Robust Systems of Cooperation

by

Cassandra Aceves

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Business Administration)
University of Michigan
2018

Doctoral Committee:

Professor Wayne E. Baker, Co-Chair
Associate Professor Maxim Sytch, Co-Chair
Professor Gerald F. Davis
Professor Scott E. Page
Professor James P. Walsh

Cassandra R. Chambers

caceves@umich.edu

ORCID iD: 0000-0001-6222-0920

This dissertation is dedicated to my husband Pete Aceves.
Your brilliantly creative mind, pain-staking attention to detail, and intellectual breadth inspire me on a daily basis. I am so fortunate to walk through this career, and this life, with you.

ACKNOWLEDGEMENTS

This dissertation is principally concerned with designing robust systems of cooperation. While writing this dissertation it occurred to me that I myself have benefited from a robust system of cooperation comprised of supporters, teachers, collaborators, and mentors, whose contributions to my development and well-being propelled me through this PhD program. I would like to take this space to formally acknowledge and thank several of these contributors, but recognize that this is invariably an incomplete list. As with all systems of cooperation, single acts of help and kindness may go unrecognized, but undoubtedly make a long-lasting impact. I am grateful to all who have contributed to my development as a scholar.

I would like to begin by thanking my two amazing co-chairs Wayne Baker and Maxim Sytch, who immediately recognized and validated the potential of the ideas found in this dissertation even when they were in their malformed, nascent stages. I have benefited immensely from my independent relationships with both of them, but this dissertation benefited greatly from the complementary nature of their joint mentorship. I only experienced the extreme upside of having co-chairs. Their suggestions for structuring the dissertation, tackling problems that arose along the way, and their general approaches to scholarship continually built off one another. As a result, I experienced double the care, creativity, and encouragement.

Before starting the PhD program, I had formed an image of what an adviser would be like; someone who had exacting standards, but was also inspiring and encouraging, someone who held high acclaim in the field, but who was really in it for the love of research, and someone

who would be as invested in my success as I was. Wayne Baker is all these things and more. Wayne was the first to get truly excited about the ideas found in this dissertation. In my second year I had written a course paper that built off one of his papers. I remember being so nervous after sending him this paper and asking if he wanted to be on the project with me. He read it right away and responded back with excitement, saying we should get started immediately. Despite being incredibly busy, he always had time to talk through new ideas, comment on drafts, and listen to my worries—there were a lot of these conversations. Ultimately, I feel as though in Wayne I not only have a great mentor, but also a great friend. I am grateful for this friendship and look forward to working together for many years to come.

Maxim Sytch's mentorship has seen me through the entire PhD program. It has been a singular privilege to learn the craft of research from him. Among other things, Maxim gave me the opportunity and confidence to continually strive for higher and higher levels of scholarship. I would often reach a bar only to find that it had moved a little higher and for that I am truly grateful. He saw in me capabilities that I myself didn't know I possessed and encouraged me to work on my weaknesses until I could consider these areas sources of strength. While he urged me to develop skills as an independent researcher, I never felt as though I was on these dissertation and job market journeys alone. I am deeply grateful for his feedback on multiple drafts of dissertation ideas and job-market packet components, as well as last minute interview-prepping sessions and his openness to 9am calls on a Sunday morning to strategize the critical wording of an email. I hope that I can be as impactful an adviser for my future students.

The remaining members of my committee were also critical for the completion of this dissertation. Jerry Davis emphasized the phenomenological importance of this dissertation and helped me flesh out real-world examples of it in action. At a foundational level he is also the reason why I had the confidence to work with the "big data" I use in Chapter 4. I benefited from his vision of a data camp that would make programing more accessible to social scientists. Scott Page's work and mentorship inspired and encouraged this dissertation's ties to complexity theory. I always left conversations with Scott buzzing with excitement about the possibilities for my data and line of theorizing. Last, by alphabetical order only, I would like to thank Jim Walsh. Jim's feedback was not only central to the completion of this dissertation—particularly in the shaping of its original direction and the refinement of my thinking on foundational constructs, but also for my progression through this program as a whole. He spent countless hours sitting with me at Amer's and Baba Dari listening to my ideas, providing feedback, and offering encouragement.

The completion of this dissertation and my PhD program also greatly benefited from a wider academic community. In particular, Sue Ashford made a lasting impact on my thinking as a scholar. Her organizational behavior class provided the rigorous theoretical training and enriching feedback mechanisms that helped me find the idea that would ultimately lead to this dissertation. Dave Mayer, Jeffrey Sanchez-Burks, Leigh Toast, Ned Wellman, and Lillian Chen provided multiple sessions of feedback on my experimental designs. Gautam Ahuja, Michael Jensen, and Derek Harmon provided support by looking in on the students in our office on a frequent basis. Their "war stories," advice, and humor were always greatly appreciated. Michael Payne and Aurora Turek made a year and a half worth of data collection both feasible and fun. Shelly Whitmer, Barb Kirby-Bloch, and Adriana Morariu were the go-to-people when I needed resources and logistical support. Brian Jones facilitated a supportive doctoral studies environment that was especially welcoming for a somewhat non-traditional student like me. Last, I am deeply grateful to my original academic mentors Bob Thomas, Gwen Lee, and Jason

Colquitt who told me that a career in academia might be a fit for me. I would especially like to thank Bob Thomas who gave me my start in research and encouraged me to keep going with my doctoral plans even after I learned that the twins were on their way.

It has been said that you are only as good as the people who surround you. In this program, I have been fortunate enough to be surrounded by an incredibly awesome group of family and friends, without whom this dissertation and a career in academia would not be possible. Above all, I am grateful for my husband Pete Aceves's support. Pete is not only an incredibly supportive spouse, but is also my most tireless colleague and friend. From countless hours commuting back and forth to Chicago to repeatedly taking on the sole care of our children over weekends so that I could work, Pete contributed a great deal to make sure that I could be successful in my program. He has always been my go-to-person for my research ruminations, my most dedicated manuscript reviewer, and the person I rely on most for emotional support. I am deeply grateful for our partnership, which has only strengthened as a result of graduate school. On every dimension, we did this together. Thank you, Pete.

I thank my sons Isaac and Nico, who at the young age of seven are already sources of intellectual inspiration and enthusiastic supporters of my academic career. Throughout the writing of this manuscript they checked in on my daily progress and cheered me on. They are both great observers of human behavior and already think deeply about many critical issues of our time. I feel incredibly privileged to be your mother and look forward to engaging with you in scientific inquiry throughout the years to come.

I am grateful to my parents, Terry and Steve Chambers. I credit my mother with inspiring my love for reading. Some of my earliest memories of my mother are of her reading to me. She also served as my first female academic role-model, who after staying home for several years to raise children, re-entered the workforce when I was thirteen. I now more than ever appreciate how she accomplished this feat and deeply admire how she did so without me perceiving a reduction in her availability and support. Her example showed me that it is always possible to reinvent oneself and that women can be both excellent mothers and professionals. My father has always been an incredible supporter of my academic inclinations. I think the magnitude of this support is best exemplified by the time he flew from California to Michigan—on the heels of a long work week—to spend days taking care of his two-year-old grandsons. He did this so that I could still attend classes while their daycare was closed. From immigration logistics to strategizing how to be an advocate for myself and my children, I am always at ease when my dad is on the case.

I am also incredibly fortunate to have an equally supportive set of in-laws, Kimberly Breeden and Pedro Aceves. I recognize the rarity and specialness of my relationship with my mother-in-law, whom I consider to be one of my closest friends. I especially admire her intellect and how she is such a keen observer of human behavior. Her insights into the underlying psychological states of individuals continually cause me to reexamine what it is that I think I know about the phenomena I research. In my opinion, the depths of these insights exceed those that are exhibited by many who hold a PhD. My father-in-law is also a huge supporter of mine. His notes of encouragement make me feel as though I walk on water. His support for my career knows no bounds, which was confirmed when he took a sabbatical from his medical practice to help us get settled abroad. Suegrito, we are moving to Italy!

My progression through this program was spurred on by several important friendships. With my cohort mate Ashley Hardin, I shared all the ups and downs that come with being an early PhD student. She was always quick to check in on me, meet me with a cup of coffee after I stayed up all night with sick kids, and most importantly told me to keep going when it felt impossible to do so. Even from afar Ashley has continued to check in and offer support. With my officemate Casidhe Troyer, I shared a great deal of my coursework and the final stages of this doctoral experience. I envy all Casidhe's future colleagues. She is incredibly giving of her time—both for work and non-work-related support. Even though we could have technically been competing for some of the same jobs, I felt nothing but warmth, joy, and validation from her. With my officemate Teddy Dewitt, I shared all the experiences of being a "macro" MO student. I am extremely grateful for his friendship and support. Whether it was taking notes during my proposal, editing drafts, loading heavy book boxes on a moving truck, or reasoning through reviews, he always had my back. It has been fun getting to know the most recent addition to our office, Sarah Gordon. I wish that I could have spent more of my program with her. Laura Sonday is a great friend who read through drafts of job market materials, offering stellar feedback and support. Chen Zhang and I weathered the job market journey together, cheering each other on. Gareth Keeves always was a source of levity and fun, both in and outside of the classroom. Shawna Smith was my first and best statistics professor and has since become a dear friend. Last, to all the past and current MO students who were not mentioned above, but have offered me advice, sat through my presentations, and cheered me on, I express my heart-felt thanks: Natalie Cotton-Nessler, Jeff Bednar, Chuck Fu Lam, Samir Nurmohamed, Laura Rees, Kristina Workman, Suntae Kim, Johan Chu, Chris Myers, Matt Karlesky, Yong Hyun Kim, Maddy Ong, Lyndon Garrett, Lindsey Cameron, Eun Woo Kim, Mrudula Nujella, Mijeong Kim, Eun Bit Hwang, Hilary Hendricks, and Katherine Bae. For each of you, I can think of a special memory that has brightened my experience in this program.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

This dissertation examines the robustness of systems of cooperation—the ability to maintain levels of cooperation in the presence of a potentially disruptive force. I examine rankings as a potentially disruptive force that is commonplace in organizations. A ranking is the ordering of individuals according to their performance on a specific dimension. Systems of cooperation often operate in contexts that feature rankings (e.g., the ride-sharing company Uber uses a "rank and yank" performance evaluation system, yet still expects cooperation on complex cooperative coding tasks) and some explicitly use rankings to motivate cooperative contributions toward a collective goal (e.g., the character improvement App "Peeple" consists of members' public evaluations of each other's character and uses a public "positivity rating" to motivate members to maintain a more collegial environment). Yet, a growing body of research is highlighting potential downsides to rankings that could undermine the maintenance of systems of cooperation. This research suggests that rankings may unexpectedly introduce new dynamics into a system of cooperation that drive actors toward uncooperative behaviors and undermine the system as a whole. This dissertation aims to address this tension by exploring how systems of cooperation interact with rankings. Specifically, it explores how rankings can both enrich and perturb a system of cooperation and how systems can achieve robust cooperation in the presence of rankings.

Chapter 1 introduces the dual role of rankings for systems of cooperation, reflects on the importance of identifying characteristics that make these systems robust, and discusses how the

changing nature of work creates a new urgency for understanding how rankings affect cooperation. This introductory chapter is followed by two empirical chapters that examine distinct pieces of the puzzle for how rankings affect the maintenance of cooperation over time. Chapter 2 examines how the introduction of a performance ranking affects established systems of cooperation. Using a between-groups, no-deception experimental design that includes 74 groups, 594 participants, and over 11,000 cooperation decisions, it examines 1) whether the self-sustaining properties of systems of cooperation are naturally able to overcome the potentially disruptive effects of rankings, and 2) in the case of disruption how managers may be able to restore cooperation in the presence of rankings—making these systems of cooperation more robust. Chapter 3 examines an online community that explicitly uses a ranking to promote cooperation. Using over 1.2 million observations of members' weekly behaviors, this chapter examines how potential losses and gains in rank inspire individuals to perform both cooperative and uncooperative behaviors and explores how the system-level implications of these behaviors may affect the robustness of systems of cooperation. Chapter 4 concludes the dissertation by synthesizing findings from the empirical chapters, discussing their joint implications for building robust systems of cooperation, and detailing areas of future research.

