest complexity leading some individuals to have greater citizenship than others occurs due to the unique gradient one experiences across time. Such an alternative explanation does not necessarily challenge existing ideas, but it has the potential to change our understanding of what generates sustained, superior behavior.

Apart from this first contribution, an alternative, parsimonious explanation regarding sustained, superior citizenship, additional contributions of this paper are as follows. First, we provide information to managers that can help them avoid misattributing causes of citizenship. If a manager were to take our literature at face value, then she should assess individual characteristics to monitor, predict, and manage helping behaviors. But such actions do not account for differences in help requests and the extent to which these requests follow a random process. Therefore, she cannot rule out chance when she witnesses sustained, high levels of OCBs and will potentially misattribute its cause to personality or motives. Any performance or promotion recommendation that she then provides – which are outcomes of OCBs – are given for the wrong reason. The employee behavior was not due to disposition, but chance opportunities.

Second, we answer recent calls for a better understanding of dynamics in the citizenship literature (DYNAMICS; dishop et al., DYNAMICS; cronin). DYNAMICS; Dishop et al., argue that, although it is now common for researchers to assess patterns in longitudinal data, many of the current approaches miss several fundamental concepts of dynamics – the notion of accumulation being one. We examine this principle here by assessing the extent to which help requests follow a random walk and therefore add more knowledge about citizenship dynamics to our literature.

Third, we extend the OCB literature by examining the nature of help requests. When researchers discuss employee citizenship in handbooks (Podsakoff et al., 2018), theory (Bolino, Harvey, & Bachrach, 2012; Organ, 1988), or in empirical articles (Gabriel, Koopman, Rosen, & Johnson, 2018; Koopman, Lanaj, & Scott, 2016), they focus almost exclusively on help itself – types, measures, predictors, outcomes, and its similarity to other constructs. But help is often, sometimes by definition, tied to a request or prompt. For instance, in their chapter distinguishing OCBs from engagement, Newton and LePine (HANDBOOK; 2018) suggest that citizenship is a response to an opportunity – an act that follows a prompt for extra work or a request for information. Similarly, in their chapter distinguishing OCBs from proactive behavior, Li, Frese, and Haider (HANDBOOK; 2018) state that, whereas proactive behavior reflects an employee volunteering help without a prompt, OCBs are actions that occur after a plea for assistance. Not all OCBs are reactions to prompts (e.g., López-Domı'nguez, Enache, Sallan, & Simo, 2013), but requests are part of the definition of at least one major type of citizenship – a type which some authors (Li et al., 2018) have argued should take the forefront of OCB research. Currently, we have many studies on helping but little on the nature of prompts. Our understanding of citizenship, therefore, is incomplete in that we have focused exclusively on one aspect of the definition of citizenship (i.e., the act), and not the other (i.e., the prompt).

Fourth, we challenge an assumption about what creates long-run, exceptional citizenship. To appreciate our stance, it is useful to describe a study by Bolino et al. (2015). These authors examine within-person variance in OCBs, depletion, and motives, and correlate the constructs over time. They motivate their study by arguing that prior research has assumed that people have stable motives and so "good soldiers," or employees that demonstrate supreme OCB levels compared to their peers, will always be good. They argue that this idea is unfounded and then demonstrate that motives do show systematic within-person variance, and that they predict OCBs. What these authors imply is that long-run behavior is unlikely when there is systematic variance in the variables that are assumed to cause OCBs. Said differently, when the causes are unstable (motives), the outcome must be unstable (OCB). This idea, though, contradicts what we know about stochastic processes, particularly the notion that no systematic variance in the cause is required to produce what looks like long-run stability in the outcome (Polson & Scott, 2012). If the cause has no systematic variance, it is still possible (and in some cases extremely likely) that the response process does contain systematic variance in the form of long streaks of exceptional citizenship. Our paper, therefore, repositions how we think about long-run citizenship behavior.

