A GOOD SOLDIER OR RANDOM EXPOSURE? CHANCE OPPORTUNITIES AS AN ALTERANTIVE EXPLANATION OF FREQUENT CITIZENSHIP

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Imagine a close colleague who 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 frequent, exceptional levels of help. 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 (Dalal & Carpenter, 2018). 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 frequent, high-levels of OCBs are labeled “good soldiers” or “extra-milers” 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 motives and personality (Bellairs & Halbesleben, 2018; Grant, 2008; Penner, Midili, & Kegelmeyer, 1997), impression management (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 (Moorman, Brower, & Grover, 2018), fit (Kristof-Brown, Li, & Schneider, 2018), leader fairness (Piccolog, Buengeler, & Judge, 2018), and interaction quality with colleagues (Bolino, Hsiung, Harvey, & LePine, 2015), how employees appraise goals and pressures to perform (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 frequent, 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 is 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 frequent, 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 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 high frequency citizenship behavior.

Third, we answer recent calls for a better understanding of dynamics in the citizenship literature (Cronin & Vancouver, 2018; Dishop, Olenick, & DeShon, 2020). Dishop et al. (2020), 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.

Fourth, 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 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 (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 (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-Dominguez, 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 (i.e., the act) and not the other (i.e., the prompt).

The goal of this paper is to describe an alternative, chance model of sustained citizenship that incorporates opportunities and accumulation. Below, we describe the role of chance in long-run patterns, 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 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 frequent, exceptional behavior. Stated simply, study two reveals the parameters and assumptions required for random walks to produce what researchers have dubbed extra milers or good soldiers.

**The Nature of Chance in Long-Run Patterns**

In his book on chance, Leonard Mlodinow states, "A lot of what happens to us -- success in our careers, in our investments, and in our life decisions, both major and minor -- is as much the result of random factors as the result of skill, preparedness, and hard work. So the reality that we perceive is not a direct reflection of the people or circumstances that underlie it but instead an image blurred by the randomizing effects of unforeseeable or fluctuating external forces" (dunkard, p. 11). Streaks of success or loss, clusters of particles or agents, movement toward or away from an object -- these are all patterns that can appear systematic but may nonetheless emerge from nothing more than chance (vehicles). George Spencer-Brown, for instance, calculated that in a random series of 101000007 zeroes and ones, we should expect roughly 10 nonoverlapping sequences of 1 million consecutives zeroes. Random variations often create what looks like orderly patterns, appearing meaningful from one perspective but becoming spurious once the true mechanism is unveiled. Research has shown that people often fail to recognize chance in their observations (cites), cannot produce patterns consistent with chance (cite), and routinely misjudge events because they downplay its effect (cites).

The tension of determining whether a pattern is meaningful or random is deeply embedded in our lives and culture. In Hollywood, executives are evaluated based on the assumption that meaning can be culled from the random spikes and dips in box-office movie performance. Sherry Lansing, who was initially praised for successfully running the Paramount Motion Picture Group, was removed after the company's percentage-of-market-share demonstrated the following decreasing trend over six years: 11.4, 10.6, 11.3, 7.4, 7.1, 6.7 -- a streak which caused BusinessWeek to state that Lansing "may simply no longer have Hollywood's hot hand." In hindsight, researchers have argued that this sequence was far too short to adequately distinguish flawed decision-making from random fluctuations, a statement supported by follow up data demonstrating that the trajectory reverted back to its mean (Mlodinow, cite). Big Tech companies have also been confronted with the idea that randomness can produce seemingly systematic patterns. When Apple released the "shuffle" function on its early iPods, users complained after hearing songs by the same artist played back-to-back, believing that the function was not actually shuffling at random. According to Steve Jobs, the company then adjusted and made the feature "less random to make it feel more random" (p. 175). In sports, fans surrender their emotions to and make bets based on the perceived streakiness of their teams. Unfortunately for them, Tversky and colleagues demonstrated that the apparent streaks in basketball free-throws -- studied among the Philadelphia 76ers, Boston Celtics, and Cornell's mens and women's varsity teams -- exhibited no evidence of systematic behavior. A similar analysis with baseball conducted by E. M. Purcell led him to the conclusion that, "nothing ever happens in baseball above and beyond the frequency predicted by coin-tossing models" (p. 179). In gambling, the problem of divying up a jackpot according to true winnings rather than randomly allocating pieces to each player is one of the most longstanding issues to date, and it was first put into a mathematical framework by Pascal and Fermet, two pionneers of modern probability and statistics.

