

A GOOD SOLDIER OR RANDOM EXPOSURE? A STOCHASTIC ACCUMULATING  
MECHANISM TO EXPLAIN FREQUENT CITIZENSHIP

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## ABSTRACT

### A GOOD SOLDIER OR RANDOM EXPOSURE? A STOCHASTIC ACCUMULATING MECHANISM TO EXPLAIN FREQUENT CITIZENSHIP

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The term, “good soldier,” refers to an employee who exhibits sustained, superior citizenship relative to others. Researchers have argued that this streaky behavior is due to motives, personality, and other individual characteristics such as one’s justice perceptions. What is seldom acknowledged is that differences across employees in their helping behavior may also reflect differences in the number of requests that they receive asking them for assistance. To the extent that incoming requests vary across employees, a citizenship champion could emerge even among those who are identical in character. This study presents a situation by person framework describing how streaky citizenship may be generated from the combination of context (incoming requests for help) and person characteristics (reactions to such requests). A pilot web-scraping study examines the notifications individuals receive asking them for help. The observed empirical pattern is then implemented into an agent-based simulation where person characteristics and responses can be systematically controlled and manipulated. The results suggest that employee helping behaviors, in response to pleas for assistance, may exhibit sustained differences even if employees do not differ *a priori* in motive or character. Theoretical and practical implications, as well as study limitations, are discussed.

I dedicate this dissertation to four family members who made my education possible. To Jim and Ruth Dishop, whose repeated financial support allowed me to attend some of the best institutions in the country. To Russ and Carol Shook, whose presence during my childhood gave me a sense of purpose and perspective. Thank you all.

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## INTRODUCTION

Organizational citizenship behaviors (OCBs) have been the focus of extensive scholarship among researchers and practitioners for more than 4 decades. Citizenship behaviors are actions conducted by employees that are discretionary and not necessarily associated with specific job requirements (Organ, 1988), and they include behaviors such as helping colleagues after being asked for assistance or accommodating the work schedules of others. 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 critical lubricants enhancing the social machinery of organizations (Bolino, Turnley, & Bloodgood, 2002; Organ, Podsakoff, & MacKenzie, 2005). Many studies document both the positive and negative outcomes of citizenship for individuals and collectives (Bergeron, 2007; Bergeron, Shipp, Rosen, & Furst, 2013; Podsakoff, Whiting, Podsakoff, & Blume, 2009; Podsakoff, MacKenzie, Paine, & Bachrach, 2000).

One topic of recent interest in this literature is a pattern which has been articulated using terms such as “extra miler” and “good soldier” (Li, Zhao, Walter, Zhang, & Yu, 2015; Methot, Lepak, Shipp, & Boswell, 2017). These labels refer to an employee who consistently offers more help than his or her colleagues – across an unspecified amount of time, he or she is typically one of the employees offering the greatest number of OCBs. The presumed causes of this behavior are individual characteristics. Methot et al., (2017), for instance, argue that personality and prosocial motives are the research-supported causes of this pattern. Stated simply, an extra miler/good soldier exhibits sustained, superior citizenship due to his or her disposition or attitude (e.g., Chiaburu, Oh, Berry, Li, & Gardner, 2011). This emphasis on individual characteristics is similar to the commonly identified predictors of OCBs in general, which include one’s

propensity to be concerned for others, personality, prosocial motives, impression management, job satisfaction and commitment, perceptions of trust, fit, fairness, and ostracism (Bellairs & Halbesleben, 2018; Grant & Mayer, 2009; Ferris et al., 2019; Kristof-Brown, Li, & Schneider, 2018; Meglino & Korsgaard, 2004; Organ & Ryan, 1995; Piccolo, Buengeler, & Judge, 2018), and, at the within-person level, one's positive affect, engagement, and perceptions of justice or supervisor support (Christian, Eisenkraft, & Kapadia, 2015; Dalal, Lam, Weiss, Welch, & Hulin, 2009; Glomb, Bhave, Miner, & Wall, 2011; Ilies, Scott, & Judge, 2006; Lin, Savani, & Ilies, 2019; Matta et al., 2020). Indeed, Bolino (1999) and Bolino et al. (2002) state that there is a consensus that OCBs stem from dispositions, motives, and fairness perceptions.

There are three underdeveloped areas within the research on extra milers/good soldiers that the current study attempts to address. First, one way to view this literature is from the perspective of the fundamental attribution error (Gilbert & Malone, 1995; Ross, 2001) such that it is driven largely by person-oriented effects and, at times, downplays the role of the situation. Relative to the person-oriented studies, little research has investigated how the observed pattern – a tendency for an employee to be among the top citizens – may be a function not only of the individual but also his or her interaction with the situation. Exceptions exist in the fit and job embeddedness literatures, but even there the emphasis is on individual perceptions rather than objective indicators of some environmental variable (Holtom & Sekiguchi, 2018; Rich, Lepine, & Crawford, 2010; Vogel & Feldman, 2009). Focusing on the person by situation interaction is necessary because the same behaviors that yield a pattern in one situation may manifest something new when circumstances change.

Second, but related to the notion of a person by situation interaction, the conversation surrounding extra milers is missing an appreciation of the pleas for help that employees receive

over time. In their cornerstone paper describing its dimensions, Smith, Organ, and Near (1983) state that many forms of OCB occur after a stimulus 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. Requests are necessary to examine for several reasons. They create a baseline for employees to react to, with some employees potentially receiving many more than others. They have the potential to change whether a given amount of help should merit the label “extra miler” or “good soldier” (e.g., the same amount of help looks different if it follows 2 versus 12 requests for assistance). And several authors (Bamberger, 2009; Ehrhart, 2018) state that most acts of affiliative citizenship happen after a plea to do so. Cain, Dana, and Newman (2014), for instance, argue that a substantial amount of prosocial behavior is prompted by appeals from others.

Third, just as the person-oriented effects occupy the foreground of this literature, researchers have tended to examine the systematic while neglecting the unsystematic. Moreover, researchers sometimes imply that systematic patterns – i.e., extra milers or good soldiers – cannot be produced by unsystematic causes, an idea that runs counter to the growing research on chance and random processes (Liu & de Rond, 2016). To appreciate this assumption, it is useful to describe a study by Bolino, Hsiung, Harvey, and LePine (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 it is unreasonable to expect (1) motives to be completely stable over time and (2) good soldiers, or employees that exhibit greater OCBs relative to their peers, to always be good. They then demonstrate that motives do show within-person variance, and that they correlate with OCBs. What these authors imply is that sustained,

exceptional citizenship (i.e., long-run “streakiness”) is unlikely when there is within-person instability 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 (random) processes, particularly the notion that no systematic variance in the cause is required to produce what looks like long-run stability in the outcome (Henderson, Raynor, & Ahmed, 2012). If the cause is random and unsystematic, it is still possible – and in some cases extremely likely – that the response process contains systematic patterns in the form of long-run streaks. What this means for the citizenship literature is that it is necessary to understand the role of randomness because the core idea underlying the notions extra miler and good soldier is that employee behaviors exhibit streakiness – a pattern which we know to be a possible byproduct of chance.

To make progress toward these areas, the current research asks how extra milers/good soldiers might be generated from a situation by person interaction. I draw from Simon (1955) to describe the framework, from citizenship theory and stochastics to reason about the movement of help requests over time, and from theories of compliance and conformity to consider employee reactions to solicited help. This research takes a generative, computational perspective focusing on simple mechanisms that yield an emergent pattern. Understanding the processes through which sustained citizenship arises offers an alternative perspective to the current literature and urges caution to managers when inferring motive from observed behaviors. The explanation offered here is unique because it does not rely on effects that *ex ante* bias individuals in the direction of the outcome to be explained. That is, frequent citizenship – a manifest pattern – can be generated from mechanisms that are not obviously congruent with the pattern itself, such as a prosocial motive.

The current effort focuses on OCBs solicited by requests rather than unprompted OCBs because (a) the goal of this research is to explain the emergence of good soldiers through the combination of requests and responses, (b) many researchers have stated that affiliative OCBs, which are often reactive, should be thought of as the core manifestation of citizenship (Li, Frese, & Haidar, 2018; Van Dyne, Cummings, & Parks, 1995; Smith et al., 1983), and (c) affiliative helping behaviors have “been identified as an important form of citizenship behavior by virtually everyone who has worked in this area” (Podsakoff et al., 2000; p. 516). That said, I acknowledge that OCBs can and do occur without a plea for help. No rule demands that an employee must be solicited by a request to challenge a dominant perspective in a meeting, offer suggestions to newcomers, or actively change protocols. Entire articles, book chapters, and careers have been dedicated to documenting the importance of what are known as challenging OCBs – behaviors which are proactive, unprompted, and disrupt current processes. It is a limitation of this study that I focus only on solicited help. I do so because a dominant perspective among citizenship scholars is that OCBs commonly manifest as affiliative actions.

### **The Citizenship Domain**

The idea that for a collective to succeed its employees must not only accomplish tasks but also promote the social functioning of the group has been around for decades. Researchers in psychology, management, education, human resources, organizational behavior, and sociology have all dedicated considerable time to exploring the nature of cooperation among those who work together. In organizational psychology, the term used to capture employee cooperation has come to be known as organizational citizenship behavior. 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 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).

Similar concepts were explored by theorists eight decades ago. Chester Barnard (1938), in *The Functions of the Executive*, noticed that company success often depended on employee activities that were not listed in protocols, job descriptions, or business memos. He used the word “informal” to describe such undocumented but useful behaviors. Roethlisberger & Dickson’s (1939) account of the Hawthorne studies explained the difference between formal and informal employee behaviors by introducing the notion of “sentiments” – an idea similar to what we would now call employee attitudes. Katz and Kahn (1966), in their presentation of organizations as open systems, often referenced “spontaneous contributions,” or cooperative acts not explicitly described in job descriptions or managerial directives.

With these concepts in hand, Dennis Organ, with a publication in the *Academy of Management Review* in 1977, placed the seed for what would become a long stream of research on OCBs. His paper described the following tension. Industrial and organizational psychologists had reached a consensus in the early 1970s that employee satisfaction, although important as a construct, was not a strong determinant of productivity. Study after study demonstrated a weak association when satisfaction was examined as a predictor of individual performance (Brayfield & Crockett, 1955; Cherrington et al., 1971; Lawler & Porter, 1967; Viteles, 1953). On the other hand, managers and union leaders – who had experiences observing real employees at work – continued to believe that the relationship existed, and that it was strong. Gannon and Noon

(1971), for instance, surveyed practicing managers and union officials and showed unprecedented agreement with the statement, “a satisfied worker is a productive worker.” Organ saw OCBs as the answer to this riddle. Managers, perhaps, had a broader, multidimensional sense of performance – one that was not being captured in empirical studies. Productivity and effectiveness, to leaders and union officials, perhaps meant more than simply “measurable time on task and output.” Organ proposed that managers may also include something similar to what Katz and Kahn called spontaneous contributions. He suggested that what managers really mean when they say “a happy worker is a productive worker” is that employees offer subtle gestures to sustain the workplace cooperative system. What was needed, then, was a dependent variable capturing not only measurable output but also nuanced actions of support among colleagues.

Following Organ’s theoretical work, measures were developed to capture this new construct. Tom Bateman, Organ’s graduate student, created surveys of quantitative (productivity) and what he termed qualitative performance (citizenship). Clare Ann Smith, another graduate student, followed with a second, comprehensive assessment capturing a multi-factor model of OCBs. Research examining additional dimensions, predictors, and outcomes of OCBs then began to blossom. At roughly the same time, Motowidlo and colleagues were publishing papers on what they called contextual performance (CP), or behaviors that support the broader social and psychological environment such as volunteering for activities, helping and cooperating with others, or endorsing organizational objectives (Borman & Motowidlo, 1993; Motowidlo & Van Scotter, 1994). As is obvious, OCB and CP overlap considerably, and both research streams shared a similar goal: to more finely partition the performance domain. They differed in the predictors that they examined – one group focused on personality (Motowidlo and colleagues;



CP) whereas the other focused on satisfaction as a predictor (Organ and colleagues; OCB).

Today, CP has been subsumed within OCB.

Since the OCB concept was first developed and reported in two articles in the early 1980s (Bateman & Organ, 1983; Smith, Organ, & Near, 1983), the amount of interest paid to OCBs has dramatically increased. As reported in Podsakoff et al. (2018), of the over 4900 articles published in the literature on OCB and related constructs from 1983 to 2017, approximately 80% have been published within the past 10 years, and over half (51%) have been published in just the past 5 years. In addition, some of the most highly cited articles in organizational psychology have focused on OCB.