CHAPTER I

Robust Systems of Cooperation, Rankings, & the Changing Nature of Work

Traditional organizational forms are becoming increasingly less relevant. Contrary to the heyday of organizations in the late 70s to early 90s, traditional forms of public corporations are disappearing form the social landscape at a rapid rate (Davis 2016). Simultaneously, we have observed both a rise in non-traditional forms of employment such as increases in temporary assignments and independent contracting (Cappelli and Keller 2013) and a dramatic increase in alternative forms of organizing such as business models built around shared assets, online communities for the creation and dispersal of knowledge, virtual teams, and work cooperatives (Puranam, Alexy, and Reitzig, 2014). This dramatic shift toward more collectively oriented business ventures and the decentralized control of assets and decision making suggests that a period of reflection surrounding our traditional management structures and theories of collective cooperation could be useful (Barley, Bechky, and Milliken 2017; Walsh, Meyer, and Schoonhoven 2006). With the absence of traditional organizational forms, maintaining cooperation may become more difficult. For example, lower rates of in-person interaction, more atomized task allocations, and lower barriers to exit the organization are common characteristics of non-traditional organizational forms. These characteristics may encourage higher rates of freeriding and reduce individuals' commitment to organizations' ongoing status and collective goals. Increases in geographic distance make monitoring and enforcing cooperation more difficult and lower barriers of exit could lead individuals to have less at stake in their membership.

Rankings as a mechanism to maintain cooperation may be particularly well-suited to this changing nature of work. Rankings are a form of social hierarchy—the explicit or implicit ordinal ordering of individuals on a valued social dimension (Magee and Galinsky 2008)[1]. Social hierarchies compare community members' past performance of cooperative behaviors and therefore serve two functions: 1) deterring uncooperative behavior by holding members accountable to standards of behavior and 2) incentivizing future cooperation by offering relative rewards to those who contribute the most. Rankings create cognitive shortcuts that provide access to these rewards. As such, rankings are often enlisted as mechanisms to maintain social order and create cooperation in communities (Thibault and Kelley, 1959; Blau, 1968; Simpson and Willer, 2015). Unlike other mechanisms utilized to elicit cooperation, which become more difficult to use with higher population sizes (e.g., norms and regulations), rankings may be more amenable to the changing nature of work. Advances in technology allow for better monitoring of members' activities and allow organizations to display more transparent data about these activities (Bernstein and Li 2017). Consequently, rankings have the potential to be more accurate and transparent than ever before, which suggests that they could be the mechanism that best facilitates cooperation in the new world of work.

However, extant research presents conflicting evidence about the outcomes that may arise in the presence of rankings; casting doubt on whether they would be appropriate for this role. On the one hand, rankings and other forms of social hierarchy have been lauded as a key facilitator of cooperative behavior in groups and organizations (Thibault and Kelley 1959; Blau 1968;

[1] Rankings can take many forms (e.g., partial, complete, cardinal, ordinal, etc.). I examine rankings as ordinal social structures. Ordinal rankings imply that each position has a unique meaning that comes from its position relative to others in the ranking.

Magee and Galinsky 2008; Willer 2009; Anderson and Brown 2010). Rankings incentivize and reward cooperative behavior and facilitate the punishment of uncooperative behavior. Attaining higher ranks is typically associated with higher material, social, and psychological rewards (Tannenbaum et al. 1974; Magee and Galinsky 2008). Rankings incentivize cooperative behavior when the ascension to higher ranks is coupled with performing cooperative behaviors (e.g., Pfeffer and Cohen 1984; Baron, Davis-Blake, and Bielby 1986). These rewards need not translate into some form of material gain or competitive advantage—simple levels of public recognition often spur cooperative behaviors. For example, in a field experiment of Wikipedia users Restivo and van de Rijt (2012) found that symbolic recognition from peers for good contributions (in the form reputation "badges" that hold no material value) increased future contributions (e.g., posts and editing activities) to the online encyclopedia of Wikipedia. Further, these rankings systems need not be formal to be effective at ensuring cooperation. Prior research shows that groups will gather information about members' relative rates of cooperation to form informal rankings and reward and sanction members according to these informal rankings (Willer 2009). For example, Feinberg, Willer, and Schultz (2014) document how groups use gossip to collect information about members' relative contributions to collective goals.

On the other hand, recent research is beginning to document a link between rankings and higher rates of uncooperative behaviors such as cheating, dishonesty, and the sabotage of other group members (Edelman and Larkin 2014; Pettit et al. 2016; Vriend et al. 2016). This research finds that individuals' drive to obtain higher positions in rankings can lead to increases in competitive behaviors (Barclay and Willer, 2007) and interpersonal conflicts (Bendersky and Hays 2012). For example, researchers of tournaments—contests in which members compete for prizes awarded based on relative rank (Lazear 1999; Connelly et al. 2014)—show that tournaments may foster aggressive behavior (Siegel and Hambrick 2005) and undermine organizational goals (Henderson and Frederickson 2001). Overall, this research suggests that rankings may unintentionally introduce new dynamics into a system that drive actors toward uncooperative behaviors. Accordingly, while rankings have been traditionally thought of as mechanisms that shore up cooperation and social order to create stable groups and organizations, they may simultaneously sow seeds of disruption that threaten future rates of cooperation.

This dissertation engages with this puzzle by examining whether and how organizations can achieve robust cooperation in the presence of rankings. Embedded within this focus is the assumption that rankings are an unavoidable element of social life. This assumption is well supported by prior research that documents the seemingly ubiquitous presence of hierarchy in society (Anderson and Brown 2010). Given this near ubiquity, I argue that explanations of the maintenance of cooperation necessitate an explicit consideration of how mechanisms that maintain cooperation interact with rankings. With this focus, this dissertation departs from extant research on the maintenance of cooperation in three ways. First, it examines cooperation as a social system. Social systems are patterned networks of actions (Parsons 1991). Past actions impart social forces on actors that inspire future actions (e.g., one actor helps another and this triggers the receiver to "pay this help forward" to another actor) (e.g., Baker and Bulkley 2014). Prior research tends to address the maintenance of cooperation by identifying intrapersonal mechanisms of maintenance (e.g., individual characteristics, prosocial emotions, and personality) or interpersonal mechanisms (e.g., norms, networks, and hierarchy) (Simpson et al. 2015). Examining cooperation as a system combines insights from both perspectives. Second, it applies a dynamic perspective of social hierarchy (e.g., Pettit et al. 2013) to investigate how movements through rankings alter actors' experiences in these rankings. Static views of rankings assume stable psychological experiences of rankings. Dynamic views of rankings expose how actors' movements through rankings alter their experiences of rankings. Accordingly, a dynamic perspective of rankings may help illuminate why and when rankings create negative externalities that may undermine cooperation. Third, it imports a robustness lens (Jen 2005) from complexity theory in the natural and engineering sciences. Through this lens, it explicitly examines how cooperation is maintained in the presence of potentially disruptive forces. Such an approach has the power to identify mechanisms that can lead to longer-lasting cooperation despite the occurrence of failure, environmental uncertainty, rapid change, and increasing complexity.

Systems of Cooperation

Cooperation occurs when an individual enacts a behavior that benefits a group at a personal cost (Nowak 2006; Ring and Van de Ven 1994). A *system* of cooperation occurs when behaviors related to cooperation (e.g., cooperative and uncooperative acts) become interlinked overtime through ongoing, regular interactions. In systems, actors' past behaviors catalyze behaviors in others. For instance, teams of developers repeatedly exchanging ideas for a project (e.g., Barghouti 1992) and sales representatives regularly passing leads amongst each other (e.g., Bailey 2008) can both be examined as systems of cooperation. Systems of cooperation also occur outside of formal organizational settings such as is the case with open-source projects (e.g., Smith and Kollock 1999; Anthony et al., 2009), online markets and communities (e.g., Restivo and van de Rijt 2012), and even across villages as seen in the ceremonial exchange system the Kula Ring (e.g., Malinowski 1922). What is common to these examples, but not cooperation in general, is the linked, ongoing, regular nature of cooperative interactions and the interdependence that ensues from these linkages.

Inspired by the biological and physical sciences, Parsons (1951) first described the concept of a social system as a patterned network of actions. The "networked" element of this definition is important as it highlights the interdependence among actions. Past actions trigger future actions among a set of actors over time. As such, social systems can be described as autopoietic in nature (Luhmann 1995). They tend to be self-reproducing. Over time, the occurrence and non-occurrence of actions strengthen or weaken social forces that regularly inspire similar actions, thereby reproducing a pattern of networked actions. While social systems can occur among the same set of individuals, they are not dependent on the continued presence of specific individuals. Instead, the focus is on the interlocking nature of actions. As Asch (1959:252) states, a social system "does not reside in the individuals, taken separately, though each individual contributes to it, nor does it reside outside them; it is present in the interrelations between the activities of individuals."

Interrelations between activities are governed by actors' mental representations of the system as a whole and their impressions of the reasons behind other actors' actions. In considering how to act in a social system, actors reflect on the past behaviors of others in the system and consider how their own actions may fit in with these behaviors (Asch 1959). During this process an actor's own motivations for acting, personal values, and impression of others' reasons for acting all factor into how they interpret the global structure of the system. Ultimately the system as a whole is a composite structure that reflects the aggregation of these interrelating activities and the micro-motivations that are embedded within them. Consequently, a social systems perspective adds to research on the maintenance of cooperation because it bridges intrapersonal and interpersonal explanations of cooperation to form a more nuanced understanding of how social forces affect rates of cooperation.

Dynamic Views of Rankings

Up until the last decade, research on actors' psychological experiences of rankings tended to assume that actors occupied stable hierarchical positions and therefore experienced stable preferences stemming from these positions. For example, Phillips and Zuckerman's (2001) theory of conformity explicitly assumed that hierarchies are stable (e.g., there is little movement of actors between qualitatively meaningful categories such as high, medium, and low); leading the lower strata to dis-identify with the hierarchical structure.[2] It is easy to see why this assumption held. At more macro-levels of analysis, social hierarchies tend to remain stable over time and confer different levels of benefits to actors within these systems, which help preserve actors' positions within the structure. Higher ranked actors tend to stay near the top and lower ranked actors tend to stay near the bottom (Merton, 1968; Podolny and Phillips, 1996). Hence, it was fair to expect that actors within these systems would experience relatively stable levels of social psychological pressures associated with one consistent position within a ranking.

In contrast, recent research is beginning to apply a dynamic perspective to actors' experiences within social hierarchies (e.g., Pettit et al. 2010; Pettit et al. 2016). Instead of assuming stable positions in a ranking, dynamic perspectives focus on how *movements* through a ranking create different psychological experiences for actors. For example, Pettit et al. (2016) show that potential status losses, more than potential status gains, are associated with higher performance comparison pressures and ultimately with higher levels of cheating. Similarly, Krishnan and Kozhikode (2015) note that increases in firms' ranking positions are associated with higher rates of illegality, citing concerns about status loss as the underlying mechanism. On

[2] Phillips and Zuckerman (2001) acknowledge that while conformity pressures would seem to imply a static social order, there must be some threat of downward mobility for the inverted U-shaped relationship between status and conformity to play out. Consequently, prior research on status hierarchy's structural effects and its related social psychological pressures includes an underlying assumption of dynamism, but until recently did not explicitly theorize around it.

this front there is still much to learn about 1) how the type of movement through a hierarchy (e.g., up, down, frequent, net, relative, etc.) affects actors' psychological experiences and subsequent behaviors, 2) how these behaviors feedback into and shape the hierarchy, and 3) how the aggregation of these *shifting* behaviors ultimately affects the organization's ability to maintain cooperation over time.

Robustness

Robustness is the featured persistence of one aspect, or the entirety, of a system in the face of perturbations (Jen 2005). Perturbations are the factors that create a system-wide change in a system's composition, core relational dynamics, or fundamental assumptions about the environment in which the system operates (Jen 2003). Perturbations can be external to the system (e.g., a new legal standard that changes "the rules of the game" for patenting), or internal to the system (e.g., shifting employee motivations resulting from their experiences in an incentive system).

It is not sufficient to simply say that a social system is "robust." One must define the aspect of the social system that exhibits featured persistence (e.g., maintaining levels of cooperation) and the source of perturbations that could disrupt it (e.g., rankings). Robustness is related to, but distinct from, the concept of stability. In complexity theory (stemming from control theory and stability theory in engineering fields) a system is said to be stable when it can remain at an "equilibrium state" over time (Jen 2003). This includes returning to this equilibrium state after experiencing small changes in the environment such as a change in levels of external inputs. Hence, stability and robustness both feature the common element of featured persistence over time, but robustness differs in two key ways: 1) Robustness explicitly examines featured persistence in the face of perturbations, whereas stability can exist without considering perturbations, and 2) Robustness can be achieved without returning to an equilibrium state—the social system *can change* in fundamental ways, so long as the performance of a social system is maintained. As an example, consider Jen's (2003) illustration of the flow of a river to further differentiate the concepts of stability and robustness: "Assuming that the flow depends on an external parameter, such as wind speed, and ignoring other factors, the flow is structurally stable if small changes in wind speed do not qualitatively change the dynamics of the flow; for example, do not produce a new structure such as an eddy" (i.e., a reverse current). This is not to say that robustness requires the presence of change. Rather, this statement illustrates the point that stability *cannot* occur with fundamental changes to a social system's core dynamics. Hence, robustness is a wider construct than stability.