Finally, this research generates new avenues; it points to unexplored scientific and applied questions that could lead to a flurry of additional work. These questions are unpacked at the end of the paper.

The goal of this paper is to describe an alternative, chance model of long-run citizenship that incorporates opportunities and accumulation. Below, we describe OCB background and theory, the notion of extra milers/good soldiers, and then present our alternative explanation with two studies. In study one, we propose and find evidence that help requests follow a random accumulation process. Specifically, we draw from probability theory and suggest that, in some cases, patterns of help requests follow random walks. In study two, we use this initial finding as a starting point – that help requests can be modeled as random walks – and then apply simulations to determine how different types of random walks lead to various forms of long-run behavior. Stated simply, study two reveals the parameters and assumptions required for random walks to produce long-run OCBs.

Organizational Citizenship Behaviors (OCBs)

The idea that there are employee behaviors beyond what we typically consider as job or task performance but that still promote individual and collective success has been around for decades. Researchers from psychology, management, education, human resources, organizational behavior, and sociology have different terms for this behavior, and different aspects that they emphasize, but in the organizational literature this behavior has come to be known as organizational citizenship. OCB is "individual behavior that is discretionary, not directly or explicitly recognized by the formal reward system, and that in the aggregate promotes the effective functioning of the organization" [Organ (1988); p. 4]. It has been described as a behavior that "lubricates" the social machinery of the organization, thereby facilitating its effective functioning (Bolino et al., 2002; Organ, Podsakoff, & MacKenzie, 2005; Podsakoff & MacKenzie, 1997). Related terms that are now less popular include organizational spontaneity (George & Brief, 1992), extra-role behavior (Van Dyne & LePine, 1998), and contextual performance (Motowidlo & Van Scotter, 1994).

Citizenship has consequences for both individuals and collectives. Employees demonstrating greater OCBs earn higher supervisor performance evaluations (MacKenzie, Podsakoff, & Fetter, 1991, 1993; Motowidlo & Van Scotter, 1994) and more promotion recommendations (Van Scotter, Motowidlo, & Cross, 2000). Meta-analytic results suggest that individuals who consistently engage in OCB are less likely to express intentions to leave, to voluntarily quit, and to be absent from work (Podsakoff, Whiting, Podsakoff, & Blume, 2009). For collectives, greater levels of OCBs relate to higher performance quality, performance quantity, and customer satisfaction (Ehrhart & Naumann, 2004; Podsakoff, MacKenzie, Paine, & Bachrach, 2000), and some studies suggest that organizations competing in changing environments are especially dependent on good citizens because the goodwill and social capital they foster are a source of competitive advantage (Bolino et al., 2002; Leana & van Buren, 1999; Nahapiet & Ghoshal, 1998). There are also studies documenting the negative consequences of OCBs, which include reduced in-role performance, depletion and exhaustion, role overload, and feelings of resentment among peers (HANDBOOK; cites). That said, several researchers claim that OCBs should be thought of as a positive act, which is highlighted in the following quotes:

> "There is considerable support in the literature for the idea that citizenship behavior at work is a positive thing" (Bolino et al., 2015; p. 56)

> "Theory and practice should acknowledge the sizable role good citizens play…because organizations rely on their continued investments" (Methot et al., 2017; p. 11)

Researchers typically pursue one of three broad ways to classify OCBs. Initially, OCB included two dimensions: altruism, or helping directed at a person after an eliciting stimulus; and generlized compliance, or an impersonal sense of conscientiousness (Smith, Organ, & Near, 1983). These two dimensions were later deconstructed into altriusm (responding to opportunities to assist a coworker), courtesy (responding with kindness), conscientioueness (on time, following rules, etc.), civic virtue (concern for the organization), and sportsmanship (tolerate less than ideal circumstances while maintaining a positive outlook) (HANDBOOK). Other researchers classify OCBs either as affiliative or challenging (HANDBOOK). Affiliative behaviors are acts such as helping or responding with courtesy in which the actor supports existing company processes. Challenging behaviors are acts such as voicing problems or initiating change in which the actor adjusts his or her circumstances. Finally, OCBs are also distinguished (e.g., Dalal, 2005) by whether they benefit individuals (OCB-I; helping, assisting, encouraging) or the organization (OCB-O; promoting the company to others).