### **Current Citizenship Research and Dimensions**

Researchers typically pursue one of three ways to partition 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 et al., 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 use the terms affiliative and challenging to partition OCBs (Carpini & Parker, 2018). Affiliative behaviors are actions which support existing company processes such as helping a coworker or responding to a work issue with courtesy. Challenging behaviors, conversely, are actions which are disruptive – the employee initiates change, actively adjusts his or her circumstances, voices problems, or adds new protocols into the system. Finally, OCBs are also divided along an individual (OCB-I;

helping, assisting, encouraging) versus organizational (OCB-O; promoting the company to others) dimension (e.g., Dalal, 2005).

In this dissertation, I refer to affiliative acts whenever I 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 link between prompts for help and reactions to those prompts. For all of these reasons, this study couches itself within the affiliative space of the construct.

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-analyses 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 citizenship 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).

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

Recently, researchers have shown an interest in extra milers/good soldiers – both of which refer to the idea that some employees repeatedly exhibit greater OCBs compared to their peers. Li et al. (2015), for instance, studied manufacturing teams in China and examined what they called “extra milers,” or employees who frequently contributed more OCBs relative to other team members. Specifically, extra milers were defined as team members who exhibited high

frequency extra-role behaviors (e.g., helping). It was operationalized as the team member with the maximum score on other-team-member-rated surveys of OCBs. 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. The measures they employed, though, only captured OCBs at one period. Nonetheless, the researchers were clearly interested in the notion of repeated, exceptional citizenship. 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). Their article explains the connection between employee life events and citizenship behaviors. 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, the terms good soldier and extra miler refer to employees that “characteristically” engage in OCB. These employees outdo the citizenship of 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? Methot et al. (2017), in their quote above, argue for the importance of individual characteristics. They call attention to predictors such as prosocial values and personality. This sentiment echoes other literature examining OCB antecedents. The most commonly identified determinants of OCBs include motives, affect,

attitudes, fairness perceptions, and engagement. In an early meta-analysis, for example, OCBs correlated with satisfaction, perceived fairness, perceptions of leadership support, and conscientiousness (Organ & Ryan, 1995). Later meta-analyses documented relationships between OCBs and (a) other personality facets such as openness to experience (Chiaburu, Oh, Berry, Li, & Gardner, 2011), as well as (b) more nuanced perceptions of leader behaviors (Ilies, Nahrgang, & Morgeson, 2007). Indeed, a vast amount of literature documents relationships between various individual characteristics and citizenship (e.g., Grant & Mayer, 2009; Ferris et al., 2019; Kristof-Brown, Li, & Schneider, 2018; Lin, Savani, & Ilies, 2019; Matta et al., 2020).

I suggest an alternative: some employees may exhibit frequent citizenship not because they are driven by unique motives, were raised on different values, or have a disposition that pushes them toward altruism, but because they receive requests in ways that differ from their colleagues. Over the course of a week, employees acquire pleas for assistance from collaborators and coworkers. Although individuals certainly differ in character, the simple fact that each may not receive the same number of requests by itself establishes unequal opportunity across the collective. As employees accumulate requests, one will emerge as the champion citizen – a good soldier – if he or she realizes and reacts to the greatest share of incoming requests. This does not mean that those with many requests always offer the greatest amount of help – it is possible for the opposite to be true. What matters is that some combination of how requests are arriving and how individuals respond may yield an emergent pattern in which one or few employees continually offer more OCBs than others. Even if employees are identical in character, motive, and personality, one may emerge as the leading cooperator because he or she receives and reacts to the greatest share of requests for help. It is therefore necessary, I suggest, to understand the role of both context (requests) and persons (reactions).

### **Theoretical Framework: Person x Situation Interaction**

Many theories propose that employee behaviors are the result of an interaction between agents and their environment. Lewin's (1951) now famous assertion that behavior is a function of both persons and situations led to a flurry of personality theories examining person by situation interactions (Cognitive affective systems theory; trait activation theory; whole trait theory; Fleeson & Jayawickreme, 2015; Mischel & Shoda, 1995; Tett & Guterman, 2000). Murray's system of needs, which describes internal (needs) and external (presses) causes of behavior but "above all emphasizes the interaction between the two" (Epstein, 1979, p. 652), is the foundation for several need-based models such as self-determination theory (Deci & Ryan, 1980). The notion that behavior arises from the combination of one's tendencies and circumstances is also described in theories of self-regulation (Dawis & Lofquist, 1978; DeShon & Gillespie, 2005). Similarly, Blumberg and Pringle (1982) petitioned to add opportunities to motivation and ability as key determinants of job performance because the environment can either enable or constrain performance (Johns, 2018; Stewart & Nandkeolyar, 2006). In the citizenship literature, researchers have examined person by environment effects but often from the perspective of fit or compatibility such that there is a perceived match between, say, one's values and those enacted by the organization (Kristof-Brown et al., 2018).

The current research uses Simon's simple rules model (DeShon & Rensh, 2009; Simon, 1955) as a theoretical starting point and builds from his account of the person by situation interaction. Across a number of papers, theories, and normative models (Simon, 1956, 1991, 1992), Simon argues that to understand the behavior of an agent it is necessary to describe (1) how goal-relevant objects are distributed around it and (2) the rules it uses to select courses of action. His framework suggests that a behavior may arise due to the objects employees are

confronted with and the mechanisms they use to select a response. The behavior that this study focuses on is the idea of a good soldier (extra miler). Applying Simon's framework to affiliative helping suggests that, over time, an employee exhibiting extra miler behavior may arise from the combination of the requests she receives and her responses to those requests. That is, requests for assistance (situation) interact with employee reactions (person) to yield a pattern (extra milers/good soldiers).

### **Situation – Requests Over Time & Sustained Lead**

A request is defined as a notification 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; An employee hears an announcement from a manager that volunteers are needed for an upcoming assignment; 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 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 indicator 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.

Requests for help are related to ideas elsewhere. Entrepreneurs respond to opportunities to enter the market (Short, Ketchen, Shook, & Ireland, 2010). Employees enact job performance after being triggered by what Stewart and Nandkeolyar (2006; 2007) call situation enabling factors. Safety reminders stimulate safety behaviors (Komaki, Barwick, & Scott, 1978).

Questions that interrupt a training intervention and prompt self-regulatory activity improve learning and performance (Sitzmann & Ely, 2010). Prompts are also examined in selection (Levashina, Hartwell, Morgeson, & Campion, 2014), forensic interviews (Sternberg, Lamb, Orbach, Esplin, & Mitchell, 2001), and in event-sampling methodology where they are used to improve participant survey responding (Laurenceau & Bolger, 2005; Shiffman, 2009).

What is missing in these other areas that becomes relevant as we consider requests over time is a discussion of sustained lead: some employees may consistently receive greater or fewer requests than others. The notion of sustained lead is well-known in literatures focusing on stocks other than requests (e.g., finance, strategy, mechanics; Denrell, 2004; Akimoto, 2008; Henderson et al., 2012; Shreve, 2004). It has not received attention in the citizenship space because studies do not often capture how requests accumulate over time (Ehrhart, 2018). Instead, most examine how to appropriately phrase a single, one-time plea (Cain et al., 2014), leaving the idea of a stockpile unspecified. An employee's pool of requests may change or stay the same as she moves throughout her week. Due to this fluidity, the size of her pool may be larger or smaller than her colleagues. Larger on some days; smaller on others, or vice versa. Sustained lead refers to a situation in which the rank order of a set of stocks remains stable over time. Applied to help requests, this would mean that employees with the most requests at time  $t$  also tend to be the employees with the most requests at  $t + 1$ ,  $t + 2$ , and so on. It captures the stability of relative positions, and it is worth considering for the following reason. If sustained lead occurs with requests, it establishes a situation where some employees continually experience more requests than others. It does not guarantee action but creates an environment with unequal opportunity. Recall that the core idea underlying extra milers/good soldiers is that some employees repeatedly



exhibit more citizenship than their colleagues. Sustained lead may be one factor gently pushing in that direction. Of course, it also depends on how employees respond.

Simon's (1955) situation by person framework suggests that the arrangement of objects in a person environment is one aspect influencing his or her behavior. In this research, I use requests over time and sustained lead to specify this broad idea. There are two schools of thought regarding the mechanisms of sustained lead: the random and the systematic.

### ***The Random School of Thought***

Probability theory and stochastics (Basu, 2003; Jaynes & Bretthorst, 2003; Lévy, 1940) offer two features that are sufficient to yield sustained lead whenever they occur in tandem. These include inertia and randomness.

#### **Inertia.**

Inertia refers to the self-similarity of a variable from one moment to the next (Cronin & Vancouver, 2020). It can be thought of as conservation or persistence in the sense that the state retains its condition until something changes it. When an employee accumulates help requests with inertia, this means that he or she 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 three help requests today, this number is added to the store of 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.

### **Randomness.**

The second feature is the extent to which requests compile randomly. The idea that chance has a stronger effect on people's lives than given credit for is expressed in social theory (Bandura, 1982; Dew, 2009; Weiss & Cropanzano, 1996), probability theory and mathematics (Dobrow, 2016), and among popular press (Mlodinow, 2008; Taleb, 2005). In the current research, the notion of randomness is drawn from the chance perspectives presented in Denrell, Fang, and Liu (2014) and Liu and de Rond (2016). An employee that accumulates requests randomly means that the likelihood of receiving a request or having a request removed is pulled from a probability distribution such that both are equally likely. It is a coin-flip whether requests join or leave. Mathematically, an employee's stock adds or subtracts requests based on a draw from a distribution with  $N(0, \sigma^2)$ .

Probability theory demonstrates that a set of trajectories (e.g., requests over time for multiple employees) exhibiting both inertia and randomness generates sustained lead. In simple terms, there is a high probability that one employee will consistently have more requests than another if requests compile randomly with inertia. If inertia is not present, however, sustained lead does not occur (Table 1).

### ***The Systematic School of Thought***

Other theories offer non-random sources of sustained lead. The principle of cumulative advantage (Aguinis, O'Boyle, Gonzalez-Mulé, & Joo, 2016) suggests that small benefits received during early periods fuel large gaps between "haves" and "have nots" at later stages. The mechanisms that create lasting advantages are numerous, and they include incumbency

effects (Saloner, Shepard, & Podolny, 2001), path dependence (Arthur, 1989), first-mover-effects (Lieberman & Montgomery, 1988), switch costs (Klemperer, 1995), resource developments (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). Due to any combination of these features, employees may exhibit sustained differences in their resource pools (such as requests for help). Social capital theory (Adler & Kwon, 2002; Galunic, Ertug, & Gargiulo, 2012; Nahapiet & Ghoshal, 1998) also captures the idea of preserved differences in pools. Some individuals accrue large stores of social capital and are therefore differentially exposed to a whole host of aspects, some of which include information, social support, direct and indirect contacts, cutting-edge technology, trust, diverse perspectives, and unique communities (Hansen, 1999, Inkpen & Tsang, 2005; Reinholt, Pedersen, & Foss, 2011; Seibert, Kraimer, & Liden, 2001). Due to this exposure, then, employees with greater social capital may persistently receive more requests than others.

Although I return to cumulative advantage and social capital in the Discussion, this research focuses on the random perspective for the following reasons. First, one purpose of this study is to counter the reasoning by Bolino et al. (2015) – to demonstrate that unsystematic factors can lead to systematic outcomes. As stated, their research takes the perspective that instability in the presumed causes of citizenship implies instability in citizenship itself. The current study suggests that, even when an underlying cause of citizenship is unsystematic, the observed behavior may still exhibit systematic patterns. Randomness is the quintessential form of an unsystematic effect, making it necessary to include to demonstrate this point. Second, Bandura's theory of chance factors (1982) suggests that randomly occurring events often have a

significant influence on behavior. This sentiment is echoed in several discussions of stochastic processes (Ross, 2014; Tijms, 2012). For at least some subset of employees, the requests they receive may follow a random pattern. From a different perspective, Liu and de Rond (2016) suggest that, even when a system is non-random, embedding randomness as a first principle into one's research is necessary when the object of study – requests for help in this case – is influenced by many uncontrollable forces. Help requests may come and go because of serendipity, luck, or determinants that employees themselves do not cause. Moreover, the true causes of arrivals and departures may not be random at all. What Liu and de Rond (2016) propose is that when many such effects operate on a stock then randomness can be an appropriate perspective because observed data on the stock itself will appear random. Fourth, Denrell et al. (2014) argue that randomness should be the theoretical starting point whenever research examines accumulating trajectories in a new domain. Most research on compliance (see below) examines a single plea. This study, instead, takes a small step in the direction toward considering requests that accumulate over time. Following Denrell et al.'s (2014) recommendation, I start with randomness because little research exists on request stockpiling. Fifth, the schools of thought need not be orthogonal – at least in the context of this research. The random and systematic schools explain accumulating through different causes, but they make the same predictions in the current study regarding whether or not good soldiers emerge. This point is easier to articulate after describing the full theoretical framework, so I return to it in the Discussion.