Separating meaning from chance is also embedded in the statistical architecture used across many scientific disciplines. Researchers often develop and present their work under the framework of hypothesis testing, an approach to conducting a study in which questions are asked, data are collected, and statistical models are applied all with respect to a single fundamental question about separating meaning from chance: what is the probability that a given hypothesis (usually called the "null") could have produced the result? Assuming that chance is the only factor operating, what is the probability of witnessing an observed result? Ultimately, the goal is to parse random, unsystematic variance from something meaningful. The same is true in measurement theory, which proposes that observations culled from an assessment contain both true and error score variance. Many of its core developments, including factor analysis, validity and reliability testing, latent score modeling, measurement equivalence, and differential item functioning (cites) were attempts to provide better appreciation of whether differences across test scores were meaningful or due to something random.

In the OCB literature, a long-run pattern has been identified, and researchers have argued that it is the result of something systematic. Researchers have placed their attention on a new “hot hand” effect, and the terms used to describe it include extra miler and good soldier. But in the same way that chance can produce seemingly systematic patters in domains as far-reaching as finance, sports, entertainment, and marketing, it is also possible that seemingly meaningful patterns identified in OCBs are due to a random process. It is therefore crucial to identify whether chance underlies this recent pattern.

**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 that 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, slower career advancement, and feelings of resentment among peers (Bergeron, 2007; Bergeron, Shipp, Rosen, & Furst, 2013; Bolino et al., 2018; Lennard & Van Dyne, 2018). 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 generalized compliance, or an impersonal sense of conscientiousness (Smith, Organ, & Near, 1983). These two dimensions were later deconstructed into altruism (responding to opportunities to assist a coworker), courtesy (responding with kindness), conscientiousness (on time, following rules, etc.), civic virtue (concern for the organization), and sportsmanship (tolerate less than ideal circumstances while maintaining a positive outlook) (LePine, Erez, & Johnson, 2002; MacKenzie, Podsakoff, & Podsakoff, 2011). Other researchers classify OCBs either as affiliative or challenging (Carpini & Parker, 2018). 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 an individual (OCB-I; helping, assisting, encouraging) versus organizational (OCB-O; promoting the company to others) dividing line.

In this paper, we refer to affiliative OCBs whenever we use the terms citizenship, helping, assistance, or OCB. This focus is necessary and appropriate for the following reasons. First, Li et al. (2018) 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) 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 (Organ, Podsakoff, & Podsakoff, 2011). 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.

**Frequent, Exceptional Citizenship: Extra Milers/Good Soldiers**

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 recurrent behavior, similar to a coin that appears to fall on heads more so than tails if one were to flip it two hundred times.

What accounts for frequently exceptional citizens? 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. (2017), point to predictors of good soldiers in the quote above: personality and prosocial values. We suggest an alternative: chance opportunities. Just as a series of coin flips could appear to favor heads even though the result was a byproduct of chance, reoccurring 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 stimulus, 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 (2018) 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 the 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, alongside 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 forum 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 helping prompts to mimic a random process, 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 form 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, 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 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:

(1)

where is the current value of , is the value of at , is a constant known as drift, and is a series with a mean zero and constant variance . 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 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 apparent in an alternative but equivalent form:

where is the initial value of , 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 will be used to assess Hypothesis 1. I plan to scrape data from several different Internet sources, 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 (), therefore I searched for platforms that contained data with large and that could be used to capture notifications for help.

**Data Sources**

**Issues on GitHub Repositories - Non-Academic**. The first set of data will be 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 I plan to collect are known as repository “issues.” When an individual posts a repository/project, other users can then download and use the code that he created. If other users want to ask questions, request features, or report bugs, they can then create an issue on the focal individual’s post, which automatically triggers a notification to the focal individual.

I plan to collect issues over time for four different software developers. That is, a single software developer has a repository that he or she maintains, and over time his or her repository has collected issues. All of the issues, from when the project first began until the most recent comment, will be collected and time-stamped. This process will then be repeated for another three software developers working in different industries on unrelated projects.