In this paper, we refer to affialiative OCBs whenever we use the terms citizenship, helping, acts of assistance, or OCB. This focus is necessary and appropriate for the following reasons. First, Li and HANDBOOKAUTHOR spend an entire chapter describing the differences between affiliative (helping) and challenging (voicing) OCBs and argue that helping should be thought of as the core manifestation of citizenship because it (a) aligns with what most people mean when they study cooperation in the broader sciences, (b) is based on different evolutionary pressures than behaviors such as voicing concerns or actively changing circumstances, and (c) leads to construct contamination and unnecessary confusion if coupled with change-oriented behaviors. Second, Van Dyne, Cummings, and McLean (1995 HANDBOOK BUT OWN TEXT) suggest that "the conceptual definition and subsequent operationalizations of OCBs should focus on citizenship behavior that is affiliative…and should not include challenging" (p. 274). Third, helping is the core dimension discussed in the original paper exploring the dimensionality of OCBs (Smith et al., 1983) and within Organ's theoretical writing about the construct (HANDBOOK OWN TEXT ORGAN). Finally, and perhaps most importantly, it aligns with the purpose of this study, which is to explore the random nature of prompts for help. For all of these reasons, this paper couches itself within the affiliative space of the construct.

Sustained, Long-Run Citizenship

Recently, researchers have shown an increasing interest in employees that repeatedly exhibit greater OCBs compared to their peers. Li et al. (2015), for instance, studied manufacturing teams in China and examined what they referred to as "extra milers" – employees who frequently provide greater help relative to their colleagues. Specifically, extra milers were defined as team members who exhibited high frequency extra-role behaviors such as helping, and the researchers operationalized it by collecting other-team-member-rated surveys of OCBs and then identifying the team member with the maximum score. Unfortunately, there was a discrepancy between how they defined extra milers and how it was studied: they defined it by referring to frequency, which implies sustained behavior over time consistent with the theory that they used to support their arguments (behavioral consistency theory), whereas the measures they employed captured single-moment levels of OCBs. Nonetheless, the researchers were clearly interested in the notion of repeated, exceptional OCBs. They found that differences across teams in the number of helping behaviors provided by the "extra miler" correlated with team backup and monitoring behaviors.

A similar idea is described in a paper by Methot et al. (2017) that explains how employees make sense of life events and its implications for OCB. They state,

> One topic of particular interest in the OCB literature is the concept of "good citizens" – employees who tend to engage in high levels of OCB… Research suggests that good citizens characteristically perform OCB because of such factors as personality traits, including agreeableness, prosocial orientation and values, and proactive personality. p. 10.

So, good soldiers or extra milers refer to employees that "characteristically" engage in OCB, or that exhibit greater helping compared to their colleagues time and time again. Such a pattern would manifest as long-run streaks of behavior, similar to a series of consecutive heads if one were to flip a coin two hundred times.

What accounts for long-run citizenship? OCB antecedents were described earlier in this paper and included individual characteristics such as motives, affect, attitudes, fairness perceptions, and engagement. Similarly, Methot et al., point to predictors of long-run citizneship in the quote above: personality and prosocial values. We suggest an alternative: chance opportunities. Just as a series of consecutive heads could be a byproduct of chance events from flipping a coin, long-run citizenship could be a byproduct of random opportunities. By opportunity, we mean a prompt that signals to an employee that an act of help can be performed, such as an email from a colleague requesting assistance. By random, we mean that help requests follow a mathematical form that incorporates chance. The overarching argument in this paper is that employees may receive help requests in a pattern that mimics a fundamental mathematical process, one that includes randomness, and so in the sections below it is necessary to articulate each aspect of our argument. First, we describe what we mean by help requests or opportunities. Then, we provide one way to specify their mathematical form.