The last reason is the most important: randomness can be an appropriate perspective at a given level of analysis. One component in this research is the concept of a help request trajectory: a time-series representing one's store of requests that can fluctuate up or down at each

step. Although little research exists on these specific trajectories, there is a massive literature showing that randomness may appear whenever studies examine accumulating trajectories. In economics, financial and visitor arrival trajectories exhibit randomness (Bhattacharya & Narayan, 2005; Cooper, 1982). In biology, foraging and movement trajectories exhibit randomness (Hill & Häder, 1997). In psychology, memory search and decision trajectories exhibit randomness (Hills, Jones, & Todd, 2012; Reike & Schwarz, 2016). None necessarily imply a fundamentally stochastic world, only that random movement exists at the level of an observed trajectory. Many trajectories captured in time-series data manifest random patterns – the same may occur for help requests. This does not mean that if we were to zoom-in on a lower level of analysis that the elements of the system would be random. They may not be. Everything underneath could in fact be non-random. The current research, though, is at a higher level of analysis focusing on the trajectory itself. At this zoomed-out level of analysis (Zaheer, Albert, & Zaheer, 1999), trajectories often express random movements. That is, despite non-random origins an observed trajectory at a higher level of analysis can fluctuate randomly from one time point to the next. A pool of help requests is one such “higher level” trajectory. For this reason, randomness isn’t something to be shunned but understood. By taking the random perspective, therefore, I am not suggesting that received help requests are fundamentally random, but that random movement may exist at the level of an observed trajectory. To the extent that random fluctuations appear in data, randomness is a meaningful perspective. A pilot study reported below addresses whether there is evidence of randomness in request trajectories.

The notion that trajectories with inertia and randomness exhibit sustained lead was originally expressed using Paul Levy’s arcsine law but it is now commonly referred to as the law of long leads in random processes. Sustained leads have been examined in studies of

organizational age (Levinthal, 1991), resource accumulation (Denrell, 2004), and firm performance (Henderson et al., 2012). The current article continues this research by considering requests for help as stocks that may rise or fall over time, potentially exhibiting sustained lead. Of course, to determine whether extra milers/good soldiers emerge it is also necessary to describe the person.

### **Person – Responding To Requests**

People comply with one-shot requests for many reasons. Typical effects include the attractiveness and tone of the person asking (Fehr, Dybsky, Wacker, Kerr, & Kerr, 1979; Gross, Wallston, & Piliavin, 1975; Waddell & Ivory, 2015), the mood, arousal, empathy, and stereotypes of the person being asked (Cialdini & Goldstein, 2004; Florey & Harrison, 1997; Forgas, 1998; Paciello, Fida, Cerniglia, Tramontano, & Cole, 2013), the number of other people present (Barron & Yechiam, 2002; Latané & Darley, 1970; Yechiam & Barron, 2003), and the framing of the message (e.g., direct, urgent, positive, specific; Ellison, Gray, Lampe, & Fiore, 2014; Enzle & Harvey, 1982; Goldman, Broll, & Carrill, 1983; Graham, 1998; Langer & Abelson, 1972). There is less research addressing how individuals respond to a dynamic pool of requests – i.e., reacting to received requests that continually update and may or may not accumulate into a large pool. To reason about this less commonly studied perspective, I draw from compliance techniques and self-regulation theory.

### ***Respond to Many***

One way employees might react is that they offer greater help when request pools are large rather than small. Control theory suggests that people monitor discrepancies between current and desired states (Lord & Levy, 1994; Powers, 1973). At any fixed point in time, action is directed toward reducing a discrepancy such that people allocate resources until it is

eliminated. When employees receive many requests for help, they may perceive a discrepancy that directs them toward action: current levels of help are not sufficient to deter incoming requests and so greater resource investments are required. With sustained lead, this type of responding would yield extra milers/good soldiers because the size of the request pool influences how individuals act. Employees with larger pools offer more help than employees with smaller pools. Moreover, relative positions of pleas persist under sustained lead. In this situation by person interaction, some employees would repeatedly offer more help than others because they continually have larger pools. Without sustained lead (i.e., when requests accumulate randomly but without inertia), this type of responding would yield similar levels of help across all employees and would therefore not yield extra milers/good soldiers.

*Hypothesis 1:* If requests accumulate (i.e., exhibit inertia and randomness) and employees offer greater help when they have many rather than few requests, then good soldiers emerge.

### ***Respond to Few***

There is also theory to suggest that employees offer help when they have few rather than many requests. According to resource allocation theory (Becker, 1965; Hockey, 1997), people have a limited capacity to direct attention to multiple aspects of their work. With fewer requests, employees may have more time and cognitive resources to devote to those asking for help. Many employees, for instance, find that they can be more effective when demands do not stretch them too thin (Brown, Jones, & Leigh, 2005). The same conclusion arises from an alternative perspective. Research on boredom (Park, Lim, & Oh, 2019) suggests that low activity situations lead to associative thought, which then prompt action. To the extent that an employee with few requests is less stimulated than an employee with many, he or she may experience greater

boredom which, in turn, acts as a catalyst for action. Bored employees, for instance, may become more creative (Baird, Smallwood, & Schooler, 2011; Mann & Cadman, 2014) and effective (Gasper & Middlewood, 2014) in their offer to help. With sustained leads, this type of responding would yield extra milers/good soldiers because help is driven once again by the size of one's request pool. Without sustained leads, conversely, help would be similar across employees.

*Hypothesis 2:* If requests accumulate and employees offer greater help when they have few rather than many requests, then good soldiers emerge.

### ***Respond to Influx***

Employees may also respond to new arrivals, meaning that they react when they experience their pools changing in the positive direction. A commonly studied effect in social psychology is the foot-in-the-door (FITD) technique, which is a strategy used to secure compliance (Freedman & Fraser, 1966). The core idea is that a small request is immediately followed by a larger one so that the target, after being lured by the original request, responds to both. Evidence for the effectiveness of this technique is mixed (Dillard, Hunter, & Burgoon, 1984; Weyant, 1996). Moreover, studies often examine a single snapshot of back-to-back requests rather than a continual influx of requests over time. In general, though, this research offers indirect support for the idea that employees may offer help when they witness an influx of requests. Research on the velocity aspect of control theory also suggests that employees may respond to the change (rather than size) of their request pool. Experiments show that information about one's changing situation relate to affective and cognitive reactions when discrepancy sizes are held constant (Chang, Johnson, & Lord, 2009; Hsee & Abelson, 1991). In the context of the current study, these lines of evidence would suggest that employees may offer help when they



experience arriving requests, or when their pools change in size (in the positive direction) from one period to the next. If employee help is a function of change, then the emergence of good soldiers would be less likely to occur (given accumulating by inertia and randomness). The intuition for this effect comes from recognizing that sustained lead – as caused by inertia and randomness – has to do with pool sizes, not change. With sustained lead, employees differ with respect to pool size, but they need not differ in the number of arrivals experienced at  $t$ . When change causes OCBs, then the continuity of pool sizes becomes irrelevant.

*Hypothesis 3:* If requests accumulate and employees offer help when they experience an influx of requests, then good soldiers do not emerge.

### ***Respond to Outflow***

The alternative is that employees offer help when requests exit. The sibling compliance strategy to the FITD technique is the door-in-the-face (DITF) technique: start with a large request but quickly withdraw and request something smaller (Cialdini & Ascani, 1976; Cialdini et al., 1975). Evidence for this effect is also mixed but somewhat more favorable (Dillard et al., 1984; Weyant, 1996). This technique suggests that employees may offer help when they experience requests leaving from rather than arriving to their pool. Under this response, employees again react to change rather than size. The hypothesized outcome, therefore, is that good soldiers do not emerge.

*Hypothesis 4:* If requests accumulate and employees offer help when they experience an outflow of requests, then good soldiers do not emerge.

### ***Norm Conformity***

A final possibility is that employees look to their colleagues to determine how much help to provide. Research on conformity suggests that people often change their behavior to match the

responses of others (Cialdini & Goldstein, 2004). They do so because they desire to form an accurate interpretation of reality or to obtain social approval (Deutsch & Gerard, 1955; Pan & Houser, 2017). Moreover, social impact theory (Latané, 1981) suggests that people conform to the attitudes, beliefs, and behavioral propensities exhibited by the people in their surroundings (although not always). Employees may therefore try to match their peers, offering help in a similar way to what they witness among their colleagues. Indeed, research suggests that perceived norms and majority tendencies relate to one's allocation of help (Bolino, Turnley, Gilstrap, & Suazo, 2009; Grant, 2014; Liu, Zhao, & Sheard, 2017). Studies of career aspirations have also shown that individuals use group averages to compare against when forming impressions of their own achievement (Nagengast & Marsh, 2012). The hypothesized outcome under this response is that extra milers/good soldiers do not emerge because employees look to others rather than requests to determine their allocation of help. Note that with norm conformity it is possible for all employees to converge on a high level of citizenship yet the notion of one or few being exceptional would be absent – no one stands out as superior if all are equally great.

*Hypothesis 5:* If requests accumulate and employees match their colleagues in offered help, then good soldiers do not emerge.

## RESEARCH OVERVIEW

This research is completed in two stages. In the first, I conduct a pilot study addressing the question: “Is there evidence that requests exhibit randomness and inertia?” Although such motion is commonly identified in other time-series data, little research has examined whether help request trajectories display these features. Assessing this first question is necessary as a preliminary step leading to the substantive hypotheses regarding good soldiers and extra milers. In the second, I develop an agent-based model to assess Hypotheses 1-5. Institutional review board (IRB) approval for this research was obtained from Michigan State University (MSU Study ID: 00004221).

## PILOT

To assess whether help request trajectories (at least some of the time) exhibit random movement, I collected archival data from the Internet. This pilot adhered to the theory-driven web scraping approach proposed by Landers, Brusso, Cavanaugh, and Collmus (2016), which states the following: Begin with a research question already determined and then develop a scraping approach to address it; Seek data that is indicative of the target behavior; Identify how the planned analysis informs one's selection of web data; Once collected, assess whether one's assumptions about web behavior manifest in the scraped data; Articulate which assumptions were and were not met, and express how the data were adjusted accordingly. In this pilot study, the research question was: "Do help request trajectories display inertia and randomness?" The planned analysis was to examine the presence or absence of these features in time-series data using unit root tests (described later). Unit root tests require data with many time points, therefore I selected GitHub as a data platform because it contains indicators of requests over long periods of time.

## Data Sources

### Issues on GitHub Repositories – Non-Academic

Data were 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 data I collected are known as repository "issues." When an individual posts a repository/project, other users can then download and use the code that she/he created. If other users want to ask questions, request features, or report bugs, they can post an issue on the focal individual's repository, which then automatically triggers a notification. The repositories I

selected were posted by single users, rather than groups, to ensure that issues were targeted at one individual. For a given repository owned by a single user, I collected all issues from when the repo was first created until July 1<sup>st</sup>, 2020. This process was repeated for 26 different users. Observations occurred at the day level.

### **Issues on GitHub Repositories – Academic**

I also collected data from GitHub repositories created by academics. University faculty often use GitHub as a version control system when writing documents, as a platform to share, monitor, and adjust tools that they develop, and as a resource for downloading data science software. Similar to above, I collected issues across 9 different repositories, each maintained by a single academic.

For each of the 35 data sets, a help request was operationalized as an issue. For each issue, I collected (a) the date it was posted and (b) when it was removed or resolved, if ever. Issues can be removed or resolved on GitHub due any number of reasons. For example, the individual who posts it may figure out the problem on his or her own. If this happens, he or she can follow-up the original issue with another notification. It is also possible for the repository owner to respond and then close the issue. Alternatively, a “bystander” – someone who did not post the issue nor did he or she create the repo but happened to come across the public system of notifications for any number of reasons (one being that he or she uses the code within the repository and so actively follows it) – can send his or her own response. For any or all of these reasons, requests can be resolved. Of course, it is also possible for them to lay dormant indefinitely. Following suggestions from Landers et al. (2016), both academic and non-academic repositories were included because it is possible to view various types of repository activity either as in-role or extra-role behavior. Podsakoff, Morrison, and Martinez (2018) also note that

the boundaries of citizenship are sometimes blurry because employees may believe certain behaviors to be in-role even though they are not part of a job description (and vice versa). Prior literature on OCBs among academics, for instance, has differentiated in-role research activity from behaviors focused on contributing to one's broader profession (Bergeron, Ostroff, Schroeder, & Block, 2014).