One of the repositories is source code for a functional computer language built to create web applications. Another is a compiler to convert declarative components into JavaScript. The third is an application which corrects console commands. The fourth is 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 are operationalized as issues. Data will be collected on (a) the date that the issue was posted and (b) when it was resolved, if ever.

**Issues on GitHub Repositories – Academic**. The second set of data I plan to collect is also based on GitHub repositories, but this time the repositories will be 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. I focus on the individual repositories of four academics, each a faculty member at a different university.

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

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

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

**Student Pools**. My fourth angle on help opportunities comes from graduate student pools. I plan to track the number of graduate students per year from the years 1999 to 2019 at three different graduate programs. One is a Political Science program located in the Northeast, another an Organizational Psychology department located in the Midwest, and the third an Accounting program in the Southwest. In this data set, a help opportunity are operationalized as an active graduate student – someone who could be mentored by a faculty – and I will collect data on the number of active graduate students per year for each department.

**Forum Posts** **& Questions**. Finally, I also plan to collect from an online forum. “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 are operationalized as a post, and posts will be collected daily from September, 2018 to September, 2019.

Table 1. *Data summary for Study one.*

A screenshot of a cell phone

Description automatically generated

A summary of the data sources is presented in Table 1. I plan to collect data across diverse platforms for several reasons. First, I want to ensure that my results are not unique to a given domain. Just as O’Boyle and Aguinis (2012) demonstrated performance power curves across various settings, my goal is to reveal random walks across various platforms. Second, I plan to collect data from several sources because each has its own limitation and strength. My hope is that something can be gleaned by taking a broad view across all of the data, even though each operationalization has its own unique error.

**Analysis**

All data will be structured as time-series such that a single unit is represented over successive time points. In total, there will be 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 forum. 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. [More description after data collection, such as the number of time points per data set]. For each data set, Hypothesis 1 is evaluated by assessing whether the series contains a unit root. I will use two unit root tests to evaluate my 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 will be administered. 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**

[Complete after data collection].

The results I plan to observe are presented in Table 2. For each data source, I will conduct both an ADF and KPSS test on the time series. When these two calculations suggest that the series does not contain a unit root, then there is evidence of a random walk present. The goal is to identify random walks across a majority of the OCB opportunity data sources.

Table 2. *Expected results for Study two.*

A screenshot of a cell phone

Description automatically generated

**Study 1 Discussion**

[This paragraph is example text, mimicking the structure of what this section will entail]

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. Hypothesis one predicted that help opportunities would follow a random walk. 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 , 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 citizenship. I take this evidence – that help opportunities follow a random walk – as a starting point for my next study.

Study 1 was a test bed for a particular idea.

Chance can produce (CEO’s example. Baseball example).

To what extent is chance present?

Identified chance

Now we need to identify its role

**Study 2**

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

There are two phrases in the literature that researchers use 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 have a tendency to help more than others. 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 was those who frequently demonstrated this maximum score. How would these ideas manifest? What is implied in how the researchers describe, study, and label this phenomenon is that an extra miler/good soldier is an employee who performs more OCBs than his or her peers and this behavior 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/good soldier, 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. Given that researchers use the words “frequency” and “tendency,” respectively, when describing extra milers and good soldiers (Lit et al., 2015; Methot et al., 2017), we focus on density within a time-span rather than consecutive streaks. That is, to be consistent with prior work we focus not on an employee being the top citizen for several steps in a row but on an employee being the top citizen for the greatest amount of time within a set. Given this lens, our goal is to document how manipulating the parameters on help requests changes the extent to which random walks yield extra milers/good soldiers. What types of extra milers emerge when we change the characteristics of the random walks governing how employees receive help opportunities? This research is the start to creating benchmarks and standards for what is required to label behavior as exceptional. Moreover, the manipulated parameters stem from three research questions – questions derived for both theoretical and statistical reasons. Before describing the research questions, though, it is informative to first explain the logic underlying the simulation.