Prompts & Opportunities

A prompt/request/opportunity is a signal to an employee that an act of help can be performed, and this idea was an important element in the early OCB literature. In their cornerstone paper describing its dimensions, Smith et al. (1983) state that helping occurs after a stimuli, or a signal that "appears to be situational, that is, someone has a problem, needs assistance, or requests a service" (p. 661). Despite this initial emphasis, Ehrhart (HANDBOOK CHAPTER) points out that there has been little follow-up research on the nature of requests and how they inform what we know about OCBs. That said, there is ample theory elsewhere that describes opportunities more broadly as they reflect aspects of the situation or environment in which an agent is conducting his or her behavior – we draw from this literature to guide our discussion.

Many researchers across several scientific disciplines have described the nature of situations and environments. Within this broad area, two ways to think about the environment are relevant for our purposes. The first is as a platform, space, or zone which holds distributed goal-relevant objects. This perspective is consistent with much of Herbert

Simon's writing that emphasized the importance of context for understanding human behavior. Across a number of papers, theories, and normative models (Simon, 1956, 1992) Simon argues that to understand the complex behavior of an agent it is first necessary to understand how goal-relevant objects are distributed around it. Applied to the current paper, this notion embodies the idea that to understand OCBs it is necessary to know how opportunities to assist are distributed about an employee. To make his writing clear, Simon usually described how objects were distributed in space, meaning that an agent was located in a matrix and the distribution was over cells. Here, we extend that idea to a distribution over time. Not only do employees receive help requests from different colleagues, they also receive requests at different moments in time, and requests happen repeatedly as an employee moves from moment to moment. This distribution over time would reflect the average number of requests that the employee would expect to receive at any moment, alongisde the expected variability in requests.

The second perspective on the environment is as a shock or disturbance that makes opportunities come and go. Random stimuli occur and these factors impinge upon actors, allowing some behaviors and constraining others. This idea is consistent with the notion of shocks in the unfolding model of employee turnover in which discrete events thwart some opportunities and create others (Lee & Mitchell, 1994), to events in affective events theory in which random stimuli cause changes in employee emotion and behavior (Beal, Weiss, Barros, & MacDermid, 2005), and to the environment in Dishop's goal sampling theory (Dishop, 2019) in which actors are only able to approach goals made available by the situation at any moment in time. Blumberg and Pringle (1982) define opportunities as "the particular configuration of the field of forces surrounding a person and his or her task that enables or constrains that person's task performance and that are beyond the person's direct control" (p. 565), and Stewart and Nandkeolyar (2007) demonstrated that even skilled and motivated workers cannot engage in performance facilitating behavior when their actions are constrained by the environment.

Across all of these perspectives, the core idea is that there are opportunities scattered about the environment that come and go. The particular form of opportunity that we examine in this study is a help request: a prompt or signal or notification to an employee that an act of assistance can be performed. Consider a few examples: A Professor receives an email from a colleague asking if she can substitute for an undergraduate course; A manager announces that volunteers are needed for an upcoming assignment; A blogger tells his writing collaborator that she is welcome to review and edit his post if she pleases; A statistician witnesses a question posted on a forumn about a statistical model relevant to her expertise; A software engineer receives a pull request; An academic receives a note from a graduate student asking for a friendly review of his paper. Moreover, any single agent may experience repeated prompts over the course of a week. On Monday, a Professor may receive an email asking for assistance teaching a class. On Tuesday, she receives two more emails about optional meetings in her department (attending optional meetings is one commonly studied manifestation of OCB). On Wednesday, a former graduate student, who is now a faculty member at a different school, asks for a letter of recommendation. On some days, the Professor has a large stock of help requests, whereas on others she has few, if any. The crux of this paper is that we expect these helping prompts to follow a specific mathematical form, which we specify below.