While perturbations have the potential to completely disrupt and even destroy a system, this is not the only outcome they can produce. Perturbations can lead to momentary setbacks for a system that it later recovers from. Systems may remain unaffected by perturbations. In some cases, systems can even thrive as a result of perturbations. All three of the latter outcomes would typify a robust system because performance levels are maintained or enhanced after encountering perturbations.

The concept of robustness is similar to the concepts of organizational resilience (e.g., Gittell et al. 2006; Sutcliffe and Vogus 2003) and high reliability organizing (e.g., Weick, Sutcliffe, and Obstfeld 2008; Weick 1987). Organizational resilience can refer to an organization's ability to recover from an adverse event or an organization's ability to thrive as a result of encountering stress (Lengnick-Hall 2011). High reliability organizing focuses on organizations that portray a "broad vigilance for and high responsiveness to potential accidents"

(LaPorte and Consolini 1991; Weick, Sutcliffe, and Obstfeld 2008:33). Robustness engages with similar themes—maintaining performance after disruptions, but robustness is a wider construct.

There are two main differences between robustness and these constructs. First, high reliability theorizing (HRT) and resilience research typically focus on unexpected exogenous events (e.g., crises). HRT examines preparation for the avoidance of, or the rebounding from, catastrophic events (e.g., a nuclear meltdown). The term organizational resilience tends to be invoked after an unexpected, exogenous event. Conversely, robustness examines potentially disruptive forces that may arise from both exogenous and endogenous sources and these perturbations do not need to be "shocks." They can be everyday externalities that create potentially disruptive forces. Similar to engineers that focus on de-bugging a system, a robustness lens can pick up on everyday perturbations that result from seemingly normal organizational activities; recognizing that at the aggregate these small perturbations could produce dramatic consequences for a system.

Second, organizational resilience and HRT tend to describe agentic, intentional responses by actors (e.g., the strategic prioritization of safety or active limitation of trial-and-error learning) (e.g., LaPorte 1994). While robustness can include human actions, it is principally concerned with the qualities and dynamics of a system. In examining an organization's ability to maintain cooperation over time, a robustness lens may be concerned with understanding how the accumulation of cooperative events produces externalities that change actors' motivations to cooperate in the future. For example, Stewart and Plotkin (2014) show that over time high rates of continued cooperation increase the benefits associated with freeriding, which in turn shifts the motivations of actors away from cooperation to freeriding and ultimately disrupts future rates of cooperation. In summary, a robustness lens enhances the study of cooperation by explicitly focusing on the maintenance of cooperation in the presence of potentially disruptive forces—both endogenous and exogenous forms—which can ultimately help explain the maintenance of longer lasting cooperation.

Overview of Chapters

The remaining sections of this dissertation are outlined below. In Chapter 2 rankings are thought of as an exogenous perturbation to a system of cooperation. Chapter 2 examines whether rankings are inherently disruptive forces that undercut cooperation, or if they can be managed to help maintain cooperation over time. Maintaining cooperation in the face of strong self-interest is a subject of longstanding inquiry in the social sciences. Much of this work has focused on understanding the antecedents and outcomes associated with cooperation, assuming that the inertial properties of a system will sustain cooperation over time. This chapter shifts the focus toward examining how cooperation is maintained in the face of potentially disruptive forces. To advance theory, research, and practice on how to maintain cooperation over time, it examines how systems of cooperation interact with, withstand, or succumb to a potentially disruptive force that is commonplace in organizational contexts: rankings. Using a longitudinal, no-deception, between-groups experimental design, it assesses how systems of cooperation respond to the introduction of performance rankings. Examining data from more than 11,000 rounds of decision-making from 592 participants clustered in 74 teams, this study finds that cooperation plummets when performance rank information is introduced. However, the addition of reputation information—other individuals' histories of prosocial contributions—enables a system of cooperation to recover from the disruptive effects of performance rankings. Actors use reputation information to make decisions that reduce perceived inequity. Reputation serves as a source of system robustness that restores cooperation, enabling a system of cooperation to withstand forces that would otherwise destroy it. This study contributes to theories of cooperation, performance feedback, macro-level prosocial behavior, and management practice.

Chapter 3 examines the online community Stack Overflow as a system of cooperation. Stack Overflow is a question and answer site for programmers. Stack Overflow solely exists because of the voluntary contributions and needs of its members and explicitly uses a ranking to motivate its members to make these contributions. This context enables a more dynamic examination of rankings by documenting the shifting pressures associated with individuals' movements through a ranking. In Chapter 3, rankings are thought of as an endogenous perturbation to a system of cooperation. Chapter 3 departs from prior studies that recognize the duality found in rankings' effects on cooperative and uncooperative behavior by relaxing the assumption that these behaviors are mutually exclusive. As such, actors have the opportunity to exhibit both cooperative and uncooperative behaviors as they approach a meaningful standard of achievement. Using over 1.2 million observations of 16,200 individuals' weekly activities on the Stack Overflow site, this chapter explores 1) whether opportunities for gains and threats of losses in the rankings equally motivate both cooperative and uncooperative behaviors, 2) whether actors that eventually exhibit uncooperative behaviors have higher rates of cooperation near ranking thresholds than actors that never exhibit uncooperative behaviors, and 3) whether actors are more likely to exhibit cooperative behaviors after being punished for uncooperative behaviors. I find that a proximity to a loss in rank *discourages* uncooperative behavior and is generally more effective at incentivizing cooperative behavior than a proximity to a gain in rank. Further, I find that incremental movements forward in a ranking are associated with increases in uncooperative behavior.

Jointly, these finding suggest that gains in rank come with potential costs to the system—they may lead to higher rates of uncooperative behavior. However, I find evidence that actors that eventually exhibit uncooperative behaviors tend to exhibit slightly higher levels of cooperative behaviors when approaching these ranking thresholds than those who never exhibit uncooperative behaviors. This finding implies that systems may be able to tolerate the negative externalities of rankings (i.e., uncooperative behaviors), because the actors that perform them are on average more cooperative. Their cooperative actions may offset their uncooperative actions. This study contributes to theories of cooperation, dynamic perspectives of social hierarchy, and research on licensing behaviors. Chapter 4 concludes the dissertation by summarizing what I have learned about achieving robust systems of cooperation and discusses avenues for future research.

CHAPTER 2

Achieving Robust Cooperation after the Introduction of Rankings

Coauthored with Professor Wayne E. Baker

Cooperation is essential for nearly every organizational endeavor. From complex international agreements to address global climate change (Barrett 2016, Ostrom 2010, Ostrom et al. 1999, Wijen and Ansari 2007) to daily teamwork and the pursuit of organizational goals (Barnard 1938, Jones and George 1998, Tjosvold 1984), organizations and communities depend on the maintenance of cooperation. However, to maintain cooperation, at least some members must limit self-interest in favor of collective interest (Hardin 1982, Cook and Rice 2003, Kollock 1993, 1998). This classic social dilemma has inspired a large, interdisciplinary body of work that seeks to understand how cooperation is sustained over time (Fehr and Gintis 2007, Salvato et al. 2017).

One well-known type of cooperation is generalized reciprocity. Colloquially known as “paying it forward,” generalized reciprocity exists when "an individual feels obliged to reciprocate another's actions, not by directly rewarding his benefactor, but by benefiting another actor " (Ekeh 1974, p. 48). Systems of generalized reciprocity are a type of social system (Asch 1959, Weick and Roberts 1993) where helping behaviors are linked over time through ongoing, regular interactions. Actors’ past cooperative behaviors trigger future cooperative behaviors in others. These systems help resolve the social dilemma of self-interest versus group-interest by relaxing the need for immediate reciprocity (Molm 1997, Molm et al. 2006, 2007, Nowak 2006).

As Putnam (2000, p. 134) put it, “I’ll do this for you now, without expecting anything immediately in return and perhaps without even knowing you, confident down the road that you or someone else will return the favor.” Once established, a system of generalized reciprocity is assumed to be self-sustaining—the inertial properties of the system should maintain it over time by continually drawing actors in to the interlocking chain of cooperative behaviors (Lévi-Strauss 1969, Molm 1997). Due to this assumed inertial property, research on generalized reciprocity tends to focus on the antecedents and outcomes of cooperation. However, even established systems of cooperation may be vulnerable to disruptions, since actors in these systems are highly interconnected and a few initial refusals to cooperate can trigger a cascade of defections by others (Fehr and Schmidt 1999). Consequently, the goal of understanding how cooperation is sustained over time may be best advanced by explicitly examining how cooperation is achieved in the face of potentially disruptive forces.

Performance rank is one potentially disruptive force that may undermine systems of generalized reciprocity. A performance ranking is a form of social hierarchy—a rank ordering of individuals along a valued social dimension (Magee and Galinsky 2008)—that confers differential benefits. Performance rankings are commonplace in organizational contexts (Greenberg 1987) and have been associated with many benefits (Anderson and Brown 2010). For example, rankings can help attract and retain top talent, reduce biases in performance evaluations, and streamline decision-making (Moon et al. 2016). However, the presence of performance rankings may be detrimental to the maintenance of cooperation if it heightens performance comparison concerns—how one is performing relative to others (Garcia et al. 2006). These comparison concerns can sometimes trigger negative behaviors inside organizations. For example, comparison concerns have been linked to decreases in members’ desires to maximize joint gains (Armstrong and Collopy 1996), unhealthy levels of competition (Garcia et al. 2006), elevated levels of cheating (Pettit et al. 2016, Vriend et al. 2016), and the sabotage of others (Poortvliet 2013, Tesser and Smith 1980)—all of which could be detrimental to the maintenance of cooperation.

An established system of generalized reciprocity may nonetheless be able to withstand or recover from such disruptions. For example, at the industrial design firm IDEO, strong norms of generalized reciprocity supported by organizational routines and practices, maintain cooperation among product designers despite a compensation system based on performance rankings (Hargadon 2003, Hargadon and Sutton 1997, Amabile et al. 2014). The ability of IDEO to maintain a system of cooperation in the presence of performance rankings suggests that system-level properties exist to withstand or recover from everyday pressures that arise with performance rankings. However, despite broad interest in the study of cooperation and the recommendation of these systems to managers (Cross and Parker 2004), social scientists have not examined how systems of generalized reciprocity interact with, withstand, or succumb to potentially disruptive forces such as performance rankings. Hence, we explore the research question: *How do systems of cooperation (generalized reciprocity) perform in the presence of social hierarchy (performance rankings) and withstand potentially disruptive forces?* We examine whether they are naturally able to withstand the pressures that performance rankings create or if they are vulnerable to disruption, and in the case of disruption, which mechanisms may make systems more robust to potentially disruptive pressures. Of the mechanisms that are known to promote cooperation in these systems (see Baker and Bulkley 2014), we pay particular attention to the role that rewarding the reputations of cooperative actors may play in allowing systems of generalized reciprocity to withstand or recover from the potentially detrimental effects of rankings.

Using a longitudinal, between-groups, no-deception experimental design that includes 74 groups, 592 participants, and more than 11,000 costly decisions to give or not give, we examine how systems of generalized reciprocity fare in the presence of performance rankings. We first establish a group norm of cooperation through 40+ rounds of decision making (the first stage). Then, in one experimental condition we interrupt the system by introducing information about performance rank after the first stage, providing participants with information about their relative standing in the group (top, middle, or bottom third) and informing them that the top third will receive a higher bonus at the end of the experiment. We then run the experiment for another 40+ rounds of decision-making (the second stage). As hypothesized, cooperation plummeted in the second stage (look ahead to Figure 4). In another condition, at the end of the first stage we introduce reputational information in addition to performance rankings. Reputation refers to a potential receiver's history of giving (or not giving) to others during the first stage. We find that reputation enables a system of cooperation to recover from the disruptive effects of performance rank. Despite an initial decline in cooperation, systems that receive information about performance rankings *and* reputation information over time return to levels of cooperation that were established prior to the disruption.

Previous studies have assumed that established systems of generalized reciprocity are self-sustaining. We take this assumption as problematic. By examining the operation of these systems in the face of potentially disruptive forces, we document both the disruptive effects of performance rankings on systems of generalized reciprocity and provide an explanation for why some systems can be robust. Without displaying prosocial contributions (reputation), performance rankings are detrimental, causing an established system of cooperation to collapse.

Displaying reputation is a remedy. Prior research shows that reputation helps to explain the emergence and maintenance of generalized reciprocity (Alexander 1987, Nowak and Sigmund 1998a,b); here, we show that reputation also makes a system of cooperation robust in the face of disruptive forces.