After scraping but prior to converting the data into a time-series format for analysis, the data were checked against my assumptions (Landers et al., 2016). My first assumption was that the data would offer observations with high frequency over long periods of time. This assumption was met (see Results for descriptives). I also assumed that repository owners would receive issues from other individuals. This assumption was partially met. I noticed that, occasionally, a repository owner would post an issue him or herself and subsequently respond – a web behavior that I had not planned for. Out of all data points gathered, self-created issues happened 11% of the time. Landers et al. (2016) recommended selecting cases that are consistent with one's data-source theory and removing inconsistencies if they occur infrequently. Self-created issues, therefore, were not included in the final data set. Only issues posted by non-owners of the repository counted toward a help request trajectory. Keep in mind that selecting cases that are representative of one's data-source theory is different from carelessly creating missing data (Newman, 2014).

### **Analysis**

The final data structure included 35 trajectories, each representing the number of received help requests (issues) across time for a single user. Each time-series represented a stock of help requests, with greater values at  $t$  indicating more requests and lower values indicating fewer requests. For each data set, the pilot research question regarding randomness and inertia was

evaluated by assessing whether the series contained a unit root. Unit root tests can be used to examine the presence or absence of random walks in time-series (for a larger discussion see Kuljanin, Braun, & DeShon, 2011). What matters for my purposes is that random walks contain both inertia and random movement, so when a unit root test cannot reject the presence of a random walk then there is evidence of both inertia and random fluctuations. The most widely used statistic to evaluate the presence of random walks in time-series data is the augmented Dickey-Fuller (ADF; Dickey & Fuller, 1979) test.

The logic underlying the Dickey-Fuller test is as follows. Consider a simple stochastic trajectory:  $y_t = \rho y_{t-1} + e_t$ , where  $y_t$  is the value of series at the current time,  $y_{t-1}$  is the value of the series one step prior, and  $e_t$  is an error term with mean zero and constant variance  $\sigma_e^2$ . The goal is to assess whether this trajectory contains a unit root, which would occur if  $\rho = 1$ . The insight discovered by Dickey and Fuller was that such a series could be rearranged, algebraically, and then subjected to the familiar hypothesis-testing frameworks more readily understood by other scientists. Various statistics within the null hypothesis framework were well-developed by the 1970s. The trick was to find a way to make unit-root testing amenable to those procedures. Here is how. After subtracting  $y_{t-1}$  from both sides, the trajectory above can be written as  $y_t - y_{t-1} = \rho y_{t-1} - y_{t-1} + e_t$ . I now have an equation that is commonly known as a first differenced series, referring to the fact that I subtracted a lag-one term from the left and right-hand sides of the equation. The first differenced series can be reduced by recognizing that  $\rho y_{t-1} - y_{t-1}$  contains two  $y_{t-1}$  terms, which means that it can be written more succinctly as  $(\rho - 1)y_{t-1}$ . The full equation then becomes  $\Delta y_t = (\rho - 1)y_{t-1} + e_t$ . Now, a test of  $\rho = 1$  is a simple  $t$ -test of whether the parameter on the “lagged level” of  $y$  is equal to zero. Moreover, the

term  $(\rho - 1)$  can be treated as an estimated coefficient of  $y_{t-1}$  and so the equation becomes  $\Delta y_t = \delta y_{t-1} + e_t$ . If  $\delta$  is equal to 0, then  $\rho$  must equal 1 since  $\delta = (\rho - 1)$ .

Dickey and Fuller (1979) used Monte Carlo techniques to compute critical values for the lag-one process above. They later developed an augmented test to accommodate unknown orders and lags in the data-generating process. Although the DF procedure can conceptually be thought of as a  $t$ -test, the estimated values assessing  $\delta = 0$  (i.e., testing for a random walk with the null hypothesis of a unit root) do not have an asymptotic normal distribution. For this reason, Dickey and Fuller computed a unique sampling distribution for the test statistics underlying the unit root assessment. MacKinnon (1991, 1994) showed how to calculate its  $p$ -values for arbitrary sample sizes. Dickey and Fuller (1979; 1981) derived the distribution under the assumption that the order of the underlying autoregressive process is finite and known. Said and Dickey (1984) extended this result for the case in which the underlying process was an invertible autoregressive moving average process. Ng and Perron (1995) and Chang and Park (2002) further relaxed restrictions by allowing tests to accommodate more complex underlying series and unknown orders. Critical values are now automatically implemented in statistical software and programs, and they are also listed in many introductory econometric textbooks.

With a process equation  $(\Delta y_t = \delta y_{t-1} + e_t)$  and null hypothesis in mind ( $\delta = 0$ ), the last step is to evaluate the hypothesis. Ordinary-least-squares regression is used to estimate delta, and the coefficient is divided by its standard error to calculate what is known as the tau statistic ( $\tau$ ). Tau is then compared to the critical values under the unique sampling distribution computed by Dickey and Fuller (and developed further by MacKinnon). If  $\tau$  in absolute value exceeds the MacKinnon critical values, then the hypothesis that  $\delta = 0$  is rejected. If tau is smaller in absolute



value than the MacKinnon critical values, conversely, then the null hypothesis (unit root) is retained.

## Results

Descriptives and ADF results are reported in Table 2. The shortest series included data across 559 days and began in January of 2019. The longest series included data across 3373 days and began in May 2011. The third and fourth columns of Table 2, respectively, report the Dickey-Fuller test statistic and  $p$ -value for each of the 35 series. Eighty-three percent of the help-request trajectories could not reject the presence of a random walk. Randomness and inertia, therefore, exist at least some of the time in the fluctuations one observes among GitHub issues. See appendices A and B for a visualization of the data alongside an additional set of trajectories in which the majority also contain a unit root.

*Exploratory Analysis.* I also explored whether the data exhibited the law of long leads. The law of long leads, also known as the arcsine law, stems from probability theory. Mathematically, it states that the proportion of time a one-dimensional random walk is positive follows an arcsine distribution. Conceptually, it says that when two units – i.e., people, players of a game, organizations, cells, particles, etc. – move as random walks, most of the sample paths leave one unit in the lead. Few paths manifest walks which alternate leads. This law, therefore, captures the mathematics underlying what is more commonly known as sustained lead. The theoretical distribution created from numerical analysis follows a U-shape, with the number of periods  $n$  on the  $x$ -axis and the probability of spending  $n$  periods in the lead on the  $y$ -axis. In the context of the current data structure, this law would mean that one series should spend most periods as the leading request pool in bi-user comparisons. Indeed, evaluating bi-user comparisons shows that the arcsine law manifests in my data. For a majority of the bi-user

comparisons, the greatest probability is that a series  $I$  spends 0 or all periods as the leading pool. See Appendix C for a visualization. Conceptually, what this analysis shows is that the data exhibit sustained lead in request pools.

### **Pilot Discussion**

The pilot study revealed that at least some help request trajectories exhibit random movement. Eighty-three percent of the trajectories examined (as well as 77% in an alternative data set, see Appendix A) could not reject the presence of random walks. This initial assessment was a brief but necessary foray into the movement of help requests over time. This manuscript, in its entirety, takes a situation by person lens. The goal is to offer a generative model of good soldiers by simulating requests and reactions over time. Before getting there, it was necessary to determine whether evidence existed for the conjecture that “higher level” trajectories – help requests over time – bounce around as random walks. Now, the empirical pattern can be used as a baseline in a simulation in which situations and persons are systematically controlled and manipulated to examine the emergence of good soldiers. The second step in this research is to create a computer model combining dynamic requests with person responses.

## STUDY

To test Hypotheses 1-5, I conduct an agent-based simulation. Agent-based models are programs written in computer code in which agents operate according to simple rules. They allow us to witness the emergence of patterns given a set of governing principles specified in a script. Prior research has used this technique to examine recruitment (Newman & Lyon, 2009), firing systems and selection validity (Scullen, Bergey, & Aiman-Smith, 2005), performance skews (Vancouver, Li, Weinhardt, Steel, & Purl, 2016), group genesis (Gray et al., 2014), crowd behavior (Bernhardsson, 2010), how people pair with romantic partners (Kalick & Hamilton, 1986), and the effects of stereotype threat on turnover (Grand, 2017). I use an agent-based model to examine whether the interaction between requests and responses induces patterns consistent with what has been described using terms such as extra milers and good soldiers.

### Simulation Heuristic

The simulation is designed to (a) build off prior research on sustained leads (Denrell, 2004; Polson & Scott, 2012), (b) incorporate the request movement identified in the Pilot, and (c) remain consistent with the idea of extra milers/good soldiers. The simulation structure follows a 2x5 design, with the first factor representing the situation and the second representing employee reactions. The levels or cells within the first, the situation, include accumulating requests (random with inertia) versus non-accumulating requests (random without inertia), and they are implemented as follows. Imagine a set of employees, each collecting help requests over time. 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. Formally, help requests for employee  $i$  at time  $t$  are  $x_{it} = ax_{i-t-1} + \varepsilon_{it}$ , where  $\varepsilon_{it}$ ,  $t = 1, 2, \dots, n$  are independently and identically distributed

random variables with zero mean and finite variance. The first level of the situation factor – accumulating requests – is implemented by setting  $a$  to one ( $a = 1$ ). When  $a = 1$ , then a situation is created in which requests follow random walks and leading stores (are likely to) exhibit sustained lead – which mimics what I found in the Pilot study. The second level of the situation factor – non-accumulating requests – is implemented by setting  $a$  to zero ( $a = 0$ ). When  $a = 0$ , then a situation is created in which leading request pools are unlikely to persist. For each Hypothesis, I compare simulation output across these two environment conditions – in one, employee requests accumulate; in the other, they do not.

The second factor represents the person (respond to many, few, influx, outflow, or conformity), and it is implemented as follows.

### **Responding to Many or Few**

In the first two person conditions, employee help is a function of the size of one's request pool. By size, I mean the number of requests that sit within an agent's stock at a given period. In the "Respond to Many" condition, employee help is a positive function of size, meaning that an employee offers more help when her request pool is large and less help when her pool is small. In the "Respond to Few" condition, employee help is a negative function size, meaning that an employee offers more help when her request pool is small and less help when her pool is large.

### **Responding to Influx or Outflow**

In the next two conditions, help is a function of pool change. That is, employees respond based on arriving or departing requests. In the "Respond to Influx" condition, help is a function of positive change such that an employee offers help when she witnesses incoming requests but does not offer help otherwise. In the "Respond to Outflow" condition, help is a function of negative change such that an employee offers help when she witnesses departing requests but

does not offer help otherwise. In both conditions, employees do not help when their pools remain identical from  $t$  to  $t + 1$ .

### **Norm Conformity**

In the last condition, help is a function of a group average (with a given probability). After the first period, employees offer help at levels similar to their peers with probability  $z$ , which represents a conformity coefficient. This conformity coefficient determines the likelihood that a given employee will choose to offer help at the same level as his or her colleagues. If she chooses otherwise, then she offers help based on the size of her pool as specified in conditions 1 and 2. The functions used to generate help are listed in Table 3.

The pattern that I monitor that connects to the notion of extra milers/good soldiers is the probability that a given agent starting in percentile  $Q$  at time  $t$  remains within  $\pm 10\%$  of this percentile for the remaining periods. Take, for example, an employee who offers the 12<sup>th</sup> highest amount of help during the first step. I ask, what is the probability that she remains within a window of  $\pm 10\%$  of that percentile in period  $t + 1$ ? Period  $t + 2$ ? Period  $t + 3$ ? For how many consecutive steps,  $n$ , is a given employee expected to stay within his or her same rank? This analysis captures the stability of relative positions. It indicates the “streakiness” of employee help. If extra milers/good soldiers emerge, then the probability of remaining within  $\pm 10\%$  of one’s percentile should peak for large values of  $n$ . Said differently, if the greatest probability for a given condition is that a randomly selected employee remains within a given percentile for all periods, then extra milers/good soldiers have emerged. Employees offering the most help remain so across time, as do the employees offering the least amount of help. If good soldiers do not emerge, conversely, then the greatest probability will appear over  $n = 0$ , meaning that there is

no stability in relative positions. Employees offering the most help do not hold their relative position across time.