Accumulating Requests As a Random Walk

To explain patterns in help requests over time, we draw from probability theory. For some employees, the pattern by which they receive help requests may mimic a fundamental mathematical process. To see how, consider the following heuristic. First, the state we are tracking is the number of help requests than an employee receives over time, with greater values indicating more notifications. Second, this state can be viewed as a dynamic stock, meaning that the employee has a pool or store of help requests – three, for example – and this number is self-similar over time such that it carries over from day to day. If the employee receives two help requests today, this number is added to the store of help requests that she had yesterday, creating a total that moves forward into tomorrow. Similarly, when help requests are removed from the pool – which could occur, for instance, after she or someone else provides help and the request is resolved or when a deadline passes and help is no longer required – then it decreases by whatever amount was withdrawn. But removing a request does not drive the pool to zero. Instead, whatever amount was removed is subtracted from the total in such a way that the pool has inertia/memory – the amount changes from where it was at the immediately prior time point, it does not arbitrarily swing to zero. This pattern, one in which an employee handles a dynamic stock of help requests such that prompts are added or removed while the stock retains inertia, mimics a common and simple stochastic process: a random walk.

A random walk is a basic concept from probability theory. Models of random walks have been used in many scientific disciplines ranging from physics, biology, and chemistry (Kenkre, Montroll, & Shlesinger, 1973; Kot, Medlock, Reluga, & Walton, 2004; Randić, 1980) to economics, sociology, and psychology (Alvarez, Atkeson, & Kehoe, 2007; Johnson, 2014; Shang, 2018), helping to understand diverse phenomenon such as memory search (Stamovlasis & Tsaparlis, 2003), particle motion (Bramson & Lebowitz, 1991), network and market behavior (Fama, 1995; Newman, 2005), and animal foraging (Sims et al., 2014).

A random walk is defined as.

$$y_t = y_{t-1} + B + e_t \tag{1}$$

where y_t is the current value of y, y_{t-1} is the value of y at $t-1$, B is a constant known as drift, and e_t is a series with a mean zero and constant variance σ_e^2. This first equation reveals that random walks contain inertia or self-similarity, which is consistent with our heuristic of helping prompts above. Although drift and error are involved, the core aspect of a random walk as represented in equation 1 is that the value of y at a given time point is a function of its value at the immediately prior time point.

Another key aspect of random walks is that they incorporate accumulation, which is more readily apparanet in an alternative but equivalent form:

$$y_t = y_0 + Bt + \sum_{i=1}^{t} \varepsilon_i \tag{2}$$

where y_0 is the initial value of y, Bt is a deterministic trend component, and the last term represents an accumulation of error. This second equation reveals that random walks capture the notion of accumulating, or adding values to a store/pool over time, which was the second component to our heuristic of help requests.

In the same way that logic can be excavated from a verbal theory to gain traction about some phenomenon, the notion of a random walk can be drawn from probability theory to better understand the nature of help requests. Specifically, we suggest that help requests follow a random walk, such that they demonstrate self-similarity and have the characteristic of accumulating over time.

Hypothesis 1: Help requests follow a random walk.

In study one, we examine a number of data sources to evaluate whether we can find evidence that help requests follow this stochastic process.

Study 1

Archival data was used to assess our hypothesis. We scraped data from several different sources on the Internet, each capturing the idea of a help request in a slightly different way. Testing for random walks requires time-series data with many time points (t), therefore we searched for platforms that contained data with large t and that could be used to capture notifications for help.

Data Sources

(1) Issues on GitHub Repositories - Non-Academic

The first set of data was collected from GitHub repositories created by software developers. GitHub is an open source website that allows users to store, manage, share, and collaborate on projects (repositories) and, although most use it for code, it can also be used for other types of documents such as Word files. The website contains a variety of features that facilitate transparency, collaboration, and networking on projects, such as version control, the ability to comment on and request edits to other user's projects, and personal pages that exhibit a given user's track-record of work. The data that we collected are known as repository "issues." When a focal individual posts a repository/project, other users can then download and use the code that he created. If other users want to ask questions about the code, request features, or report bugs, they can then create an issue on the focal individual's post. The focal individual is then notified that an issue has been placed.