**Base Simulation Heuristic**

The base simulation was designed to (a) build off prior research examining chance models and accumulating processes in areas such as firm performance (Denrell, 2004; Polson & Scott, 2012) and (b) remain consistent the idea of extra milers/good soldiers to the greatest degree possible. Imagine two employees, each collecting help requests according to a random walk. From to , 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. Formally, help opportunities for employee at time are , where are independently and identically distributed random variables with zero mean and finite variance. This structure exactly mimics the random walks identified in Study one. At any given time, help requests lead to helping such that the employee with the greatest number of opportunities provides the most help. Mathematically, if represents the set of employees whose help requests we are tracking over time, with being the focal employee, then provides the most help at time when . 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, consistent with the ideas of extra milers and good soldiers, is the frequency with which employee is the moment citizen across a discrete window of time. Specifically, let denote the number of times that the focal employee is the moment citizen. We ask, how likely is it that is close to , such that the focal employee is frequently the moment citizen, or the moment citizen across nearly all ? The backbone of the simulations is to examine the probability of different values of as produced by help request random walks. What is the probability that an employee is the moment citizen for times? This framework maps directly onto the notions of extra milers and good soldiers described above.

The research questions described below are queries regarding how changing any single aspect to this base simulation alters the extent to which opportunities produce extra milers/good soldiers, and again the questions were derived directly from relevant theory.

**Theoretically Derived Research Questions**

The first research question examines the extent to which help request random walks yield extra milers as the requests begin to drift. Drift refers to a random walk moving in a systematic direction – positive or negative – despite moving stochastically at each step. Random walks without drift (i.e., ), conversely, move randomly from moment to moment but do not produce positive or negative trend. The notion of drift is apparent in several theoretical lines of thinking with respect to OCBs. The double reinforcing spiral of trust and OCB (Moorman et al., 2018) suggests that employees mutually reinforce one another’s citizenship through their own actions and perceptions of trust. Over time, more trust begets more OCBs, and less trust begets less OCBs, producing a spiral (drift) either in the positive or negative direction. Although this idea was described in the context of helping acts rather than opportunities, it follows naturally that an employee who accumulates trust among his or her colleagues may also experience an increase in help requests, driving drift in the positive direction. For instance, prior research has shown that trust is related to an employee’s propensity to ask for advice (Hofmann, Lei, & Grant, 2009). Similarly, the circular model of job crafting proposed by Clegg and Spencer (2007) suggests that opportunities may drift up or down over time. After an employee crafts his or her position, he or she puts herself in a better position to perform his or her task well, be perceived as competent by his or her colleagues, and subsequently receive more opportunities to assist from others. The authors argue that a similar phenomenon may occur but in the negative direction when the employee fails to craft appropriately. Finally, leadership theory suggests that subordinates can experience spirals of abuse when they fail to implement coping strategies in efforts to alter the course of abusive supervision (Wee, Liao, Liu, & Liu, 2017). If this continues over time, abusive managers then perceive the subordinate as an out-group member (Dansereau, Graen, & Haga, 1975; Graen & Schiemann, 1978) which may reduce the number of possible opportunities to assist the subordinate is granted. According to each of these theoretical lines of thinking, OCB opportunities may move systematically up or down over time. Drift is also important to examine for statistical reasons. Trends – the manifest patterns of mechanisms that contain drift – are perhaps the most widely discussed issue leading to spurious inferences in the application of statistical models to time-series data (Braun, Kuljanin, & DeShon, 2013; Kuljanin, Braun, & DeShon, 2011). Across many disciplines, understanding the implications of trending data is a necessary first step because without this knowledge future empirical research evaluating more complicated models with elaborate directions of influence across many variables is more likely to find erroneous relationships (Granger, 1980, 1981).

[*Research question 1*]. What is the probability that employee spends *k* periods as the moment citizen as the drift parameter on helping opportunities changes from 0 to 1?

*[alternate phrasing]*: What is the probability of witnessing an extra miler as the drift parameters on helping opportunities change from 0 to 1?