This study makes several contributions. First, we make a general contribution to theories of cooperation by introducing a theoretical robustness lens (Jen 2003, 2005) to the study of cooperation (Baker and Bulkley 2014, Smith et al. 1995, Tjosvold et al. 2014). A robustness lens explicitly focuses on the maintenance of a system's performance (e.g., cooperation levels) in the face of perturbations (e.g., performance rankings) that could disrupt a social system.[3] By identifying what creates robust systems of cooperation, we can help shape capable of achieving long-term cooperation despite the occurrence of system-wide failure, environmental uncertainty, and increasing complexity. Second, we contribute to research that examines rankings as tools for performance feedback (Moon et al. 2016), showing that they can adversely affect cooperation, which may undercut their purported performance-enhancing effects. Third, we contribute to macro-level theories of prosocial behavior, which focus on the benefits of systems of generalized reciprocity for groups and organizations (Baker and Dutton 2007, Penner et al. 2005). Our research shows that due to performance rankings, which are commonplace in organizations, these systems may be more difficult to maintain than previously thought. However, we show and explain how introducing reputation information can reduce and even reverse the negative consequences of performance rankings permitting organizations to continue extracting benefits from these systems despite the presence of potentially disruptive pressures. Finally, we

[3] The concept of robustness is related to the concept of stability. Both feature the common element of persistence over time, but robustness explicitly examines persistence in the face of perturbations, and can be achieved without returning to an equilibrium state—the social system can change in fundamental ways, so long as the functionality of a social system is maintained—whereas stability can exist without considering perturbations, and tends to emphasize a return to equilibrium (Jen 2003).

contribute to management practice with the implications of our findings: (1) leaders who desire a prosocial culture must pay careful attention to the disruptive effects of performance rankings, and (2) it may be possible to sustain or restore cooperation *without* changing competitive performance appraisal systems by displaying employees' prosocial contributions and offering recognition for prosocial activities.

THEORETICAL FRAMEWORK

Cooperation occurs when actors make expected contributions to jointly held goals (Gulati et al. 2012). These social conditions often arise in contexts that have a mixture of conflicting and complementary interests (Axelrod and Keohane 1985, p. 2226). Generalized reciprocity is one well-known form of cooperation with competing individual and collective interests. In contrast to direct reciprocity between two actors (*A* helps *B* and *B* helps *A*) (Gouldner 1960), generalized reciprocity involves at least three actors, where a recipient of a benefit "pays it forward" to a third party, rather than returning the favor to the original benefactor (*A* helps *B* who then helps *C*) (Ekeh 1974). Systems of generalized reciprocity consist of helping behaviors that become interlocked over time through ongoing, regular interactions. This regularity delays expectations for immediate reciprocity, which helps to resolve the dilemma of self-interest versus group-interest (Molm 1997, Molm et al. 2007). Actors forgo immediate opportunities to maximize self-interest in favor of contributing to group-interest, expecting to receive benefits in the future. Hence, a system of generalized reciprocity is considered a stable form of cooperation that can balance collective and individual interests (Blau 1968, Nowak 2006).

Prior research on generalized reciprocity has mainly focused on its antecedents or its outcomes. Antecedents include, for example, group size (Pfeiffer et al. 2005), the spatial structure of relationships (Nowak and Roch 2007), similarity among actors (Axelrod et al. 2004, Queller 1985, Santos et al. 2006), and the frequency and diversity of actors' interactions (Rankin and Taborsky 2009). Outcomes include social solidarity (Molm et al. 2007), social capital (Baker and Dutton 2007, Putnam 2000), organizational commitment (Adler and Kwon 2002), prosocial organizational cultures (Penner et al. 2005), and organizational performance (Cross and Parker 2004). Our research fits between antecedents and outcomes. We focus on the mechanisms that sustain generalized reciprocity and the extent to which they may enable a system of generalized reciprocity to recover from disruptions.

Mechanisms of Generalized Reciprocity

Reputation is widely recognized as a key mechanism that drives cooperation in systems of generalized reciprocity (Alexander 1987, Nowak and Sigmund 1998a,b, Nowak and Sigmund 2005, Seinen and Schram 2006, Wedekind and Milinski 2000). For example, evolutionary theorists consider reputation to be the reason why generalized reciprocity evolved in the human species (Alexander 1987). Reputations are actors' personal histories of actions to others within a social system. Evolutionary theorists refer to reputations as "image scores" (Nowak and Sigmund 1998b) and argue that they are essential for fostering cooperative behavior among self-interested actors (Sigmund et al. 2001). Rewarding reputation occurs when actors provide help to those who have been cooperative in the past. Multiple economic experiments document actors' tendencies to reward positive image scores—actors preferentially help those who are perceived as being cooperative members of the social system (Milinski et al. 2002, Seinen and Schram 2006, Wedekind and Milinski 2000)—even at the expense of their own personal resources (Rabin 1993). For instance, in a laboratory experiment modeling generalized reciprocity, Wedekind and Melinski (2000) found that donations were more frequent to receivers who had been generous in earlier rounds of the experiment; even those who rarely gave were more likely to transfer when paired with a participant with a high image score. Actors, aware of this contingent access to future benefits, may strategically construct their reputations. Cooperation implies that actors are "good citizens," though they may only be "good actors" engaging in impression management (Bolino 1999). Either way, those with positive images (i.e., reputations) are more likely to be rewarded in the future than those with negative images.

Alternatively, systems of generalized reciprocity can be maintained by actors paying received help forward (Baker and Bulkley 2014). Paying-it-forward occurs when an actor receives help, but rather than repaying the benefactor, the actor helps a third person. Paying-it-forward could be driven by feelings of obligation (Ekeh 1974), but may also be driven by positive emotions such as gratitude (Bartlett and DeSteno 2006, DeSteno et al. 2010, McCullough et al. 2008). In general, gratitude motivates future prosocial behaviors. For example, Emmons and McCullough (2003) found that individuals who wrote daily about things they were grateful for were more likely to report that they provided tangible help to others in a future period. Economic experiments document the cooperation-enhancing effects of paying-it-forward behaviors (Greiner and Vittoria Levati 2005, Dufwenberg et al. 2001, Pfeiffer et al. 2005). By paying-it-forward, actors may help maintain generalized reciprocity, while disregarding any strategic effects from their actions.

Prior research documents the cooperation-enhancing effects of both mechanisms (reputation and positive emotions), but debate exists about their relative strengths. Some research suggests that paying help forward should be less effective than rewarding reputation for the maintenance of generalized reciprocity. For example, Nowak and Roch (2007) find that the pay-it-forward mechanism only produces cooperation when it is linked to other information such as direct or spatial reciprocity. Other research suggests that the mechanism of rewarding reputation may have limitations. For example, punishing an uncooperative person by denying help harms one's own reputation for generosity (Leimar and Hammerstein 2001). Experiments that demonstrate the effects of reputation typically run for short periods of time (Seinen and Schram 2006, Wedekind and Milinski 2000), whereas reputations are formed over long periods of time (Zinko et al. 2012). In a critical test of these two mechanisms in an organizational setting over three months, Baker and Bulkley (2014) find that both mechanisms help sustain systems of generalized reciprocity, but that paying-it-forward resulted in stronger, longer-lasting effects than rewarding reputation. Further, there is evidence that these mechanisms may jointly enhance cooperation. Using laboratory and online experiments, Simpson et al. (2017) find that systems with both mechanisms outperform systems with just one mechanism present.

A system of generalized reciprocity may be supported by the self-generating nature of such systems (Lévi-Strauss 1969, Molm 1997, Molm et al. 2007). For example, using computer simulations, evolutionary theorists propose that systems of generalized reciprocity should be stable over time (Nowak and Sigmund 1998a,b). However, scholars also recognize that systems of generalized reciprocity feature a well-known vulnerability that could threaten their continued maintenance (Lévi-Strauss 1969, Molm 1997). Each member does not depend on a specific actor (as with direct reciprocity), but rather on multiple, often unspecified, others to maintain the system (Molm et al. 2007). Benefactors are not guaranteed repayment. Imbalances may occur (e.g., helpers do not receive help when it is needed), triggering a cascade of defections that undermine the system.

The Disruption of Cooperation

A social system may be disrupted by exogenous or endogenous forces. We focus on the introduction of information about performance rank as a potential exogenous disruption.

Performance rankings are a form of social hierarchy—the implicit or explicit ranking of individuals on a valued social dimension (Magee and Galinsky 2008). There are many examples and contexts in which performance rankings are used to produce benefits for groups and organizations. Organizations, for example, often employ incentive systems based on performance rank, such as bonuses, promotions, or other rewards for higher levels of performance (Greenberg 1987). Rankings can help streamline decision-making, improve intragroup coordination, and heighten group performance (Anderson and Brown 2010). A contextually similar, yet controversial, example is the use of Forced Distribution Ratings Systems (FDRS)—colloquially known as "rank and yank"—in which those at the bottom are fired (Mulligan and Bull Schaefer 2011). However, FDRS can produce beneficial organizational outcomes, such as the cultivation of talent and more accurate, less biased evaluations (Moon et al. 2016). Rankings are common in informal settings as well. Observations of preschool age children engaged in free play (Charlesworth and La Freniere 1983, Strayer and Strayer 1976) and adolescent peer groups (Paikoff and Savin-Williams 1983, Savin-Williams 1976) reveal stable dominance relations and linear hierarchical structures. In general, there is a large body of work that demonstrates both the prevalence and benefits of rankings in social groups (Anderson and Brown 2010).

Despite potential benefits, performance rank may impede cooperation. Performance rankings can intensify competition among group members. Competition raises the personal costs of cooperation (Alexander 1987, Axelrod 1997, Deutsch 1949). Evolutionary biologists argue that natural selection favors "cheaters," or those that can benefit from a community without paying the personal costs of cooperation (West et al. 2007a,b). Factors that increase competition will increase the perceived benefits of defection and decrease the benefits of cooperation. For example, individuals at upper levels of a ranking may experience loss aversion (Tversky and Kahneman 1991) and decrease cooperation to preserve the superior benefits associated with their high rank. Those in lower ranks may decrease cooperation if they perceive outcomes to be inequitable or unfair. Believing that some members of the system are experiencing unfair outcomes may undermine members' trust that others will continue to cooperate in a system, thereby weakening the perceived strength of the norm of cooperation (Ring and van de Ven 1994, Salvato et al. 2017). Indeed, economic experiments find that even small perceptions of inequity can trigger defections (Fehr and Schmidt 1999). Further, low-rank individuals may experience relative deprivation and negative emotions, even when they receive benefits from the system (Greenberg 1987, Martin 1981). Ultimately, these lines of research suggest that the introduction of performance rankings with differential benefits will decrease cooperation and disrupt the continuation of these systems. Therefore, we expect:

> **H1:** The introduction of performance rankings tied to differential rewards reduces cooperation in systems of generalized reciprocity.

Restoring Cooperation

How might systems of generalized reciprocity withstand or recover from disruptions? An answer, we argue, lies in the principle of inequity aversion and the mechanism of rewarding reputation. Performance rankings can become problematic when they reveal differential benefits that are perceived to be inequitable or unfair. Rankings engender calculations of fairness. Individuals regularly reflect on whether their position in a ranking is commensurate with their contributions to a system (Thibault and Kelley 1959). When individual performance is affected by others' cooperative behaviors, it may lead to a sense of inequity—a suspicion that some actors are paying the costs of cooperation, but are not receiving enough benefits to outweigh these costs. For example, sales representatives who advance in rankings due to their personal sales totals may have higher levels of sales as a result of receiving leads from others. Performance is then affected by others' cooperative behaviors (e.g., passing leads). Inequity aversion occurs when an individual resists instances of inequity—when someone receives too much or too little compared to someone else (Fehr and Schmidt 1999, Walster et al. 1978). Inequity aversion appears to be an innate, universal behavioral norm (Blake and McAuliffe 2011, Fehr et al. 2008, Kahneman et al. 1991). Other primates (Brosnan et al. 2005, Brosnan and de Waal 2003) and even canines (Range et al. 2009) demonstrate a preference for fairness and equity.

Compelled by inequity aversion, actors may adjust their behavior to reduce perceived inequity (Fehr and Schmidt 1999, Walster et al. 1978). The willingness of actors to "sacrifice their own material well-being to help those who are being kind" is well documented (Rabin 1993, p. 1283). Economic experiments show that participants in cooperative games will incur personal costs in order to adjust others' incomes and this behavior is associated with enhanced levels of cooperation (Andreoni et al. 2003, Fehr and Gächter 2002). Actors often practice a form of "reciprocal fairness"—rewarding kindness with kindness and harm with harm (Falk and Fischbacher 2006, Rabin 1993). Dawes et al. (2007) find that this behavior is driven by egalitarian motives, whereby actors will punish or reward alters to reduce perceived inequity and restore fairness. In a series of laboratory experiments, they show that subjects experienced negative emotional reactions to top earners—even when earnings were randomly generated—and that these emotional reactions were associated with costly redistribution behaviors.