It is important to recognize that, although the simulation uses mathematics from the random school of thought to generate requests, it is conceptually consistent with both the random and systematic schools of thought. The schools differ in their reasons for accumulating pools. One focuses on causes such as social capital, network and Matthew effects, and compounding. The other focuses on stochastic processes. But they converge in predicted outcome: the presence of accumulating pools – and it is at this point where my simulation begins. My simulation starts by establishing two competing situations, one where requests accumulate and another where they do not. I generate that contrast by manipulating  $\alpha$ , as described above. There are an infinite number of ways one could create such a contrast in a computer. Some would be consistent with the random school of thought, and others consistent with the systematic school of thought. But my simulation does not end there. It starts there. It focuses on the downstream consequences of combining such a situation with employee reactions. I examine the stability of rank OCBs after interacting situations with persons. If good soldiers emerge when the situation level “requests accumulate” is crossed with the person level “respond to many,” then technically the requests were generated stochastically, but conceptually the notion of accumulating requests is consistent with both random and systematic determinants. I unpack this idea further in the Discussion.

### **Analysis & Results**

Simulations were completed in Julia and are available at the following repository (<https://github.com/Cdishop> → dissertation repository). In a single run, the number of periods was set to 20 and the number of employees to 300. Results are based on 10,000 realizations. The design was fully crossed, with each situation factor paired with every person factor. For the

conformity condition, three different values were selected for the conformity coefficient,  $z$ . These included 0.2 (low), 0.5 (moderate), and 0.8 (high). Conceptually, this parameter refers to the likelihood that an agent offers help at the same level of his or her colleagues.

To understand the simulations and their output, it helps to develop some intuition for concepts in computer modeling. The first is that realizations/replicates differ from periods/time points. A realization is a single run through the simulation, and it includes all 20 periods. A period, conversely, is a single step or time point within any realization. In a single realization, agents receive and respond to requests over 20 periods. The computer then saves the results, resets, and runs another realization, with agents again receiving and reacting across 20 steps. This procedure is repeated 10,000 times. The second concept is that the simulations are stochastic, meaning that error influences what happens. Understanding the role of error is important not only for the aforementioned theoretical reasons but also because it demands one to evaluate output over many realizations. When error influences whether requests arrive or depart, both periods and realizations differ from one to another. An employee may or may not receive the same number of requests at each step. Similarly, an employee may or may not receive requests in the same way across realizations. At both levels, behaviors manifest differently from one instance to another because the situation is stochastic. Contrast that idea with a deterministic system. In a deterministic model, there is no need to evaluate multiple realizations because the same behavior manifests across each stimulation run. (Technically, deterministic systems can produce chaos so this statement isn't always true).

With concepts one and two in mind, the results I present immediately below become more straightforward. My model assesses the probability over realizations of witnessing stable ranks. Stable ranks occur when employees who offer the greatest help at early periods also offer

the greatest help at later periods. This concept – stable ranks/percentiles – is synonymous with the idea of a good soldier as described in our literature. The best employee at period one is often the best employee at subsequent periods. Stability in rank, however, does not require that help itself remains stable. The best employee at period one will not necessarily offer the same number of OCBs at the next period, or at any subsequent period. All employees have fluctuating citizenship behaviors over time. The relevant question is whether those offering more at early periods are those offering more – relative to their colleagues – at later periods. Because the computer simulations are stochastic, requests and behaviors will vary over both periods and realizations (even though the parameters of the system do not change within a condition). What is reported below is the probability over realizations of witnessing ranks (percentiles) remain stable across  $n = 1, 2, 3, 4$ , etc. periods. A high probability is synonymous with the phrase, “the most likely realization to occur.” A low probability means “the least likely realization to occur.” When the greatest probability occurs over high values of  $n$ , this means that the given condition is likely to yield stable ranks across any realization. Said differently, most realizations are ones which manifest stable ranks. When the greatest probability occurs over low values of  $n$ , then the given condition is unlikely to yield stable ranks. Most realizations are instead those manifesting unstable OCB ranks.

### **Respond to Many or Few**

Figure 1 presents the probability of spending  $n$  periods in the same percentile of offered help. Peaks near  $n = 19$  mean that extra milers emerge: a given employee is most likely to spend all periods after the first step in the same relative position – if he or she offered the 12<sup>th</sup> largest amount of help at time  $t = 1$  then she offers the 12<sup>th</sup> largest amount of help thereafter. Peaks near  $n = 0$  indicate no good soldiers: a given employee is most likely to spend zero periods after



the first step in the same relative position – the exceptional citizens lose their rank. Rows in Figure 1 represent different levels of the situation factor (requests that accumulate vs requests that do not accumulate). Columns in Figure 1 represent different levels of the person factor (“Respond to Few” vs “Respond to Many”). The first row of Figure 1 demonstrates results from the first level of the situation factor, accumulating requests, crossed with the first two person factors, “Respond to Many” and “Respond to Few.” As shown, the greatest probability occurs at  $n = 19$  for both person factors and so good soldiers emerge. Moving to the second row of Figure 1, the effects are the opposite. When requests do not accumulate and employees either respond to many or few, good soldiers do not emerge (i.e., the greatest probability occurs near  $n = 0$ ). Hypothesis 1 predicted that if requests accumulate and employees offer greater help when they have many rather than few requests, then good soldiers emerge. This prediction was supported in the simulation output. Hypothesis 2 predicted that if requests accumulate and employees offer greater help when they have few rather than many requests, then good soldiers emerge. This prediction was also supported in the simulation output.

To appreciate boundary conditions for this first simulation it helps to consider aspects that would change the output. First, the emergence of good soldiers would disappear in the “requests accumulate” condition if agents could help at such high levels so as to effectively drain their stockpiles to zero at each period. This is unlikely to occur in the current simulation because requests are (independently) stochastic and OCBs are a linear function of requests. As an example, it is unlikely for an agent to experience, say, 3 arriving requests and then to offer so much help that 8 requests are removed from her pool. It is even less likely that this cycle continues across subsequent steps. In the current simulation, offering help does not necessarily remove a request for help (more on this in the Discussion). Moreover, the magnitude of help is

limited by the size of one's pool (as defined by the "Respond to Many" function). There is a small chance, therefore, that help is larger in magnitude than the size of one's pool. If this were not the case, the emergence of good soldiers would disappear. Second, the emergence of good soldiers would reappear in the "requests do not accumulate" condition if OCBs were constrained to have self-similarity across periods. Adding an autoregressive effect on help would generate behavioral persistence. An agent offering the most help at period one would have a greater probability of remaining in her rank due to the constraint that OCBs remain close to prior levels. Effectively, adding autoregression on help would remove the effect of inertia on requests and place it instead on the agent's behavior.

### **Respond to Influx or Outflow**

Figure 2 presents the probability of spending  $n$  periods in the same percentile of offered help, but this time for two other levels of the person factor. Rows again represent levels of the situation factor (requests that accumulate vs requests that do not accumulate). Columns represent the person levels "Respond to Influx" and "Respond to Outflow," respectively. As above, peaks near  $n = 19$  indicate extra miler emergence. In these conditions, good soldiers do not emerge irrespective of the different interaction effects. When employees offer help after experiencing an influx of requests, good soldiers do not emerge across both the accumulating and non-accumulating situations. Similarly, when employees offer help after experiencing an outflow of requests, good soldiers do not emerge across both the accumulating and non-accumulating situations. The intuition for this observation is that responding to change rather than size removes the differences across the situations. Trajectories with randomness have vastly different implications for pool size depending on whether inertia is or is not present. But this distinction is not relevant for arriving/departing requests – in both, requests join or leave randomly and so they

operate similarly across employees. Hypothesis 3 predicted that if requests accumulate and employees offer help when they experience an influx of requests, then good soldiers do not emerge. Hypothesis 4 predicted that if requests accumulate and employees offer help when they experience an outflow of requests, then good soldiers do not emerge. Simulation results were consistent with both predictions.

Again, there are aspects to consider revealing the boundary conditions of the simulation. First, the emergence of good soldiers would reappear in the “Respond to Influx” and “Respond to Outflow” conditions if requests were directional – if a subset of employees were more likely than others to experience arrivals. In the simulation, employee  $x_i$  was no more likely to experience arrivals than employee  $x_{(i+1)}$ , meaning that arrivals were not spatially or locally dependent. There is a vast literature on the notion of interdependence in organizations, which refers, broadly, to the ways in which work, information, and rewards flow across employees and jobs. When the work of 2<sup>nd</sup> shift coal miners depends on those who worked earlier in the day, then those operating in the 2<sup>nd</sup> shift are said to have received interdependence, meaning that their performance is affected by the work arising from other positions. Similarly, anti-aircraft guns during WW2 were operated by two people. The first handed shells to the second, who then loaded and fired the weapon. The first would be said to have initiated interdependence. If a manager with a visible, front office receives more arrivals than a subordinate working in an isolated basement, then the environment would be amenable to the emergence of a good soldier. The same would happen if employees had to direct their requests toward a specialized, expert target. This type of nuance was not captured in the simulation. Second, good soldiers would also reappear if autoregression were added to OCBs. Even if requests pools were to fluctuate with no

accumulation, self-similarity on OCBs would make it more likely for top citizens to hold their position over time.

### **Norm Conformity**

Figure 3 shows the probability of spending  $n$  periods in the same percentile of offered help across different degrees of conformity. Rows in Figure 3 represent the situation levels (requests that accumulate vs requests that do not accumulate). Columns in Figure 3 represent the amount of conformity. Conformity values (0.2, 0.5, or 0.8) refer to the probability of following the norm. In the high conformity condition, for instance, agents had an 80% chance of offering help at the same level of their peers. Once again, peaks near  $n = 19$  indicate the emergence of good soldiers, whereas peaks near  $n = 0$  indicate instability in OCB rank. As shown, extra milers emerge only when conformity is low and requests accumulate. They become increasingly less likely to emerge as conformity increases or when requests do not accumulate. At low levels of conformity, extra milers emerge when requests accumulate – they do not emerge when requests do not accumulate. At moderate levels of conformity, extra milers do not emerge irrespective of whether requests accumulate. At high levels of conformity, extra milers do not emerge irrespective of whether requests accumulate. Hypothesis 5 predicted that if requests accumulate and employees match their colleagues in offered help, then good soldiers do not emerge. This prediction was supported.

Conceptual moderators that would change the results of this last simulation are as follows. Good soldiers would reappear if conformity caused agents to choose similar but not identical levels of help. In the conformity simulation, a coefficient of 0.2 meant that an agent had a 20% chance of choosing help identical to the social norm. There are other ways to mathematically portray the notion of conformity. Perhaps conformity causes agents to mimic but

not perfectly match the social norm. That is, agents flinch but don't break. Another direction would be to say that conformity causes similar behavior deviations across the collective. Imagine a social pressure – initiatives, training, a new policy – calling for employees to increase their citizenship. Perhaps employees are expected to increase their help by, say, 2. Those already offering many OCBs would go up, as would those offering few OCBs. But a boost of 2 across all employees would not allow the last-place citizens to catch those at the top. In this hypothetical case, good soldiers would be robust to conformity. More broadly, any feature of organizational life that would dirty the chances of employees selecting the same level of OCBs would increase the likelihood of extra miler emergence. Such features could include perceptual errors or biases, limited information about social norms and colleague behavior, anchoring effects, clustering of similar others, or technological limitations removing courses of action.

## DISCUSSION

Organizational scientists have recently identified a pattern among employees at work. The greatest portion of cooperative acts are sometimes granted by a small subset of employees – one or few individuals out-cooperate their peers time and time again. Some employees, so the idea goes, frequently offer assistance to those around them. They provide advice when asked, support the company at optional events, or resolve issues created by the underperformance of others – and the hallmark of such individuals is that they repeat these actions over extended periods of time. When an employee offers sustained, exceptional citizenship, she is said to be an extra miler. In the past, researchers have argued that this behavior is caused by individual characteristics such as motives, values, and personality. I suggested that it may be necessary to consider this behavior through the lens of a person by situation interaction because cooperative acts are often linked to prompts for assistance. Two studies were executed. The first – a Pilot – examined the movement of requests for help over time. The second assessed generative mechanisms yielding good soldiers. Results supported my Hypotheses, suggesting that an alternative mechanism is capable of yielding this streaky pattern. This research has implications for both theory and practice.