The data we collected were issues posted to single repositories, and we collected data on four different software developers. That is, a single software developer had a respository that he or she maintained, and over time his or her repository collected issues. All of the issues, from when the project first began until the most recent comment, were collected and time-stamped. This process was then repeated for another three software developers working in different industries on unrelated projects.

One of the repositories was source code for a functional computer language built to create web applications. Another was a compiler to convert declarative components into JavaScript. The third was an application which corrects console commands. The fourth was a facial recognition application programming interface. Three of the four software developers work full time for a given company, whereas the fourth is an external consultant.

For each data set, help opportunities were operationalized as issues. Data were collected on (a) the date that the issue was posted and (b) when it was resolved, if ever.

(2) Issues on GitHub Repositories - Academic

The second set of data was also based on GitHub repositories, but this time we used repositories posted by academics. University faculty often use GitHub as a version control system when writing documents, as a platform to share, monitor, and adjust any applications or tools that they develop, and as a resource for downloading data science tools. We focused on the individual repositories of four academics, each a faculty member at a different university.

One of the repositories was an R package for structural equations modeling. Another was the source code and package for a popular Bayesian analysis textbook. The third was an R package for multivariate analysis of genetic markers, and the fourth was a package for population genetics. As before, help opportunities were operationalized as issues and we collected (a) the time the issue was placed and (b) when, if ever, it was resolved.

Potential Data Sources.

(3) first author own emails

The third set of data was a series of emails received by the first author. From October, 2019 to August, 2020, the first author saved any emails from colleagues that seemed relevant to the notion of helping opportunities. This process was not systematic on the front end: the author stored emails based on his own discretion, storing only those emails that appeared relevant as they were received. We tried to make the process more systematic on the back end: after collecting all of the emails and removing any identifying information, 300 undergraduate students underwent a sorting procedure in which they classified the emails either as helping opportunities or as irrelevant. We describe this process in more detail below.

Three hundred undergraduates at a large Midwestern university were recruited to take part in a classification study, which participants completed online. After giving consent, the participants were provided with a definition of helping opportunities and several example items used in prior empirical research. They were then presented with the content of a single email, asked to read it, and then were told to determine if the content was consistent with a helping opportunity or not. Participants rated each email with a bipolar scale including "yes" or "no." Agreement indices were collected. In this data set, help opportunities were operationalized as emails that raters agreed represented requests for citizenship.

(4) student pools

Our fourth angle on help opportunities came from graduate student pools. We tracked the number of graduate students per year from the years 1999 to 2019 at three different graduate programs. One was a Political Science program located in the Northeast, another was an Organizational Psychology department located in the Midwest, and the third program was in Accounting and located in the Southwest. In this data set, a help opportunity was operationalized as an active graduate student – someone who could be mentored by a faculty – and we collected data on the number of active graduate students per year for each department.

(5) forumn questions

Finally, we also collected data from an online forumn. "Psychological Dynamics" is a Facebook group which provides users with a platform to share and discuss news, publications, tools, and other aspects related to psychological research. The community draws researchers from all over the world, and posts are created every day. In this data set, help opportunities were operationlized as a post, and posts were collected daily from September, 2018 to September, 2019.

[table with each data type]

A summary of the data sources is presented in Table 1. We collected data across diverse platforms for several reasons. First, we wanted to ensure that our results were not unique to a given domain. Just as Aguinis and colleagues demonstrated performance power curves in different settings, our goal was to demonstrate random walks across various platforms. Second, we collected data from several sources because each has its own unique limitations and strengths. Our hope was that we could learn something about help requests in general by taking a broad view across all of the data, even though each has its own unique error. The set as a whole can tell us something about help requests, even if each has a slight weakness.