Rewarding reputation (prosocial contributions) occurs when one actor makes costly decisions to give to another actor who has been generous in the past (or does not give to an actor who has been stingy). Reputation is an actor's history of (un)cooperative behaviors, which actors could use to compensate for an inequitable system and reduce perceived inequity (Fehr and

Schmidt 1999, Rabin 1993). Hence, the presence of reputation information may reduce temptations to defect that arise from the presence of performance rankings because it permits actors to respond to perceptions of inequity. Instead of defecting in response to increased costs of cooperation and perceptions that a system of generalized reciprocity is unfair, actors may continue to cooperate to seize opportunities to reward the cooperative citizens of a system. Correspondingly, systems of generalized reciprocity that introduce reputation information alongside performance rank information should be more cooperative than those that only introduce performance rank information. Reputation information is therefore a potential recovery mechanism that can offset the disruptive effects of performance rankings, leading to more robust systems of cooperation. Hence, we expect:

> **H2:** The introduction of performance rank tied to differential rewards and reputation information increases cooperation compared to the introduction of just performance rank information.

While all actors, regardless of their rank, could be at risk of experiencing inequity aversion and hence exhibit efforts to correct for inequity, this behavior may be more visible among actors for whom inequity is more salient. Inequity is more salient for actors that are on the disadvantageous end of inequity (Fehr and Schmidt 1999). For example, Tannenbaum (1962) shows that individuals in lower ranks disproportionately feel that they should be receiving more than actors in higher ranks. In contrast, actors on the advantageous end of inequity are more prone to attribution biases—causing them to view their ranking positions as legitimate, fair outcomes (Flynn 2003, Major 1994)—which may limit the salience of inequity. Therefore, we expect that inequity will be highly salient for actors that gave at high levels, but ended up in the bottom of the ranking. We anticipate that these actors will be even more likely to transfer to alters' with higher reputations for transferring in order to reduce perceived inequity.

Accordingly, we expect:

> **H3:** The higher the salience of inequity, the higher an actors' likelihood of rewarding participants with high reputations for cooperation.

RESEARCH DESIGN, DATA, AND METHODS

We designed a laboratory experiment based on the "indirect helping game" (Engelmann and Fischbacher 2009, Wedekind and Milinski 2000). The indirect helping game is a no-deception, repeated decision-making game programmed in zTree (Fischbacher 2007), which allows actors to participate in a closed system of "helping" opportunities (e.g., opportunities to give and receive valuable resources with the same group of anonymous actors). Consistent with other cooperative economic games that ask actors to make choices between allocations that benefit themselves or others, the indirect helping game asks actors to keep points or transfer points to another participant. Points convert to money at the end of the game. The indirect helping game simulates the classic social dilemma wherein actors incur a personal cost for helping the collective, but if all members of the collective pursued the same action, all would benefit from the collective's success. This experimental design is well-suited to the analysis of systems of generalized reciprocity because it does not include deception and it allows groups of actors to interact regularly over multiple periods. Accordingly, each group (i.e., system) organically develops a norm of generalized reciprocity, generating its own, unique system-level dynamics that may not be as reliably manipulated in shorter-term experimental settings that include deception.

Experimental Procedures

A total sample of 592 actors consisting of students, staff, and community members was recruited at a large university in the American Midwest. Upon arrival at the laboratory, actors were randomly assigned to one of 16 cubicles with a laptop. The laptop was randomly assigned to a networked group of eight laptops and one of four experimental conditions. The appearance of a larger group limits the perception of opportunities to engage in direct reciprocity. Actors were not permitted to communicate with each other during the experimental session. Before the experiment began, a laboratory instructor distributed and read aloud a set of instructions that included the decision-making roles and rules. It was also stated that the information on the actors' screens reflected their own and others' actual behaviors during the experiment. After the instructions were presented each participant took a comprehension test.

The game consists of multiple decision-making rounds where actors can choose to transfer points to other actors in their group. At the start of the game, each actor receives an initial endowment of 33 points and is told that their final point balance, earned across all stages of the experiment, will be converted into a cash bonus of 2 cents per point.[4] This cash bonus is on top of a base pay for participation. The experiment consisted of two stages of 40+ decision-making rounds.[5] During each decision-making round, actors are paired randomly and anonymously. Within each pair, actors are randomly assigned roles: Role A or Role B. The participant in Role A makes the decision to "transfer" points (or not) to the participant in Role B. The participant in Role B does not make any decisions. Consistent with prior generalized reciprocity research in which benefits (b) received are greater than the cost (c) of providing benefits (b > c) (e.g., Engelmann and Fischbacher 2009; Greiner and Vittoria Levati 2005), if Role A decided to transfer, the participant's balance *decreased* by two points and Role B's balance *increased* by five points. A decision to not transfer results in no change to Role A's

[4] Points were used instead of dollars and cents to avoid any biases associated with money. However, actors knew that points would be converted at the rate of 2 cents per point, which they would receive as a bonus in addition to their participation fee ($10.00) at the end of the experiment. They were also told that their bonus amount may or may not change throughout the experiment. With 33 points, the initial endowment was equivalent to $0.66. This amount was set by considering rates used by past reciprocity studies and in consultation with the Institutional Review Board.

[5] All actors participated in a minimum of 40 rounds of decision making in each stage. To avoid end-game effects, each participant faced a 10 percent probability that they would participate in additional decision making rounds. Participants were told of this probability in the instruction period and were asked about it during the comprehension test.

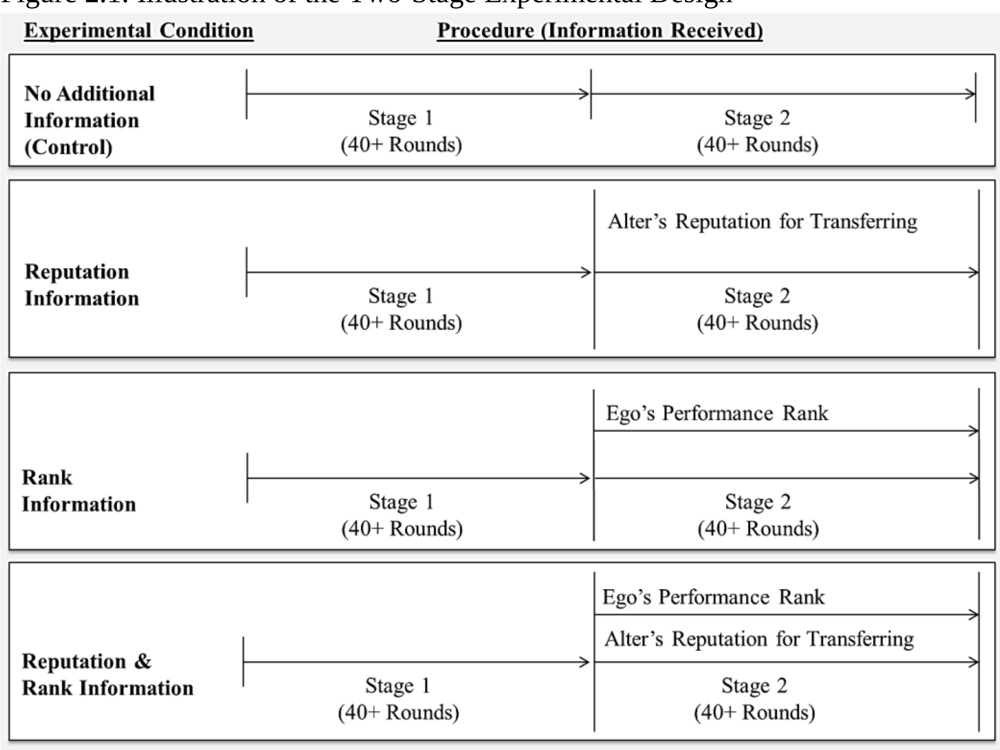
balance. While the roles were always referred to as Role A and Role B in the experiment to avoid a social desirability bias, for ease of interpretation we will henceforth refer to them as the “ego” (Role A—the person who is able to make the decision to transfer points) and the “alter” (Role B—the person who is not able to make a decision to transfer points).

Experimental Conditions

In Stage 1, all actors, regardless of their experimental condition, experience the same decision-making game of 40+ rounds with no additional information (i.e., no information about performance rank or reputation). This allows groups to establish norms of generalized reciprocity that can then be affected by the introduction of new information. All manipulations occur at the start of the second set of 40+ rounds of decision-making (Stage 2) (see Figure 2.1 for an illustration). A 2 x 2 factorial design crossed access to information about ego’s performance rank for total performance in points earned across Stage 1 (no performance rank information vs. performance rank information) and access to an alter’s reputation for transferring in Stage 1 (no reputation information vs. reputation information) resulting in four conditions.

The first condition, labeled the “No Additional Information condition,” repeats the same procedure that occurs in Stage 1 and does not provide any additional information. The second condition, labeled the “Reputation condition,” makes available information about the alter’s reputation for past cooperative behaviors: the percentage of times the alter transferred in Stage 1 when in Role A. With this information, the donor can infer the receiver’s level of generosity (e.g., “the person I am randomly matched with in this round has been stingy in the past”). The third condition, labeled the “Rank condition” includes information about ego’s performance rank in the group. Before beginning Stage 2, all actors that receive rank information (those in the Rank condition and the Reputation and Rank condition) are told that the bonus structure will change (e.g., actors are ranked by total points and those in the top third will receive a bonus of 7 cents per point, whereas the middle and bottom thirds will receive the standard payment of 2 cents per point). During each decision-making round, a reminder is displayed on the bottom of the screen that shows the ego's rank at the end of Stage 1. From information about rank, egos can infer whether they are in general benefiting from this system as much as their peers (e.g., "I'm in the bottom third and most of the others are earning more than me"). The fourth condition, labeled the "Reputation and Rank condition," includes both information about ego's own performance rank in the system and the alter's reputation for cooperation. This experimental design resulted in 11,833 post-interruption decision-making observations by 592 individuals clustered into 74 groups.

Figure 2.1: Illustration of the Two-Stage Experimental Design



Notes:

1. Interruption (treatment) occurs after Stage 1, before Stage 2 begins.
2. The Ego is the decision-maker in the current round (the participant with the ability to transfer points). The Alter is the receiver in the current round (cannot transfer points).
3. All groups in Stage 1 follow the same procedure (40+ rounds of decision-making without any additional

information). In Stage 2 decision-makers have access to different types of information—depending on what condition they are in.

4. The first condition, labeled the "No Additional Information Condition," repeats the same procedure as in Stage 1 without participants receiving any additional information.
5. The second condition, labeled the "Reputation Information Condition" makes available information about the alter's reputation for cooperative behaviors (the percent of times the alter transferred points when she was in Role A in Stage 1).
6. The third condition, labeled the "Rank Information Condition" includes information about the ego's performance rank in the group. Before beginning Stage 2 all actors in the Rank Information condition are told that the bonus structure is changing. Actors that rank in the top-third of total points receive a higher bonus of 7 cents per point, whereas the middle and bottom-third receive the standard payment of 2 cents per point. During each decision-making round a reminder is displayed on the bottom of screen that shows the ego's rank at the end of Stage 1.
7. The Fourth condition, labeled the "Reputation and Rank Information Condition," includes both information about the ego's own performance rank and alters' reputation for cooperative behaviors.

Measures

Dependent Variable. Cooperative behavior is modeled as a binary variable, where 1 = ego transferred and 0 = ego did not transfer. All models examine transfer decisions in Stage 2 of the experiment only (post-interruption). All constructs, variables, and their operationalizations are included in Table 1.

Independent Variables. The four experimental conditions were noted by indicator variables that reflected the type of information the actor received in Stage 2 (e.g., *No Additional Information, Reputation Only, Rank Only, and Reputation and Rank)*. Each variable is dichotomous, where 1 = received the type of information specified, and 0 = did not receive the type of information specified. No additional information is the default comparison group.

High salience of inequity is denoted by a dichotomous variable, where 1=the actor was one standard deviation above the mean rate of transferring in Stage 1 *and* was ranked in the bottom of the ranking in stage 1. In other words, high salience of inequity occurs when an actor has put the most inputs into a system, but received the least in outputs from the system relative to other actors.

Individual-Level Control Variables. Recent research shows that gratitude is a powerful mechanism of cooperation (Baker and Bulkley 2014). Actors feel positive affect after receiving help, which motivates paying help forward to others. Consistent with past research (Baker and Bulkley 2014, Nowak and Roch 2007), we measure *gratitude* with a proxy variable: the percent of times an actor received points when they were in Role B prior to the current decision-making round.

Prior giving may predict future giving. For instance, research on charitable giving shows that past donors are more likely to be donors in the future and in general tend to give more (Lindahl and Winship 1994, Sudhir et al. 2016). We measure *generosity* as the percent of times an actor gave when they were in Role A prior to the current decision-making round.