### **Theoretical Implications**

The present work contributes to OCB science by broadening our perspective to more readily acknowledge both persons and situations. Several researchers have suggested that requests, despite being fundamental to most incidents of helping, are underexamined in the citizenship literature (Cain et al., 2014; Ehrhart, 2018). They are alive and well in related literatures such as advice and help-seeking (Bohns, 2016; Bonaccio & Dalal, 2006), but are not commonly included in discussions of citizenship. The idea that requests are overlooked is

matched by an emphasis in the other direction favoring individual characteristics such as motives, personality, and justice perceptions (Podsakoff et al., 2018). My research adds to this work by offering a situation by person framework capturing the role of requests and responses over time. I built from Simon's simple rules model and integrated notions of sustained lead, compliance, and self-regulation to articulate how frequently exceptional citizens may arise from the combination of one's circumstances and reactions. I found that, across the respond to many, few, and low conformity conditions, good soldiers emerged when requests exhibited inertia and randomness. These findings enhance our theoretical understanding of how the circumstances employees encounter (captured by requests over time) may combine with reactions to yield citizenship.

This research also contributes to the OCB literature because it provides mechanisms are not *a priori* congruent with the outcome they attempt to explain. Methot et al. (2015) argue that streaky good soldiers are due to traits such as agreeableness, proactive personality, and prosocial orientations and values. Bolino et al. (2015) provide a similar suggestion. These explanations rely on motives that in advance dispose individuals in the direction of the pattern to be explained – a common tactic used in the social and behavioral sciences (Heider, 1944). As a first step in reasoning about an observed pattern, researchers often target causes that are similar to or congruent with an outcome. Egocentric attributions are explained by presuming egocentric memory (Ross & Sicoly, 1979). Stereotypes are explained by suggesting that stereotype-consistent information is more readily encoded, stored, and retrieved in memory (Friedrich, 1993; Greenberg, Pyszczynski, & Solomon, 1982; Kunda, 1990). Similarly, a frequent helper is explained by suggesting that the individual is prosocial. My research adds to the literature on streaky citizenship by demonstrating how a situation by person interaction may yield this pattern.

The explanation was unique because it did not begin with biases pushing some employees toward citizenship before movement began. Extra milers emerged even though employees were homogeneous within conditions. Extra milers emerged even though the processes by which employees received help requests were identical. No *a priori*, between-employee differences were required. This research, therefore, offers a unique perspective demonstrating how a seemingly systematic, between-person outcome need not require systematic, between-person causes. Of course, personality and motives matter. My intention was to present a parsimonious theoretical explanation to which such additional constructs were not strictly necessary.

The current findings also contribute to the budding literature on chance explanations in organizational science. Several papers have recently called for a greater appreciation of randomness in organizational theory (Denrell et al., 2014; Liu & de Rond, 2016). As stated, such a perspective does not imply that an investigated system is fundamentally random, only that this approach can be useful given the granularity of one's research. As Denrell et al. (2014) describe, "A chance explanation explains a regularity by adding the assumption of random variation and demonstrating how a mechanism involving random variation can be used to derive the regularity in question" (p.). So far, explanations using randomness as a first principle have tended to focus either on macro or cognitive applications. These include studies on firm growth (Bottazzi & Secchi, 2003; Riccaboni, Pammolli, Buldyrev, Ponta, & Stanley, 2008), performance (Henderson et al., 2012), and risk (Denrell, 2008), and, at the opposite end of the spectrum, probability estimates and predictions (Hilbert, 2012). The findings presented here reveal how randomness may play a role in the citizenship literature. Understanding how it operates is necessary not because all acts of helping are random, or because received requests are unpredictable, but because at a given level of analysis a trajectory over time may exhibit random movement. Such



was the case with prompts on GitHub, the majority of which followed random walks. Similar data structures – with observations collected over many time points – are becoming common in our literature. Yet, few examine the extent to which random patterns exist in their data. When randomness goes unevaluated, then arguments for systematic causes are untenable. To expand on this point, I conducted a brief review of articles published in the *Journal of Applied Psychology* (JAP), *Organizational Behavior and Human Decision Processes* (OBHDP), and the *Academy of Management Journal* (AMJ). Articles were collected from the start of 2019 until August 10<sup>th</sup>, 2020. For JAP, this search resulted in 180 papers (8 issues). For AMJ, this search resulted in 96 papers (10 issues). For OBHDP, 87 papers (10 volumes) were collected. All 363 studies were examined. I gathered descriptives on each study's collected data and marked whether or not unit root, stationarity, or random walk procedures were undertaken. Ninety-three of the articles collected data across 3 or more waves. Of those, none evaluated the presence of unit roots in their series. One can also observe little appreciation for randomness in psychological/organizational behavior textbooks on longitudinal data analysis. Among some of the more popular titles (e.g., Bolger & Laurenceau, 2013; Bollen & Curran, 2006; Grimm, Ram, & Estabrook, 2017; Hoffman, 2015; Singer & Willett, 2003), there are no chapters describing stochastic processes like those presented in this article. The reverse is true in economics (e.g., Croissant, 2018; Racine, 2019; Wooldridge, 2013). All of the cited books, which are by no means unique, have one or more chapters on unit root testing, stochastic processes, random walks, and stationarity. The take-away from this (small) review is that randomness sits unevaluated in our literature. The world may be systematic, but the majority of our longitudinal research has not ruled out random causes. This paper offers theoretical insight into the downstream consequences randomness can lead to, especially when it is paired with inertia.

It is worth reflecting on the fact that this work was different from typical presentations in organizational psychology and management. There were no regression coefficients, no multi-level models, no interviews or surveys. Instead, this research was consistent with a generative or computational perspective, or what is sometimes called the third scientific discipline (Ilgen & Hulin, 2000). A generative explanation describes a social phenomenon in terms of the internal and external mechanisms that may produce it, rather than by inferring causes from observed covariations (Smith & Conrey, 2007). The goals of a computational approach are many: identify mechanisms that can generate a pattern of interest, suggest alternatives to previously agreed-upon predictors, call attention to variables whose importance might not otherwise be recognized, demonstrate how complexity can emerge from simple components (Epstein, 2008). It focuses less on prediction and more on the logic of an explanation. It tries not to fully represent the real world but abstract to something simple in order to provide insight. It eschews ambiguous language in favor of reproducible code, but at the cost of breadth. Theorists have called for researchers to use the approach (Smaldino, Calanchini, & Pickett, 2015), but it is far from common in organizational psychology and behavior. This work is a small step in that direction. Without such an approach, it is harder to recognize alternative mechanisms because the dynamics of a system are not easily simulated in one's head (Cronin, Gonzalez, & Sterman, 2009). Moreover, researchers are forced to study only that which can be measured and analyzed under the covariation paradigm, naturally limiting our ability to generate theoretical insight.

Finally, the perspective presented in this research, although random, need not be incompatible with theories of cumulative advantage or social capital. The level of analysis in this study was simply one step removed. Cumulative advantage and social capital offer reasons for why some individuals may experience greater or fewer requests than others. It is not a

contradiction to say that, at a lower level of analysis, cumulative advantage and social capital may explain why some are afforded more requests than others while, at a higher level of analysis, observed requests trajectories exhibit random movement. Both could occur. This research simply started with trajectory movement and offered downstream consequences. Others may glean insight by going lower and instead focusing on upstream causes of movement. Another consistency is that, in terms of downstream consequences, cumulative advantage and social capital offer identical predictions to the Hypotheses presented here. If requests exhibit sustained lead due to reasons of cumulative advantage and social capital, the same outcome – whether or not good soldiers emerge – is predicted across all person responses. For example, Hypothesis 1 predicted that if requests accumulate and employee responses are a positive function of pool size, then good soldiers emerge. The prediction stays the same regardless of whether accumulation/sustained lead is due to random movement or social capital and cumulative advantage. The current research, therefore, need not act in opposition to these literatures, but instead as a complimentary starting point for each.

### **Practical implications**

There are two practical implications. The first is that managers need to be weary of attributing motive after witnessing patterns of citizenship. Given the possibility of long leads from the processes described in this research, presuming that a frequent citizen has prosocial motives may be misleading. Even if there are no systematic differences across individuals in motive or personality, there could still be different patterns of behavior. The reverse is also true: employees exhibiting the same level of citizenship need not have the same motives. The importance of understanding this insight can be expressed using Grant's (2014) book on helping. In it, he describes a study by Hui, Lam, and Law (2000). The study examines employee

citizenship before and after a promotion opportunity. The researchers find that some employees exhibit lower OCBs after being promoted whereas others retain high levels before and after promotion. Grant (2014) explains:

Of the seventy tellers who were promoted, thirty-three were genuine givers: they sustained their giving after the promotion. The other thirty-seven tellers declined rapidly in their giving. They were fakers: in the three months before the promotion, ... they went out of their way to help others. But after they got promoted, they reduced their giving by an average of 23 percent each. P 246.

His description infers motive from behavior: some employees were genuine because they exhibited one pattern of citizenship whereas others were not because they exhibited a different pattern. When an employee lowered her citizenship from one period to the next, she was classified as fake. The point Grant makes in his book, which I agree with, is that motives are necessary to account for, otherwise unexpected changes in citizenship can occur. Indeed, perceptions of instrumentality were an important aspect to Hui et al.'s (2000) research. My point is that drawing meaning from observed citizenship patterns, be they stable or volatile, is much harder than given credit for – especially when only two time points are assessed.

Additional examples abound. Peter Singer's award-winning book on philanthropy, *The Life You Can Save*, documents donating patterns across nations, states, families, and individuals. Those who repeatedly donate are often referred to as altruistic whereas those offering one-off contributions are described as selfish. What goes unmentioned is fact that inferring underlying dispositions from manifest behavior is subject to error. In the home-improvement industry, Robert Nardelli, formerly the CEO of Home Depot, was called one of the "worst CEOs of all time" during his seven-year tenure because the company's stock fluctuated stochastically.

Lowe's stock, comparatively, doubled during the same period. The idea even presents itself in the methods of otherwise sound psychological and organizational research. Camilleri and Newell (2019), for instance, ignored the possibility of streaky performance in the task they presented to their participants – they created an artificially perfect (non-stochastic) situation. The goal of their study was to determine whether participants could accurately predict a coworker's true mean performance after witnessing his or her manifest performance across ten trials. The participants were presented with trial information either sequentially or simultaneously in summary form, and they were shown one of the two following performance schemes: [8, 8, 8, 8, 8, 9, 9, 9, 9, 9, 9]; [1, 9, 9, 9, 9, 9, 9, 10, 10, 10]. For both schemes, participants were asked to guess the true performance mean of their coworker (which was 8.5). Notice, however, that both vectors are artificially split: one value does not dominate the sequence in either scheme. In true data-generating mechanisms, there is some non-zero probability that an entire run – especially one as short as ten trials – will manifest a number unrepresentative of the true average. The law of large numbers was embedded into a small number sequence, which is erroneous because the law of large numbers says nothing about the behavior of small samples.

Managers need to be aware that seemingly meaningful patterns can be generated by unsystematic causes. This idea of course connects to a long history of research on attributions. Citizenship relates to supervisor impressions, liking, and attributions of motive – which then relate to performance judgments (Allen & Rush, 1998). Performance judgments are themselves subject to a menu of effects, including gain or loss framing, decoys, dilution, anchoring, and the correspondence principle (Connolly, Reb, & Kausel, 2013; Highhouse, 1996; Thorsteinson, Breier, Atwell, Hamilton, & Privette, 2008; Wong & Kwong, 2005). There are also studies examining how supervisors rate trajectories, often finding that the within-person mean, trend,

and variability influence ratings (Ferris, Reb, Lian, Sim, & Ang, 2018). What this study adds to this conversation is a probability theory perspective: whereas performance management literatures tend to focus the extent to which supervisor ratings are more favorable given one trajectory or another (Highhouse, Dalal, & Salas, 2013), probability theory researchers often spend considerable time trying to understand whether a given trajectory can be meaningfully parsed from chance in the first place. Such a simple effort is not without its consequences. 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” (Grover, 2003). In hindsight, researchers have argued that this sequence was far too short to distinguish flawed decision-making from random fluctuations, a statement supported by follow up data demonstrating that the trajectory reverted back to its mean (Mlodinow, 2009). So it is with citizenship: managers need to be armed with the tools necessary to differentiate meaning from chance because employees who are identical in character may nonetheless exhibit different patterns of citizenship. For a greater discussion, see Henderson et al. (2012).