Analysis

All data are structured as time-series such that a single unit is represented over successive time points. In total, there are 13 data sets: 8 from the GitHub repositories, 1 from the first author's emails, an additional 3 from the PhD student pools, and 1 from the public forumn. Each of these time-series represents the stock of help opportunities over time, such that greater values indicate more helping opportunities and lower values indicate fewer helping opportunities. For each data set, hypothesis one is evaluated by assessing whether the series contains a unit root. We use two unit root tests to evaluate our hypothesis. The first, the augmented Dickey-Fuller (ADF; Dickey & Fuller, 1979) test, is the most widely used statistic to evaluate the presence of random walks in time-series data. The null hypothesis of this test is that the data are generated from a random walk, so when the ADF test cannot reject its null our hypothesis is retained. There are also unit root tests in which the null hypothesis is instead the absence of a unit root, and the most well-known test of this second type is the Kwiatkowski, Phillips, Schmidt, Shin, and others (1992) statistic (KPSS). Both tests were administered to evaluate our hypothesis. Stated simply, if the ADF test cannot reject its null while the KPSS test can, then the data provide evidence in two ways that the series follows a random walk.

Results

[Fill after data collection].

Study 1 Discussion

Study one demonstrated that, at least in some cases, help opportunities can be modeled as random walks. Time-series data were collected from multiple sources, and each series represented an accumulating pattern of help opportunities over time. For 12 out of the 13 data sources, both unit root tests provided evidence that the series was consistent with a random walk. In the last data set, which consisted of X, only the ADF test returned evidence that a random walk was present. Identifying random patterns in help requests was the first step toward our chance model of long-run citizenship. We take this evidence – that help opportunities follow a random walk – as a starting point for our next study.

Study 2

Our second study reveals the ways in which random walks may produce different forms of long-run citizenship. Its purpose is to document patterns of long-run citizenship that emerge from different types of random walks. Given that we identified random walks in study one, the next step is to assess how varying the parameters of random walks, as well as our assumptions about the connection between opportunities and acts of help, changes the extent to which they produce extra milers. We pursue this study by using simulations, which allow us to witness the effects of varying crucial paramters in systematic ways. First, though, it is necessary to articulate again the idea of extra milers and long-run citizenship.

There are two phrases in the litarture that researchers have used to describe long-run citizenship: good soldiers and extra milers. Methot et al. (2017) state that good soldiers are people who characteristically engage in higher levels of OCB relative to their colleagues. They are people who provide more help, relative to others, in "characteristic" ways. Similarly, Li et al. (2015) operationalized extra milers as employees who provided the most (as rated by team members) OCBs at a given time point, even though their theoretical definition of extra milers were those that had this maximum score across repeated time points. How would these ideas manifest? What is implied in how the researchers describe, study, and label this phenomoneon – which we refer to here as long-run citizenship – is that some employees perform more OCBs than their peers and this effect has some form of consistency. At time t, the individual performs more OCBs than her colleagues, she does so again at time $t + 1$, again at $t + 2$, and this pattern continues until $t + n$, n being any future time point in which she is outdone by a colleague. The value of n that determines whether a person is labeled as an extra miler or not remains unspecified, as does the number of consecutive "wins" required. Said differently, it is unclear for how long someone must sit as the top citizen to be considered an extra miler, and it is also unclear whether the streaks must be consecutive or if someone who is frequently a top citizen but never the top citizen for more than two time points in a row merits the label. Our interest is not in providing a definition or argument about what truly does and does not count for employees to be labeled as extra milers by researchers or their managers. Our interest, instead, is on what kinds of streaks emerge given different random walk parameters and different assumptions about the relationship between opportunities and OCBs. What types of streaks, or consecutive "wins" by one colleague compared to another with respect to their helping behavior, do we witness under different random walks? Our research is the start to creating benchmarks that can be used in later research to determine what is really required to label something as exceptional.

Again, the purpose of study two is to assess patterns in long-run citizenship, or the extent to which one individual provides greater help compared to others across consecutive time points, based on different parameters applied to help requests. We use simulations for this study, and the computer models are structured as follows.