We include demographic characteristics typically measured in studies of cooperative behavior: age, gender, and formal education. Prior research shows that age can be associated with decreases in levels of generosity (Murnighan and Saxon 1998). While levels of generosity often grow in childhood (Bryan and London 1970), adulthood is generally associated with more strategic and less generous behavior (Murnighan and Saxon 1998). *Age* is measured in years. In our sample, age varies from 18 to 75, with most participants (82 percent) between 18-22 years of age.

Prior research finds inconsistent effects of gender on levels of generosity (Eckel and Grossman 1998, 2008, Grossman et al. 2008). In their review of economic experiments related to prosociality, Eckel and Grossman (2008) observed that exposure to risk of financial loss, exploitation, or the judgment of others was associated with no significant differences between men and women's rates of generosity. It was only in studies where actors were not exposed to these pressures that women exhibited more prosocial tendencies than men. Therefore, gender is included as a control variable, where *male*=1 if the actor specifies male, and 0 if the actor specifies female.

Education is a commonly measured control variable in studies that use cooperative games (Rand et al. 2014). Cooperative games include elements of strategy. Education could serve as a proxy for task performance ability in strategic games, such as problem solving and critical thinking. *Education level* is an indicator variable for levels of education, which includes high school, some college, associate's degree, bachelor's degree, and post-doctoral degree. High school is the default comparison category.

Reflective and deliberative cognitive style may also impact cooperative decision-making. On average, actors that exhibit less reflective cognitive styles tend to engage in more automatic decision-making and higher rates of cooperation. Actors with higher reflective cognitive styles exhibit more calculated decision-making and higher rates of selfishness (Rand et al. 2014). We employ Frederick's (2005) widely used cognitive reflection test (CRT) to create a measure of reflective cognitive style. The CRT includes three problem-solving tasks that appear to have obvious, simple answers that promote intuitive thinking and quick responses, but require more reflective thinking. We ask participants to answer these three questions in a questionnaire that follows the experiment. Results from the CRT are averaged to create a measure of reflective cognitive style. A higher value for the variable *short-term thinking*, indicates lower average performance on the CRT and a higher tendency towards short-term thinking.

Group-Level Controls. An alternative explanation for the likelihood that an actor will exhibit cooperative behaviors in later stages of the experiment is that it depends on each actor's unique normative climate. Specifically, if actors reside in a highly generous community they may be more likely to exhibit cooperative behaviors later on in the experiment than those that reside in stingy communities. We measure the group's normative climate as the group's average transfer rate in Stage 1 (before the interruption): *group percent transfers in Stage 1*. Since actors are nested in closed groups and others' decisions may affect a focal actor's decision-making climate, we included two measures that aggregate individual level controls at the group level: the session's average short-term thinking level and the percentage of the group that is male. The *Group's Average Short-Term Thinking Tendency* averages the group's short-term thinking tendency. *Percent of Group that is Male* reflects the percent of group members that are male.

This experiment necessitated many decision-making rounds, both to establish a group norm of generalized reciprocity and judge responses to events that may disrupt this norm. In past studies with economic games, cooperation tends to decline over time in contexts with many repeated interactions (Ledyard 1995). The concern with these cases is that actors will expect that their defections will have less of an impact on others' rates of cooperation because others have observed trends of behaviors over the prior time periods (Axelrod 1984). Similarly, because of the duration of the experiment (45 minutes) and the repeated nature of the task (80+ decision-making rounds), concerns of decision-fatigue may exist. One's decision-making capabilities may change as the experiment goes on. Vohs et al. (2009) report that multiple rounds of decision-making may impair actors' self-regulation abilities—the ability to substitute one action for another that better conforms to a norm or fits with a specific goal. While Vohs et al.'s (2009) study examines effects of more cognitively taxing choices (e.g., choosing college courses from a course catalogue), we anticipate that the nature of a repeated decision task may similarly affect actors' rates of attention and cause some amount of decision-fatigue or disengagement. While we anticipate that these negative effects of the repeated measures design will be mitigated by the presence of a performance bonus, we include time as a control. *Increasing time* is modeled as a linear effect of increasing decision-making rounds. Table 2.1 reports descriptive statistics.

Table 2.1: Description of Constructs and Variables in Chapter 2

Construct	Variable	Definition	Level
Cooperative Behavior (DV)	Transferred points	When in the donor role, chose to transfer points	Round
Rank Information	Condition dummy	1=in condition with rank only information	Group
Reputation Information	Condition dummy	1=in condition with reputation only information	Group
Rank & Rep. Info.	Condition dummy	1=in condition with both rank and reputation information	Group
Social Hierarchy Position	Rank	0=bottom, 1=middle, 2=top third	Individual
Alter's rep. for cooperation	Alter's % times gave	The percent of times an alter gave when they were in Role A, lagged	Round
Risk for inequity aversion	Bottom rank & giving	1=in bottom rank and above average level of generosity (see below)	Individual
Controls			
Decision Fatigue	Time	Modeled as a linear effect of increasing decision-making rounds	Round
Gratitude	% times Received	The percent of times an actor received when they were in Role B, lagged	Round
Generosity	% times Gave	The percent of times an actor gave when they were in Role A, lagged	Round
Age	Age	Mean centered	Individual
Gender	Male	1=male	Individual
Education Level	Education	Categorical variable with education buckets	Individual
Short-term Thinking	CRT Score	Averaged score for questions from the cognitive reflection test (Frederick 2005), higher values indicate more tendency toward short-term thinking	Individual
Group's composition of short-term thinking	Group CRT	the percent of group members that are low on cognitive reflection style	Group
Generosity of Group	% transfer part 1	Group's percent transferred in part 1	Group
Group's gender composition	% male	Percentage of the group that is male	Group

Table 2.2: Summary Statistics for Chapter 2

Variable	Mean	SD	Min.	Max.
Level 1: Post-Interruption Decisions (*N*=11,833)				
Transferred	0.52	0.50	0	1
Ego's Percent Gratitude	0.60	0.20	0.06	1
Ego's Percent Generosity	0.60	0.32	0	1
Level 2: Ego (*N*=592)				
Gender	0.36	0.48	0	1
Age	21.82	6.58	18	75
Education	2.27	1.24	1	5
Short-term Thinking	0.53	0.37	0	1
Level 3: Groups (*N*=74)				
No Additional Information (Control)	0.25	0.43	0	1
Reputation Information Condition	0.24	0.42	0	1
Rank Information Condition	0.26	0.44	0	1
Reputation and Rank Information Condition	0.26	0.44	0	1
Group's Percent of Short-term Thinkers	0.53	0.15	0.17	1
Percent of Group that is Male	0.36	0.23	0	1
Group's Percent Transfers in Stage 1	0.63	0.23	0.28	0.93

Notes:
1. The Ego is the decision-maker in the current round (the participant with the ability to transfer points). The Alter is the receiver in the current round (cannot transfer points).

Analytical Strategy

Two model specifications were used to explore the effect of various interruptions on systems of generalized reciprocity. First, given the nested structure of the data, we employed a multilevel mixed effects logistic regression model to assess the effect of various manipulations (interruptions). Multilevel models allow us to rule out alternative explanations at the decision-making round, individual, and group levels of analysis. Second, an interrupted time series analysis allows us to account for the autocorrelated nature of the data, ensure that comparison groups are appropriate counterfactuals, and permits us to examine both the initial and long-term effects of interruptions.

Multilevel Mixed Effects Logistic Regression. Our design yields clustered longitudinal data with a binary dependent variable. This design creates a three-level hierarchy: 11,833 binary transfer decisions in Stage 2 of the experiment (level 1), nested within 592 actors (level 2), nested within 74 groups of eight actors (level 3). Given this nested structure, we used a multilevel mixed-effects logistic regression for longitudinal data (Rabe-Hesketh and Skrondal 2008). Fixed effects are specified as regression parameters and random effects are specified for the individual and group levels, with a maximum likelihood estimation. This type of model allows us to assess the variation within individuals and between groups over time. Traditional methods for analysis of experimental data (e.g. an ANOVA or repeated measures MANOVA) are not able to control for multiple levels of analysis.

Our first model includes the level one covariates of gratitude and generosity as controls, as well as the linear effect of increasing rounds of decision-making. The second model introduces the level two covariates age, gender, education, and propensity toward short-term thinking as controls[6]. The third model includes the level one, level two, and level three covariates: indicator variables for information conditions and group level controls for the group's gender and short-term thinking composition and the group's overall transfer rate in Stage 1. We include post-hoc analyses of the interaction between group's transfer rates in Stage 1 and condition in Model 4.[7] A final model tests whether highly salient inequity is associated with higher levels of cooperation in the presence of alters' high reputations for transferring. The final multi-level mixed effects logistic regression model solely examines the Reputation and Rank condition as it is the only condition with both sets of information (see Table 2.4).

[6] In models 2 and 3 the number of individuals decreases to 574 and the number of observations decreases to 11,496 due to missing values. Sixteen individuals did not report their age, one chose to not declare a gender, and one did not report an education level. Only one group featured more than one individual with missing data. As a robustness check we examined our results with and without this group. The elimination of this group does not have any material effect on our results or interpretations. We also examined our results with and without the covariates of age, gender, and education. The elimination of these covariates does not have a material effect on our results or interpretations.

[7] As a robustness check, we follow Heisig, Schaeffer, and Giesecke (2017) and include random slopes for level 2 (ego level) covariates in our Model 3 specifications to examine whether there are cross-cluster differences in the effects of controls. The inclusion of these random slopes does not have a material effect on our results or interpretations. These analyses are not shown here, but are available on request.

Interrupted Time Series Analysis. An interrupted time series analysis (ITSA) is appropriate for research designs that include interventions that are expected to "interrupt" a data trend (Glass et al. 2008, Shadish et al. 2002). Our research design explores how different interruptions (our experimental manipulations) can disrupt a system of cooperation. An ITSA model further permits us to examine both the immediate effects of an interruption (e.g., what happens in the first few rounds of Stage 2) as well as the long-term effects of the interruption (e.g., overall trend in Stage 2) (Linden and Adams 2011). The dependent variable is calculated as the percent of transfers for all individuals in a specified condition, in a given Stage 2 decision-making round. Our model uses OLS regression with Newey-West standard errors to account for autocorrelation and heteroskedasticity (Linden 2015).

The models assess the impact of performance rank information on cooperative behaviors, using multiple-group comparisons. We examine both the immediate effect of the interruption and the overall post-interruption trend. We compare these interruption effects for the Rank Information condition with the Reputation and Rank condition to examine reputation as a recovery mechanism for the potentially disruptive effects of performance rankings.

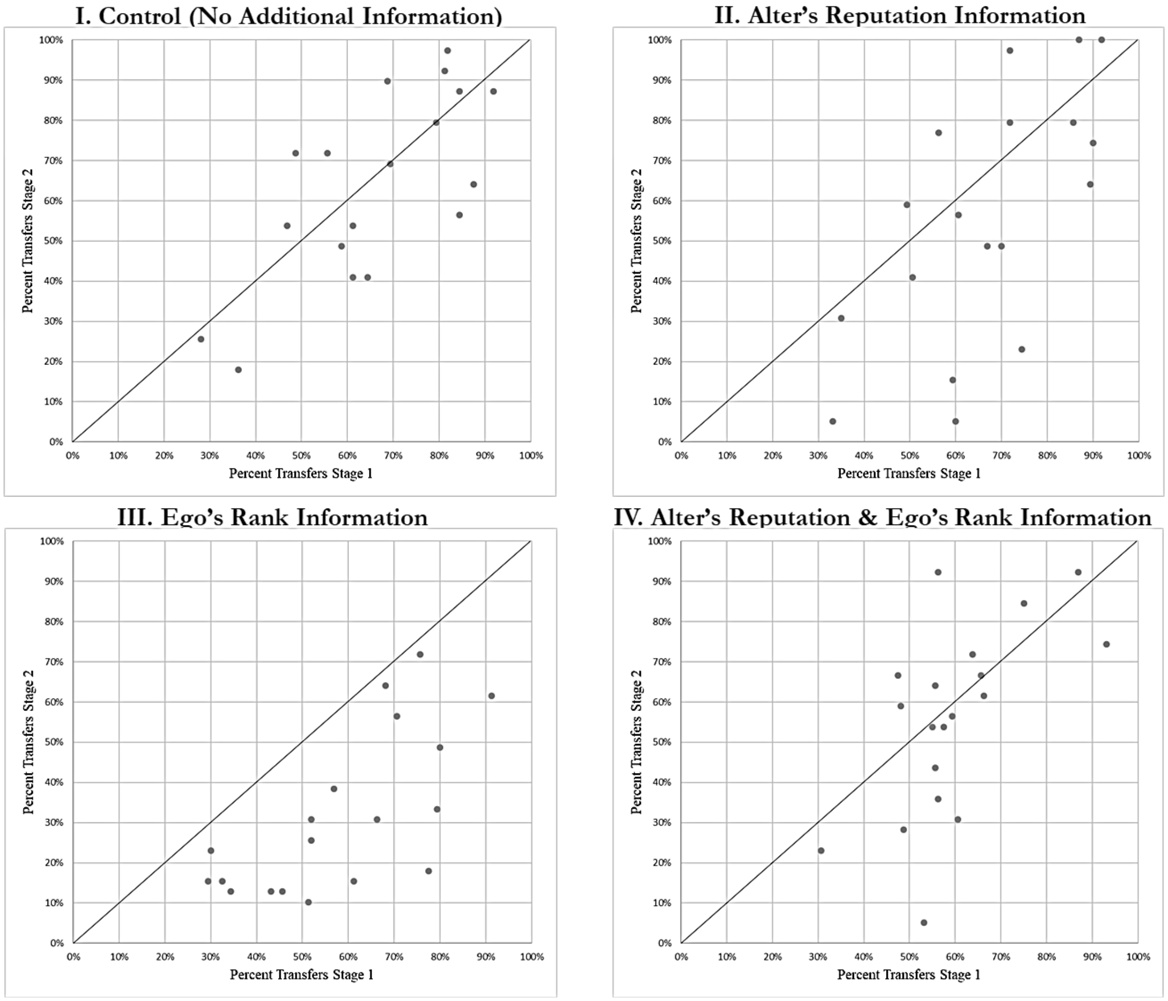
RESULTS

We begin our analysis by plotting group-level average transfer rates in Stage 1 against group-level average transfer rates in Stage 2 to visually assess the effect of interruptions (Figure 2.2). We then report results from multilevel mixed effects logistic regressions that examine an actor's likelihood of exhibiting cooperative behavior (transferring points) (Table 2.3). Last, we report results from an interrupted time series analysis (Table 2.4).