This work also offers direction for organizational helping interventions. Many strategies exist, including the helpful skills technique (Hill et al., 2008), the helpful organizational behavior paradigm (Bandura & Lyons, 2012), manager-directed initiatives (Tews & Tracey, 2009), mentor or peer-based efforts (Hill & Lent, 2006), or interventions based on the mutual-investment model (van Gerwen, Buskens, & van der Lippe, 2018). Organizations hoping to

promote certain outcomes may want to take heed of the fact that the type of citizenship response employees enact informs the outcome that occurs across the collective. Organizations will need to consider whether they value similar or dissimilar levels of help across employees, the type of responding a given intervention calls for, the nature of requests employees experience, and the extent to which a suggested intervention will promote the outcome of interest. If an intervention, for example, promotes citizenship such that employees respond to request size rather than change, then it will be much more difficult for the organization to create similar levels of citizenship across the collective. Employees may also benefit from a systematic assessment that provides feedback on how they receive variations in requests over time. Based on such detailed feedback, employees could identify their own response patterns, compare to others, and adjust accordingly in-line with espoused values of the organization.

### **Limitations**

There were several limitations that should be acknowledged. Concerning the simulation, one might add or consider any of the following for future research. The first is that employees may work through a sequence of decisions when responding with help rather than the single command as implemented here. In the current research, the decision to help (a binary “yes” or “no”) was not treated separately from the decision of how much help to provide (given “yes,” what level of help should be offered?). Studies have shown that different decisions call on unique aspects of one’s environment (Wegwarth, Gaissmaier, & Gigerenzer, 2009). One could conceive of situation cues such as influx, outflow, and pool size as informing one decision whereas some of the unexamined cues, such as the framing of a message, as informing another. Both may then combine to influence help. Second, this research did not include a 1 to -1 correspondence between help and resolved requests. There are conceptual reasons for and against this position.

Employees may feel that they offered inadequate help and return to a request at a later period. It also, functionally, captures the notion of a delay such that employees are unable to act the moment requests are received. Alternatively, one could argue that employees perceive requests leaving every time they help. Concerning the pilot study, the goal was to maximize my within-person sample size but doing so came at the cost of a between-person sample. Moreover, request trajectories were only examined in a single context, so they may not generalize to other situations.

### **Conclusion**

Leonard Mlodinow (2009) wrote, “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” (p. 11). Whereas existing research examined individual dispositions, motives, and personality as the systematic forces underlying citizenship, I proposed that fluctuating help requests combine with self-regulatory actions to yield streaky helping behaviors. This perspective fits within the recent citizenship and chance perspectives as well as the long-standing situation by person frameworks in psychology and management. It opens the literature to both context and individual effects, highlighting how their combination plays a critical role in frequent citizenship. It advances the citizenship literature by asserting that employees need not differ in motive, personality, or altruism to nonetheless exhibit sustained differences in helping. It calls attention to the importance of requests, and the aspects of which employees may or may not attend to. Finally, it



offers a generative perspective capturing simple mechanisms yielding the emergence of streaky citizenship.

## APPENDICES

## APPENDIX A:

### Additional Time Series Data

To demonstrate the prevalence of random walks in time-series observations, data were also collected on the number of graduate students per department at a large, Midwestern University. Ninety-two series were obtained from the school. Each trajectory captures the number of active graduate students in a given department across all terms – from when the department first began until Summer 2020. Greater scores indicate more active graduate students, and lower scores indicate fewer active graduate students. These data, of course, do not represent specific notifications or help requests. The purpose of this data, instead, is to reiterate that randomness is a legitimate perspective because such fluctuations will occur at higher levels of analysis. A graduate student is not synonymous with a request for help. But a graduate student is an agent through which a help request may be developed and then delivered. Moreover, the process by which graduate students enter and exit graduate school is not, at its core, random. But observed trajectories at a higher level of analysis may still exhibit random movement. Indeed, of the 92 trajectories collected, 77% could not reject the presence of a unit root. Visualizations of each series, as well as the series located in the GitHub data sources, can be accessed using the link below.

<https://cdishop.github.io/diss.appendix/>

## APPENDIX B:

### Time Series Visualization

All GitHub trajectories can be viewed at the following website:

[\*https://cdishop.github.io/diss.appendix/#github-issues\*](https://cdishop.github.io/diss.appendix/#github-issues)

All MSU student trajectories can be viewed at the following website:

[\*https://cdishop.github.io/diss.appendix/#msu-students\*](https://cdishop.github.io/diss.appendix/#msu-students)

## APPENDIX C:

### Law of Long Leads

The GitHub empirical data exhibited the long of law leads (also known as the arcsine law). This law states that random walks infrequently change lead. When two move over time, the greatest probability is that one will spend most periods at a greater value than the other. This law manifests in my GitHub data. Find a demonstration of the law at the following website:

[\*https://cdishop.github.io/diss.appendix/#law-of-long-leads\*](https://cdishop.github.io/diss.appendix/#law-of-long-leads)



## APPENDIX D:

### Tables

*Table 1. Stochastic requests for help yield different outcomes depending on whether they retain inertia.*

Inertia	No Inertia
Sustained Lead	No Sustained Lead
- Leading help request stores persist	- Leading help request stores do not persist

*Table 2. Unit root tests and descriptives for each issue time series.*

Repo ID	Start Date	Length (Days)	Dickey-Fuller	P-Value	Unit Root
1	2017-03-06	1239	-3.65	0.03	No
2	2014-07-31	2188	-2.25	0.47	Yes
3	2013-11-22	2439	0.04	0.99	Yes
4	2017-07-25	1098	-2.58	0.33	Yes
5	2013-04-15	2660	-3.93	0.01	No
6	2014-03-10	2331	-6.78	0.01	No
7	2013-12-06	2425	0.44	0.99	Yes
8	2017-10-12	1019	-2.79	0.24	Yes
9	2015-04-24	1921	-0.92	0.95	Yes
10	2014-01-08	2392	-3.35	0.06	Yes
11	2012-02-28	3072	-2.90	0.20	Yes
12	2014-10-02	2125	-2.33	0.44	Yes
13	2013-07-04	2580	-3.64	0.03	No
14	2016-02-16	1623	-6.15	0.01	No
15	2011-09-22	3231	-1.79	0.67	Yes
16	2015-02-06	1998	-2.75	0.26	Yes
17	2017-02-25	1248	-3.06	0.13	Yes
18	2015-03-13	1963	-2.84	0.22	Yes
19	2015-12-11	1690	-1.86	0.64	Yes
20	2018-08-24	703	-2.70	0.28	Yes
21	2016-02-22	1617	-2.55	0.34	Yes
22	2016-12-07	1328	-2.18	0.50	Yes
23	2015-11-09	1722	-3.98	0.01	No
24	2015-04-17	1928	-2.16	0.51	Yes
25	2016-12-16	1319	-2.58	0.33	Yes
26	2014-12-29	2037	-0.76	0.97	Yes
27	2013-06-11	2603	-0.54	0.98	Yes
28	2019-01-15	559	-2.59	0.33	Yes
29	2015-03-10	1966	-1.89	0.63	Yes
30	2015-03-14	1962	-2.47	0.38	Yes
31	2016-05-16	1533	-1.88	0.63	Yes
32	2015-03-20	1956	-2.45	0.39	Yes
33	2011-05-03	3373	-4.70	0.01	No
34	2017-05-19	1165	-1.40	0.83	Yes
35	2018-06-18	770	-2.20	0.50	Yes

Note: 80% contained a unit root.

Table 3. OCB generating functions for each person condition.

Person Condition	OCB Generating Function
Respond to Many	$f(R_{it}) = b * R_{it}$
Respond to Few	$f(R_{it}) = -b * R_{it}$
Respond to Influx	$f(A_{it}) = \begin{cases} 1, & \text{if } A_{it} > 0, A_{it} \leftarrow N(0, \sigma^2) \\ 0, & \text{otherwise} \end{cases}$
Respond to Outflow	$f(D_{it}) = \begin{cases} 1, & \text{if } D_{it} < 0, D_{it} \leftarrow N(0, \sigma^2) \\ 0, & \text{otherwise} \end{cases}$
Conformity	$f(x) = \begin{cases} m, & \text{if } x \leftarrow U(0, 1) < z \\ b * R_{it}, & \text{otherwise} \end{cases}$
<p>where</p> <p><math>R_{it}</math> = the number of requests for employee <math>i</math> at time <math>t</math></p> <p><math>A_{it}</math> = the number of arrivals for employee <math>i</math> at time <math>t</math></p> <p><math>D_{it}</math> = the number of departures for employee <math>i</math> at time <math>t</math></p> <p><math>b</math> = the parameter relating requests to OCBs</p> <p><math>z</math> = the conformity coefficient</p> <p><math>m</math> = the number of OCBs expected by the social norm</p>	

## APPENDIX E:

### Figures

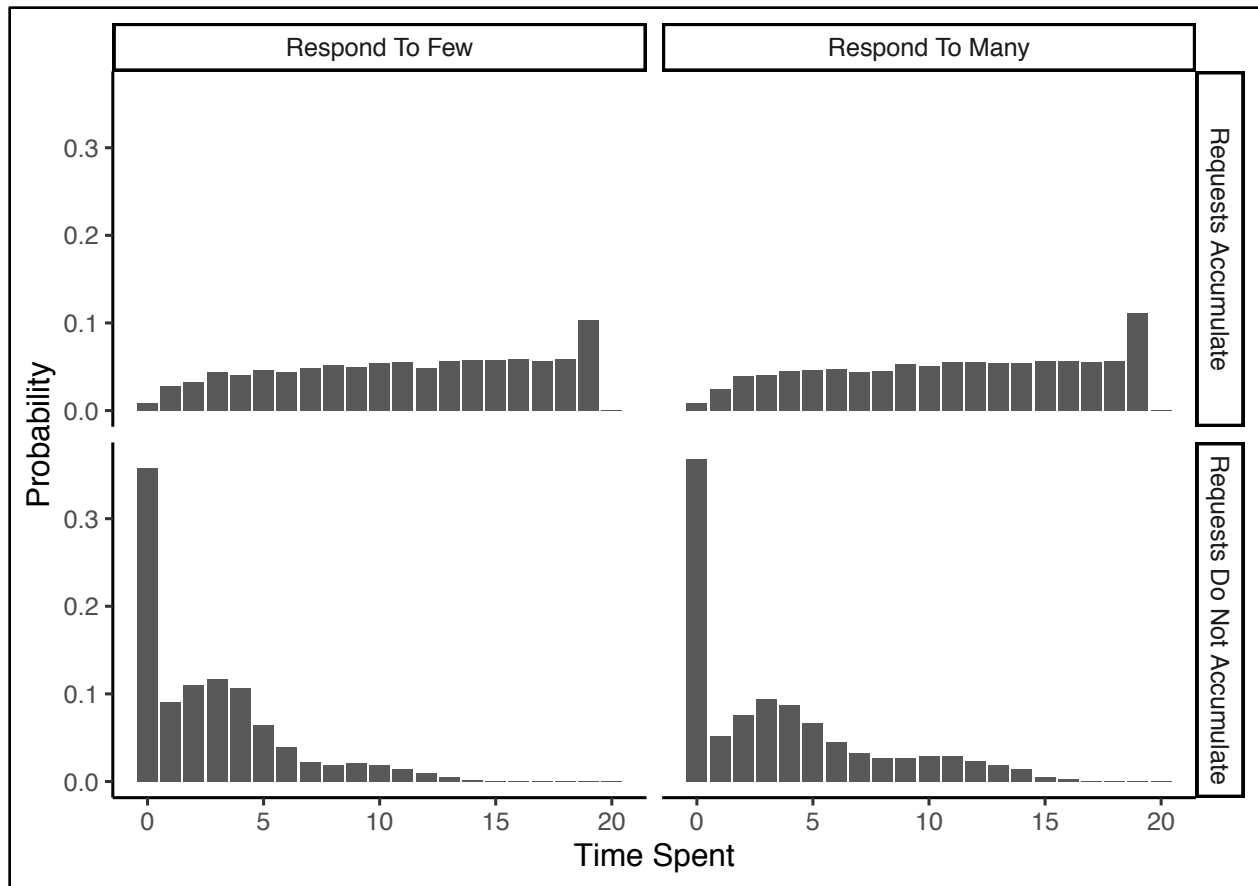


Figure 1. Probability that employee  $x_i$  spends  $n$  periods in the same percentile across person conditions one and two.