Simulation Heuristic

The simulation was designed to build off prior research examining chance models and accumulating processes in areas such as firm performance (Denrell, 2004; Polson & Scott, 2012). Imagine two employees, each collecting help requests according to a random walk. From t to $t+1$, each employee retains his or her stock of help requests but the pool increases or decreases by an amount drawn from a stochastic term, meaning that the value by which it increases or decreases is random at each moment. This structure exactly mimics the random walks identified in study one. At any given time point, help requests lead to helping such that the employee with the greatest number of opportunities provides the most help. Mathematically, if $(x_i, x_{i+1}, \ldots, x_n)$ represents the set of employees whose help requests we are tracking over time, with x_i being the focal employee, then x_i provides the most help at time t when $x_i > x_n$. We refer to the employee that provides the most help at a given time the “moment citizen,” which naturally embodies the idea of a single time point. The pattern that we monitor is the number of consecutive times employee x_i is the moment citizen, which ties back to the notions of good soldier and extra miler. Said differently, the ideas represented in how researchers have described good soldiers and extra milers manifests whenever employee x_i has long-run streaks of being the moment citizen, whereas if the moment citizen changes from time point to time point, such that no long-run streaks emerge, then the random walks produced no evidence of these labels. Ultimately, we are asking the broad question, *What types of long-run streaks do we witness when we vary the parameters on random walks?* We conducted synthetic experiments, or experiments within a computer program in which we wiggle key parameters and witness the output, to tackle this question. Moreover, the parameters that we manipulate stem from three research questions.

> Research Question 1: What are the patterns in long-run citizenship as the drift parameter on helping opportunities changes from 0 to 1?

Research question 1 was designed to address how trending help requests change the results. A trend or drift term is an essential property of a random walk, although not all random walks have drift. Drift, or trend, refers to whether the random walk moves systematically in the positive or negative direction over time, despite moving stochastically at each time step. Random walks without drift, conversely, move randomly from moment to moment but do not show positive or negative trend, unless cut short due to sampling limitations. Plotting the random walks from study one revealed that both types occurred, so it is necessary to evaluate how this characteristic informs our results. Moreover, an ever-growing amount of evidence (Braun, Kuljanin, & DeShon, 2013; Kuljanin, Braun, & DeShon, 2011) suggests that researchers need to account for the implications of stochastic trends in their content areas whenever effects are explored over time, so it is a crucial aspect to incorporate here.

> Research Question 2: What are the patterns in long-run citizenship as the autoregressive parameter on helping opportunities changes from 0 to 1?

One fundamental characteristic of random walks is that they have strong autoregressive effects. As this effect goes to zero, the trajectory approaches a white noise process, which is another fundamental stochastic trajectory. The difference is that white noise processes only move according to the error term – they contain no self-similarity from moment to moment. We examine this feature because (a) it captures the essence of what it means for opportunities to follow a random walk and (b) is consistent with growing calls to examine the implications of different strengths of self-similarity among dynamic trajectories (DISHOP HANDBOOK).

> Research Question 3: What are the patterns in long-run citizenship as the number of employees in the simulation increase from 2 to 1000?

Research question 3 was designed to assess how the size of the collective influences patterns in long-run citizenship. Organizational science has been and continues to be a science focused on individual differences and collectives. Nearly all studies in the organizational literature are multiple unit, meaning that they examine their effects across multiple people, teams, departments, or companies. This effect was therefore important to examine given the collective nature of our field.

Analysis & Results

[Fill after data collection]. [Some expected results shown in tables 1-3].

table 1 - data source, help opportunity operationalization, sampling frequency

Or I could just do code. Code for base simulation - how will the code change for rq1? - how will the code change for rq2? - how will the code change for rq3?

figure 1 - expected result from rq1 simulation

figure 2 - expected result from rq2 simulation

figure 3 - expected result from rq3

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