Interruptions may produce three main outcomes: 1) no effect, 2) decreased cooperation, or 3) increased cooperation. Each graph in Figure 2.2 plots group-level percent transfers for all rounds in Stage 1 versus all rounds in Stage 2 for all groups that experienced the same experimental condition. A point on a graph's 45-degree line indicates that the percent transferred in Stage 2 was the same as the percent transferred in Stage 1. Points on or near the 45-degree line indicate that an interruption had no effect on transferring. Points above the 45-degree line show that transferring increased in Stage 2; points below show that transferring decreased in Stage 2.

As expected, the level of cooperation in Stage 2 versus Stage 1 is not markedly different for groups in the No Additional Information condition (Figure 2.2, graph I). Points are scattered around the 45-degree line, some on the line, some above, and some below. Adding reputation information shows a similar pattern, though more points are below than above the line (Figure 2.2, graph II). As hypothesized, groups in the Rank condition are less likely to transfer in Stage 2 (Figure 2.2, graph III). Regardless of the level of cooperation in Stage 1, all points in this graph are below the 45-degree line, indicating that the introduction of performance rank information disrupted every system of cooperation established in Stage 1. The introduction of both rank and reputation information yields patterns that are generally similar to the Reputation condition and No Additional Information condition (Figure 2.2, graph IV). This pattern is our first indication that reputation may be a recovery mechanism for the deleterious effects of performance rankings on cooperation.

Figure 2.2: Empirical Comparison of Group-Level Transfer Rates Before and After an Interruption



Notes:

1. Figure 2.2 plots the relationship between each group's overall percent of transfers in Stage 1 (pre-interruption) and Stage 2 (post-interruption), separated by experimental conditions. A point of observation on the 45-degree line means that groups' transfer rates in stages 1 and 2 were the same. Observations that are close to the 45-degree line suggest that a group was unaffected by the interruption it experienced in between stages 1 and 2.
2. The Ego is the decision-maker in the current round (the participant with the ability to transfer points). The Alter is the receiver in the current round (cannot transfer points).
3. In the Ego's Rank Information Condition (plot III) decision-makers could view where they stood in the performance ranking of total points earned after Stage 1 (e.g., top, middle, or bottom third of earners).
4. In the Alter's Reputation and Ego's Rank Information Condition (plot IV) decision-makers could view their performance ranking information and information about alters' levels of generosity in Stage 1(i.e., how generous the person they are randomly paired with in the current round was during the times that they were in the role of the decision-maker in Stage 1).

To determine if these effects are statistically significant in the presence of controls at the decision-round, actor, and group levels, we examine multilevel mixed-effects logistic regression models. Table 2.3 reports log odds coefficients from four models. Predicted probabilities and odds ratios are reported in the text. Model 1 introduces controls at the decision-round (level 1). Consistent with prior research (Baker and Bulkley 2014), gratitude and generosity were associated with an increased likelihood of transferring in Stage 2 (post-interruption). These findings confirm that both the act of receiving help and an ego's prosocial tendencies are drivers of cooperation. We consider gratitude and generosity as control variables, but these findings add validity to our design and model because they are consistent with previous empirical work. Model 2 introduces controls at the individual-level (level 2). While gratitude and generosity remain strongly associated with the likelihood of exhibiting cooperative behavior, the individual-level controls of age, gender, education level, and short-term thinking tendencies are not statistically associated with our outcome of interest. Model 3 introduces group-level controls (level 3) for the group's percentage of transfers in Stage 1 (pre-interruption), the percentage of the group that is male, and the percentage of the group that exhibits short-term thinking tendencies. These controls are not significantly associated with the likelihood that an individual will transfer.

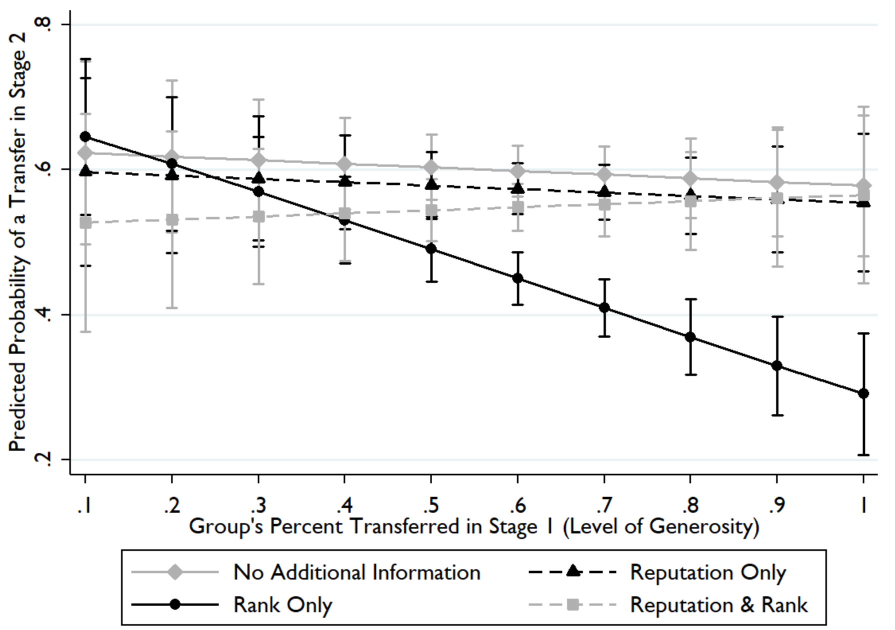
Model 3 includes indicator variables for the experimental conditions with the No Additional Information condition as the (omitted) comparison group. Compared to groups that received no additional information, an interruption that revealed performance rank information was associated with a sharp decrease in the likelihood of a transfer, controlling for many factors. Given the estimated random effects for a unique individual and her respective group, and all other factors held at their means, the odds of transferring for an ego in the Rank condition are only 0.360 times as great as those of an individual in the No Additional Information condition. This disruption is higher in generous groups. Post-hoc analyses (model 4) reveal a relationship between group generosity in Stage 1 and an individual's predicted probability of a transfer in Stage 2. The higher a group's generosity in Stage 1, the lower an individual's predicted probability of a transfer in Stage 2 for groups in the Rank Information condition. For all other conditions, a participant's likelihood of transferring is not influenced by the group's level of generosity in Stage 1 (see Figure 2.3).[8] We theorized that this disruption would be due to either concerns about losing one's rank position (i.e., loss aversion), or perceptions of unfairness. Participants open-ended responses to questions about their strategies in the experiment were consistent with these two themes. For example, those in the Rank Condition said they transferred less in Stage 2 because they wanted to preserve their position. As one put it, *"[A]fter I was ranked in the top third, I transferred only a couple of times because I was not sure if I was helping someone else achieve the top third ranking and extra bonus or if I was helping someone already in the top third and possible [sic] booting myself out."* Similarly, another participant said, *"After I saw that I was in the top third of the activity, I started to give less points away. I would still give points away but it would [be] less often because I wanted to secure my spot in the top third."*

Other participants in the Rank condition perceived unfairness and adjusted their strategies—that their transferring behaviors declined in Stage 2 because they were not receiving benefits in proportion to their levels of generosity: "*[Stage] 2 showed me I was in the bottom third. As [stage] 2 started I noticed I was rarely gaining points when I was [in] role B and I realized most*

[8] Reputation is typically associated with an increase in cooperative behavior (Nowak and Sigmund 1998a,b), but we did not find a statistically significant difference between the Reputation Information condition and the No Additional Information condition. However, supplemental analyses reveal that there are significant reputation effects, that vary with the group's level of generosity in Stage 1 (see Model 3 in Table A.1 in the Appendix).

people were clicking no, so I started clicking no every time because I knew having faith in others was pointless at this point and I was just going to be losing money by clicking yes." Similarly, another participant said, *"I tried to maximize total economic surplus in the first part of the activity but then when I found out I was in the middle third I became more selfish and stopped transferring points."*

Figure 2.3: Predicted Probability of a Transfer in Stage 2 by Condition and Group's Level of Generosity in Stage 1



Note: All groups experienced the same decision-making conditions in Stage 1 (no additional information), regardless of the conditions in which they were placed in Stage 2.

These results provide strong support of H1. Transferring declines in systems that are interrupted by the introduction of information about performance rank. Further, this decline is heightened by the strength of the norm of reciprocity established in Stage 1. This suggests that participants in highly generous groups may react more negatively to the introduction of performance rankings, compared to participants in groups with lower levels of cooperation.

To test our hypothesis that reputation information can act as a recovery mechanism in the presence of disruptions (H2), we examined the effects of simultaneously introducing both reputation and performance rank information. We find that the disruptive effect of performance rank is substantially reduced when reputation information is also provided (Model 3, Table 2.3). Given the estimated random effects for a unique individual and his respective group, and all other factors held at their means, the odds of transferring for an individual in the Reputation and Rank Information condition are 1.865 times that of an individual in the Rank Information condition.[9] Consistent with H2, these results suggest that reputation information can offset the negative effects of performance rankings.

[9] See Table A.2 in the Appendix

Table 2.3: Mixed-Effects Logistic Regression: The Likelihood of Transferring in Stage 2