Research question 2 examines the extent to which random walks yield extra milers as the requests lose memory. The base simulation described in the simulation heuristic assumes that opportunities accumulate – they compile from moment to moment and so changing the stock from a large to small value requires many time points. In such a situation, help opportunities obtained in a previous period have lasting effects in that they remain relevant at later times. The tension between long-lasting versus immediate effects is prevalent in several theories. Beginning with the former, the theory of cumulative advantage (Aguinis, O’Boyle, Gonzalez-Mule, & Joo, 2016) suggests that initial advantages such as OCB opportunities have lasting effects for employees, meaning that benefits in starting periods persist through time. The mechanisms that create lasting effects are numerous, and they include incumbency advantages (Saloner, Shepard, & Podolny, 2001), path dependency (Arthur, 1989), first-mover-effects (Lieberman & Montgomery, 1988), switching costs (Klemperer, 1995), resource development (Nelson & Winter, 1982; Dosi, 1988), lucky early detections (Barney, 1986), productivity multiplicity and ceilings (Aguinis et al., 2016), network effects (Gnutzmann, 2008), and Matthew effects (e.g., Vancouver, Li, Weinhardt, Steel, & Purl, 2016), but the core idea relevant to our purposes is that the probability of superior citizenship in current periods is largely driven by accumulated opportunities from previous periods rather than momentary affect, motives, or fairness perceptions. Similarly, Gersick’s punctuated model of equilibrium (1991) suggests that initial conditions persist such that any behaviors resulting from what the environment affords, such as help requests, continue across time until disturbed by a large enough force so as to break the inertia. Conversely, there are also models that draw attention to immediate effects such that opportunities obtained in the past become less relevant than opportunities obtained in recent periods. An employee may be more likely to react to immediate cues when deadlines change (Schmidt & Dollis, 2009; Schmidt, Dolis, & Tolli, 2009; ), when the specific and difficult goals in her surroundings are those that relate to her current rather than past behavior (Donovan & Williams, 2003; Donovan & Radosevich, 1998), or when past opportunities become liabilities and are avoided, which may occur due to mechanisms such as span of control (Thiel, Hardy, Peterson, Welsh, & Bonner, 2018). In statistics, the continuity of a variable or the extent to which it persists/has inertia is known as autoregression. Alongside the theoretical arguments above, varying the autoregressive parameter is also important statistically because it reveals the implications of changing the underlying effect from a random walk to its sibling stochastic process: white noise. A white noise trajectory is another fundamental stochastic process from probability theory, but the difference is that it moves only according to the error term – it contains no self-similarity from moment to moment. Varying the autoregressive term allows us to waive our microscope over multiple perspectives, from theories of persistence and continuity to those of immediacy and urgency, and from the mathematics of random walks to those of white noise.

*Research Question 2*: What is the probability that employee spends *k* periods as the moment citizen as the autoregressive parameters on helping opportunities change from 0 to 1?

*[alternate phrasing]*: What is the probability of witnessing an extra miler as the autoregressive parameters on helping opportunities change from 0 to 1?

Research question 3 was designed to assess how the size of the collective influences the results. Organizational science has been and continues to be a science focused heavily on differences across people and collectives. Nearly all studies in the organizational literature are multiple unit, meaning that they examine their effects over multiple people, teams, departments, or companies (Scandura & Williams, 2000). Moreover, a persistent theme throughout our literature is the idea that a core aspect of what it means to study organizational science is to focus on effects as they operate in collectives. In its centennial special issue, the *Journal of Applied Psychology* published a series of papers on areas such as training (Bell, Tannenbaum, Ford, Noe, & Kraiger, 2017), turnover (Hom, Lee, Shaw, & Hausknecth, 2017), climate and culture (Schneider, Gonzalez-Roma, Ostroff, & West, 2017), work design (Parker, Morgeson, & Johns, 2017), teams (Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017), safety (Hofmann, Burke, & Zohar, 2017), and leadership (Lord, Day, Zaccaro, Avolio, & Eagley, 2017), among others, and most identified a strong tendency for research to examine context and the nature of their phenomena embedded in organizational systems. Some of the core topics that have created lasting debates in our field, such as issues of level (Klein, Dansereau, & Hall, 1994), the unit problem (Freeman, 1980), and the notion of an emergent property being different from its individual parts (Campbell, 1958), arise due to our fundamental focus on collectives. Finally, several reviews (Kozlowski & Ilgen, 2006; Marks, Mathieu, & Zaccaro, 2001; Mathieu, Tannenbaum, Donsbach, & Alliger, 2014) have concluded that much of the work in today’s organizations occurs in the context of teams such that multiple agents operate simultaneously with complex workflows. This effect was therefore important to examine given the field’s emphasis on collectives.

*Research Question 3*: What is the probability that employee spends *k* periods as the moment citizen as the number of employees in the simulation increases from 2 to 800?