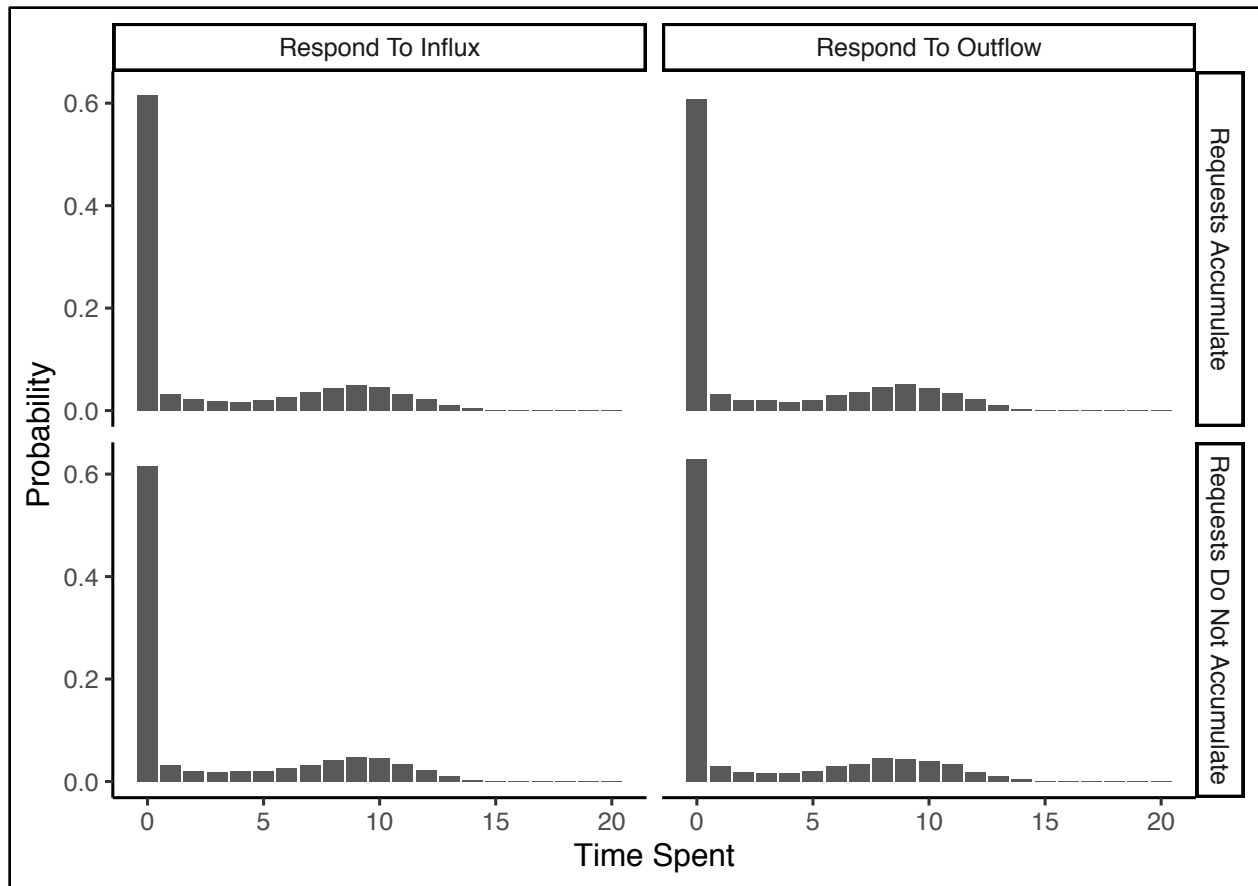


Figure 2. Probability that employee  $x_i$  spends  $n$  periods in the same percentile across person conditions three and four.

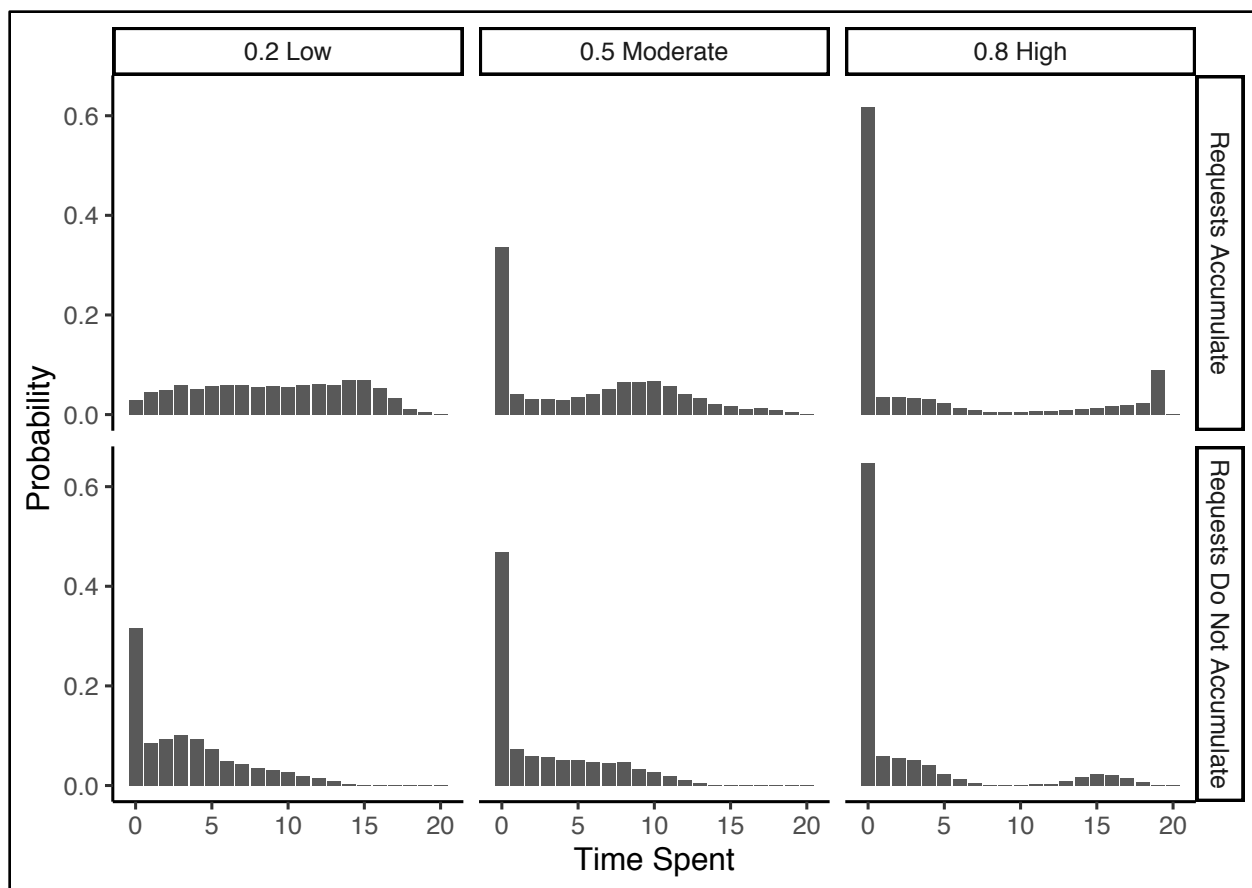


Figure 3. Probability that employee  $x_i$  spends  $n$  periods in the same percentile across the conformity condition.

## APPENDIX F:

Computer code for the simulation condition “Requests Accumulate & Respond to Many.”



using DataFrames, DataFramesMeta, Query, Statistics, CSV, CSVFiles, Distributions, Random, PrettyTables, RCall

```
# common parameters
sims = 10000
num_employees = 300
steps = 20
function initial_value()
    x = (rand()*20)[1]
    return(x)
end

#####
# sim1a: respond to many: inertia

store_it_sim1a = DataFrame(
    simulation = zeros(sims),
    moment_citizen_counts = zeros(sims)
)

counter = 0

for sim in 1:sims
    global counter = counter + 1

    df_requests = DataFrame()
    df_help = DataFrame()

    for walk in 1:num_employees

        requests = zeros(steps)
        requests[1] = initial_value()

        help = zeros(steps)
        help[1] = 0.5*requests[1]

        for step in 2:steps

            requests[step] = requests[step - 1] + rand(Normal(0,1), 1)[1]
            if requests[step] < 0
                requests[step] = 0
            end
        end
    end
end
```

```

    end

    help[step] = 0.5*requests[step]

end

insert!(df_requests, walk, requests, Symbol(walk))
insert!(df_help, walk, help, Symbol(walk))
end

@rput df_help
@rput num_employees
R"""
library(tidyverse)
df_help <- data.frame(df_help)
moment_counts <- 0
ecdf_fun <- function(x, perc) ecdf(x)(perc)
location <- ecdf_fun(as.numeric(df_help[1,]), df_help[1,1])

for(row_i in 2:20){

    row <- df_help %>%
        slice(row_i)

    location_later <- ecdf_fun(as.numeric(row[1,]), row[1,1])
    location_window <- seq(from = (location_later - 0.10), to = (location_later + 0.10), by =
0.01)

    yes_it_is_contained <- location > min(location_window) && location <
max(location_window)
    if(yes_it_is_contained == TRUE){
        moment_counts <- moment_counts + 1}

    }
}
"""
@rget moment_counts

store_it_sim1a[counter, :simulation] = sim
store_it_sim1a[counter, :moment_citizen_counts] = moment_counts

end

```

```

prob_steps = collect(0:1:steps)
probability_list_2 = zeros(length(prob_steps))

for prob in prob_steps
    result = count(
        k == prob for k in store_it_sim1a.moment_citizen_counts) /
length(store_it_sim1a.moment_citizen_counts)
    probability_list_2[[prob + 1]] .= result
end

sim1a_results = DataFrame(
    k = [0,1,2,3,4,5,6,7,8,9,10,
        11,12,13,14,15,16,17,18,19,20],
    probability = probability_list_2)

cd(dirname(@__FILE__))

CSV.write("sim-results/sim1a.csv", sim1a_results)

```

## APPENDIX G:

Computer code for the simulation condition “Requests Do Not Accumulate & Respond to Few.”

using DataFrames, DataFramesMeta, Query, Statistics, CSV, CSVFiles, Distributions, Random, PrettyTables, RCall

```
# common parameters
```

```
sims = 10000
```

```
num_employees = 300
```

```
steps = 20
```

```
function initial_value()
```

```
    x = (rand()*20)[1]
```

```
    return(x)
```

```
end
```

```
#####
```

```
# sim1b: respond to many: no inertia
```

```
store_it_sim1b = DataFrame(
```

```
    simulation = zeros(sims),
```

```
    moment_citizen_counts = zeros(sims)
```

```
)
```

```
counter = 0
```

```
for sim in 1:sims
```

```
    global counter = counter + 1
```

```
    df_requests = DataFrame()
```

```
    df_help = DataFrame()
```

```
    for walk in 1:num_employees
```

```
        requests = zeros(steps)
```

```
        requests[1] = initial_value()
```

```
        help = zeros(steps)
```

```
        help[1] = 0.5*requests[1]
```

```
        for step in 2:steps
```

```
            requests[step] = 0*requests[step - 1] + rand(Normal(0,1), 1)[1]
```

```
            if requests[step] < 0
```

```

        requests[step] = 0
    end

    help[step] = 0.5*requests[step]

end

insert!(df_requests, walk, requests, Symbol(walk))
insert!(df_help, walk, help, Symbol(walk))
end

@rput df_help
@rput num_employees
R"""
library(tidyverse)
df_help <- data.frame(df_help)
moment_counts <- 0
ecdf_fun <- function(x, perc) ecdf(x)(perc)
location <- ecdf_fun(as.numeric(df_help[1,]), df_help[1,1])

for(row_i in 2:20){

    row <- df_help %>%
        slice(row_i)

    location_later <- ecdf_fun(as.numeric(row[1,]), row[1,1])
    location_window <- seq(from = (location_later - 0.10), to = (location_later + 0.10), by =
0.01)

    yes_it_is_contained <- location > min(location_window) && location <
max(location_window)
    if(yes_it_is_contained == TRUE){
        moment_counts <- moment_counts + 1}

}
"""
@rget moment_counts

store_it_sim1b[counter, :simulation] = sim
store_it_sim1b[counter, :moment_citizen_counts] = moment_counts

end

```

```

prob_steps = collect(0:1:steps)
probability_list_2 = zeros(length(prob_steps))

for prob in prob_steps
    result = count(
        k == prob for k in store_it_sim1b.moment_citizen_counts) /
length(store_it_sim1b.moment_citizen_counts)
    probability_list_2[[prob + 1]] .= result
end

sim1b_results = DataFrame(
    k = [0,1,2,3,4,5,6,7,8,9,10,
        11,12,13,14,15,16,17,18,19,20],
    probability = probability_list_2)

cd(dirname(@__FILE__))

CSV.write("sim-results/sim1b.csv", sim1b_results)

```

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## REFERENCES

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