*[alternate phrasing]*: What is the probability of witnessing an extra miler as the number of employees in the simulation increases from 2 to 800?

**Analysis & Expected Results**

Simulations will be completed in Julia. The Figures on the following pages demonstrate the type of plots I will create to evaluate the results. Figure 1 will contain data from the base simulation. Figure 2 will contain data evaluating RQ1. Figure 3 will contain data relevant to RQ2, and Figure 4 will contain results relevant to RQ3. The syntax for running the simulations can be found in the supporting HTML file.



*Figure 1.* Probability that employee *xi* spends *k* periods as the moment citizen. Greater probabilities at extremes (*k* ≠ 10) indicate extra milers/good soldiers. [Expected pattern plotted, not the expected values of the actual probabilities]

Expected results for the base simulation are plotted in Figure 1. The base simulation evaluates the extent to which employee *xi* spends *k* periods as the moment citizen, and greater probabilities near extremes, meaning where *k* is less than 5 or greater than 15, indicate extra milers/good soldiers. The reasoning for this expected result is as follows. In a single simulation run, an extra miler/good soldier emerges if the focal employee spends few or many periods as the moment citizen. In other words, if employee *xi* is the moment citizen for 19 time points out of 20, then he or she emerges as the extra miler/good soldier for that single simulation. Similarly, if employee *xi* is the moment citizen for 2 time points out of 20, that means the other employee emerges as the extra miler/good soldier for that single simulation run. In either situation, one employee is most frequently the person providing the greatest number of OCBs. In the cases just described, *k* would equal 19 when the employee spends 19 time points out of 20 as the moment citizen, and *k* would equal 2 when the employee spends 2 out of 20 time points as the moment citizen. In either case, one employee out of the set demonstrates frequent, exceptional citizenship, meriting the label “extra miler.” In situations where the focal employee spends roughly half the time points as the moment citizen (*k* = 10), no extra miler/good soldier emerges because neither employee spends a majority of the time, relative to the other, contributing exceptional OCBs.

The cases just described were single runs through the simulation. On subsequent runs, the focal employee might spend 4 time points out of 20 as the moment citizen (*k* = 4), or 10 time points out of 20 (*k* = 10) as the moment citizen. If you continue to repeat runs for 1000 replicates, each capturing how many times employee *xi*spends as the moment citizen, then you can capture the probability of different values of *k*, which is what Figure 1 will reveal. Any single simulation run is one tally toward a given value of *k*, and after 1000 replicates each tally is divided by the number of simulation runs (1000) to turn tallys into probabilities. When the probability of *k* = 20 is high relative to the probability that *k* = 10, that indicates that the most likely run through a single simulation is one in which the employee spends all time points as the moment citizen (and is therefore the extra miler). Similarly, when the probability of *k* = 0 is high relative to the probability that *k* = 10, that indicates that the most likely run through a single simulation is one in which the employee spends no time points as the moment citizen (and therefore the other employee is the extra miler). As shown, the results I expect are large probabilities near extreme values of *k* and small probabilities near values of *k* = 10. If this pattern emerges, then the base simulation provides evidence of random walks producing extra milers/good soldiers.

Results from the base simulation will serve as a benchmark to subsequent simulations evaluating RQs 1, 2, and 3. I do not have predictions about what will emerge by changing the parameters described in RQs 1, 2, and 3, which is why they were presented as questions rather than hypotheses, but the type of plots I will create are shown without data below. Overall, the goal is to assess how the results from Figure 1 do or do not change after manipulating a crucial parameter in the simulation.



*Figure 2.* Probability that employee *xi* spends *k* periods as the moment citizen as the drift parameter changes from 0 to 1. Greater probabilities at extremes (*k* ≠ 10) indicate extra milers/good soldiers. [Evaluating research question 1].



*Figure 3.* Probability that employee *xi* spends *k* periods as the moment citizen as the autoregressive parameter changes from 0 to 1. Greater probabilities at extremes (*k* ≠ 10) indicate extra milers/good soldiers. [Evaluating research question 2].



*Figure 4.* Probability that employee *xi* spends *k* periods as the moment citizen as the number of employees changes from 2 to 800. Greater probabilities at extremes (*k* ≠ 10) indicate extra milers/good soldiers. [Evaluating research question 3].

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