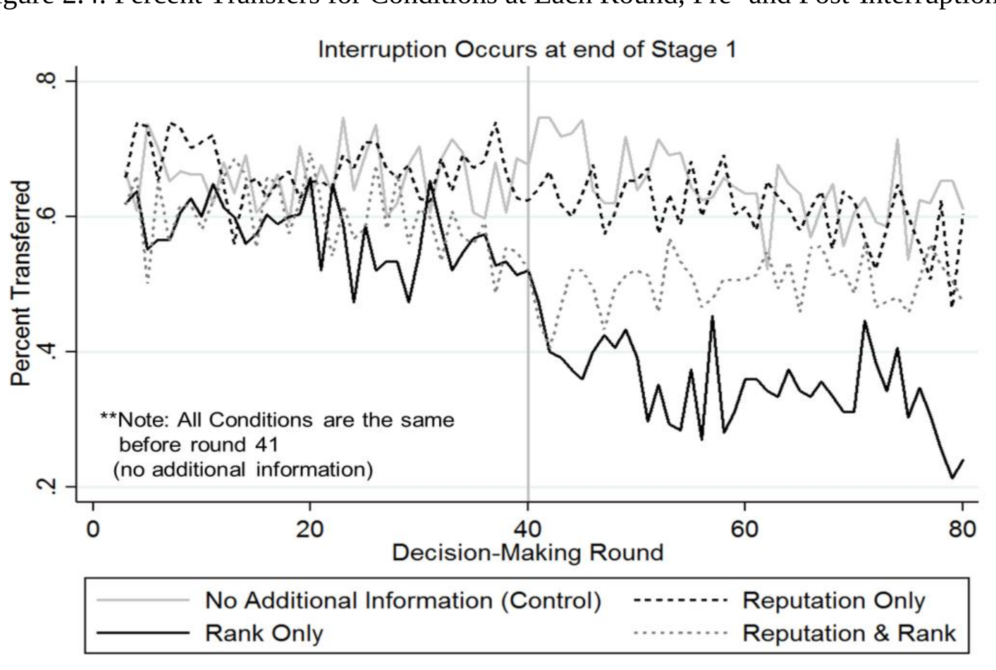
	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Level 1: Decision Rounds Post-Interruption				
Ego's Percent Gratitude	0.017***	0.017***	0.019***	0.019***
	(0.003)	(0.003)	(0.005)	(0.005)
Ego's Percent Generosity	0.049***	0.049***	0.049***	0.049***
	(0.002)	(0.002)	(0.002)	(0.002)
Increasing Decision Rounds	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Level 2: Individual (Ego)				
Male		-0.075	-0.059	-0.059
		(0.116)	(0.121)	(0.121)
Age (mean-centered)		-0.004	-0.009	-0.007
		(0.011)	(0.011)	(0.011)
Education: Some College (dummy)		-0.045	0.008	0.006
		(0.125)	(0.123)	(0.123)
Education: Associate's Degree (dummy)		0.180	0.357	0.289
		(0.573)	(0.567)	(0.564)
Education: Bachelor's Degree (dummy)		-0.122	-0.085	-0.128
		(0.167)	(0.165)	(0.164)
Education: Post-Doc (dummy)		0.173	0.270	0.204
		(0.284)	(0.279)	(0.278)
Short-term Thinking Tendency (CRT)		-0.002	-0.001	-0.001
		(0.116)	(0.002)	(0.002)
Level 3: Groups				
Group's Average Short-Term Thinking Tendency			-0.004	-0.005
			(0.005)	(0.005)
Group's Percent Transfers in Stage 1			-0.010	-0.004
			(0.006)	(0.009)
Percent of Group that is Male			-0.002	-0.002
			(0.003)	(0.003)
Reputation Information Condition			-0.171	-0.190
			(0.180)	(0.656)
Rank Information Condition			-1.020***	0.392
			(0.181)	(0.602)
Reputation and Rank Information Condition			-0.396*	-0.734
			(0.178)	(0.710)
Reputation Cond. x Group's Percent Transfers in Stage 1				0.000
				(0.010)
Rank Cond. x Group's Percent Transfers in Stage 1				-0.023*
				(0.009)
Reputation and Rank Cond. x Group's Percent Transfers in Stage 1				0.006
				(0.011)
Random Effects				
Standard Deviation Individual	0.505***	0.507***	0.303***	0.240***
	(0.073)	(0.076)	(0.083)	(0.091)
Standard Deviation Group	0.951***	0.959***	0.954***	0.954***
	(0.055)	(0.057)	(0.056)	(0.057)
Intraclass Correlation	0.264	0.264	0.233	0.227
Number of Observations (Post-Interruption Decisions)	11,833	11,496	11,496	11,496
Number of Individuals (Ego)	592	574	574	574
Number of Groups	74	74	74	74

Notes: Standard errors in parentheses. *p<0.05; ** p<0.01, *** p<0.001

1. Omitted categories for comparison: High school degree (level 2), No Additional Information Condition (level 3)

To further explore the restorative effect of reputation information, we considered the short-term and long-term effects of an interruption. Figure 2.4 presents a line graph of the average transfer rate by condition for each decision-making round. Recall that in Stage 1, all participants experience the same decision-making conditions (the absence of any additional information), regardless of the condition they would experience in Stage 2. The patterns in Stage 1 are similar for each condition. Clear differences appear in Stage 2. Both the Rank Information and the Reputation and Rank Information conditions show immediate drops in average transfer rates; however, the Reputation and Rank Information condition eventually recovers, returning to transfer rates on par with the No Additional Information and Reputation only conditions.

Figure 2.4: Percent Transfers for Conditions at Each Round, Pre- and Post-Interruption



Notes:

1. In Stage 2, decision-makers (those in Role A in the current round—participants who can transfer points) that are in the Reputation Information Condition have access to alters' (those in Role B in the current round—participants who cannot transfer points) reputations for generosity (percent of times they transferred when they were in Role A in Stage 1).
2. In Stage 2, decision-makers (those in Role A) that are in the Rank Information Condition have access to information about their own performance rank after Stage 1 (relative rank is derived from the total points they earned in Stage 1).
3. Before beginning Stage 2 all actors in the Rank Information Condition and the Reputation and Rank Information Condition are told that the bonus structure is changing. Actors that rank in the top-third of

Notes Figure 2.4 Continued:

total points receive a higher bonus of 7 cents per point, whereas the middle and bottom-third receive the standard payment of 2 cents per point. During each decision-making round a reminder is displayed on the bottom of screen that shows the ego's rank at the end of Stage 1.

4. In Stage 2, decision-makers in the Reputation and Rank Information Condition have access to both information about alters' past transferring behaviors and their own performance rank after Stage 1.

An interrupted time series analysis (Linden 2015) adds statistical support to our visual interpretation of the patterns in Figure 2.4. In this analysis, we compare the Rank condition and the Reputation and Rank condition to assess how having access to reputation information affects individuals who also have access to rank information. As shown in Table 2.4, pre-interruption intercepts and trends are not significant, supporting our interpretation of Figure 2.4 that there are no significant differences between the Rank condition and the Reputation and Rank condition in Stage 1 (pre-interruption). There is no statistically significant difference in the intercepts for these two conditions in the period immediately after the interruption, suggesting that groups in both conditions experienced *the same* initial negative impact of the interruption. However, there is a significant overall post-interruption trend. For every additional 10 rounds, the model predicts a difference of 8.7 points between the conditions' average transfer rates (see Figure 2.5). Both conditions exhibited the same initial negative impact, but then transfer rates in the Reputation and Rank condition increase steadily over time while transfer rates in the Rank condition steadily decrease over time. These results support H2, demonstrating the restorative effect of reputation information in the presence of performance rankings.

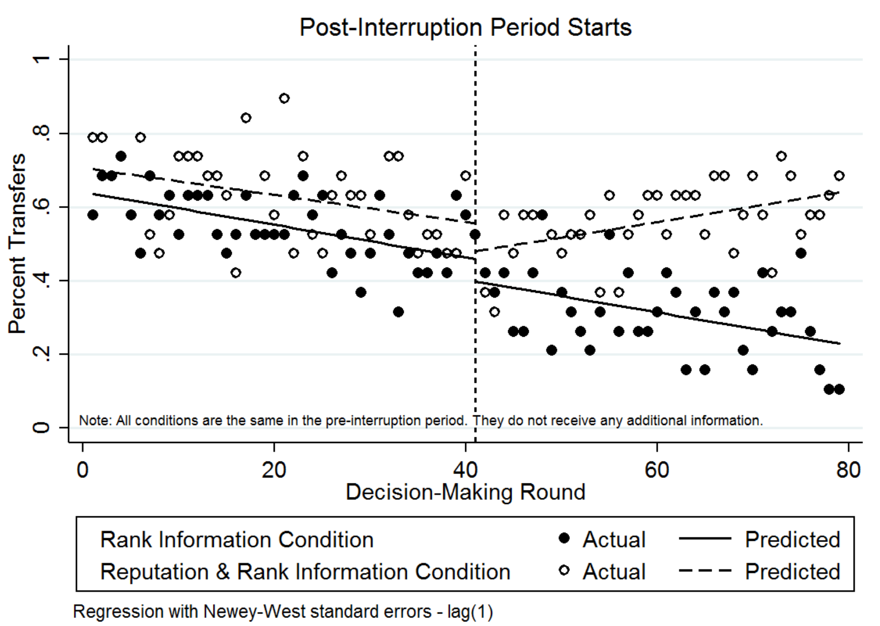
Table 2.4: Interrupted Time Series Analysis of Post-Interruption Effects on Transfer Rates

	Model 1: Rank Information Condition vs. Reputation and Rank Information Condition
Pre-Interruption Difference in Intercepts	-0.065
	(0.043)
Pre-Interruption Difference in Trends	-0.001
	(0.002)
Post-Interruption Difference in Intercepts	0.0167
	(0.063)
Post-Interruption Difference in Trends	-0.009***
	(0.003)
Post-Interruption Rank Condition Trend	-0.004***
	(0.002)
Post-Interruption Rep. and Rank Cond. Trend	0.004***
	(0.001)
Observations	158

Notes:

1. Standard Errors in parentheses, *p<0.05; **p<0.01, ***p<0.001
2. Non-significance in the pre-interruption difference in intercepts and trends (i.e., slopes), indicates that the control group (Rank Information Condition), and treatment group (Reputation and Rank Information Condition) are appropriate counterfactuals (Linden 2015).

Figure 2.5: Illustration of Interrupted Time Series Analysis Comparing Rank Information and Reputation and Rank Information Conditions before and after an Interruption



Notes:

1. All groups experience the same decision-making context in Stage 1 (no additional information), regardless of the conditions in which they were placed in Stage 2.
2. The first round of decision-making after the interruption is the beginning of Stage 2.

We theorized that a system's ability to withstand or recover from the potentially disruptive effects of performance rankings would occur because actors reduce inequity by rewarding prosocial contributions. Correspondingly, we hypothesized that this behavior would be most pronounced in individuals for whom inequity was more salient (i.e., those who gave the most to others in Stage 1, but received the least—placing them in the bottom of the ranking) (H3). We find that the higher an alter's reputation for transferring, the more likely an individual will transfer. This effect is even higher when inequity is salient. Table 2.5 reports coefficients in log odds. Given the estimated random effects for a unique individual and her respective group, and all other factors held at their means, when an individual is paired with an alter that has a 90% transfer rate the predicted probability of transferring is 0.92 for individuals with highly salient inequity and 0.71 for all other individuals (see Table 2.5 & Figure 2.6).

Participants' open-ended responses to questions about their strategies in the experiment reflected sentiments in line with inequity aversion. For example, many participants in the Reputation and Rank condition viewed their rank positions as a consequence of others' behaviors and sought to reward and punish reputations accordingly. As one said, *"During [stage] two of the experiment I changed my strategy so that I could try to punish those who were not liberal enough in their transferring of points in the first [stage] because I was in the bottom third of the group and I felt that my actions in [stage] one were not reciprocated by my fellow participants."* Another participant put it this way: *"When I knew that others had not transferred, I did not transfer to them, especially knowing that I was in the bottom third. However, even if I was worried about the amount of money I had left, I continued to give to those who had transferred, as I wanted to in a way reward them."* Jointly, these results suggest that reputation information can offset the negative effects of rankings because it permits actors to respond to inequity.

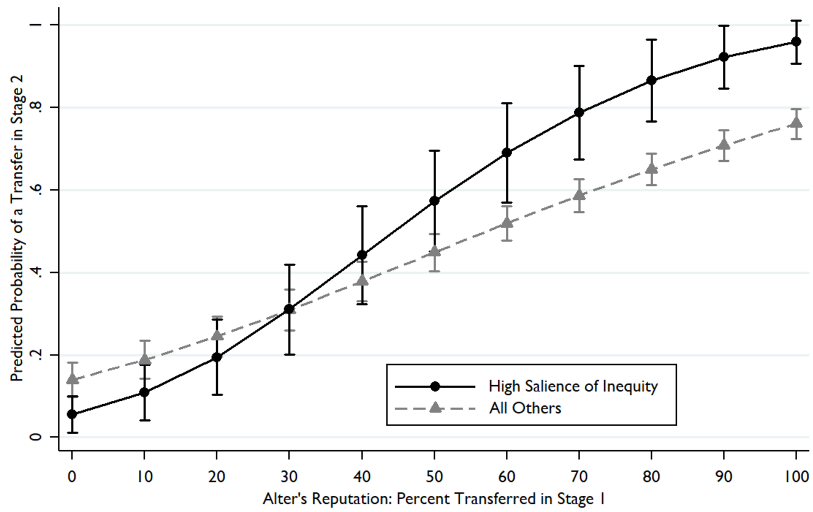
Table 2.5: Mixed-Effects Logistic Regression: The Likelihood of Transferring in Stage 2 (Reputation and Rank Condition Only)

	Model 1
Fixed Effects	
Level 1: Decision Rounds Post-Interruption (*n*=2,942)	
Alter's Reputation for Transferring	0.045***
	(0.002)
High Salience of Inequity x Alter's Reputation	0.040***
	(0.010)
Ego's Percent Gratitude	0.032***
	(0.010)
Ego's Percent Generosity	0.056***
	(0.005)
Increasing Decision Rounds	0.015**
	(0.005)
Level 2: Individual (Ego) (*n*=147)	
High Salience of Inequity	-1.181*
	(0.518)
Male	-0.194
	(0.259)
Age (mean-centered)	0.440
	(0.029)
Education: Some College (dummy)	-0.181
	(0.272)
Education: Associate's Degree (dummy)	0.244
	(0.831)
Education: Bachelor's Degree (dummy)	-0.423
	(0.404)
Education: Post-Doc (dummy)	-0.459
	(0.709)
Short-term Thinking Tendency (CRT)	-0.006
	(0.029)
Level 3: Groups (*n*=19)	
Group's Average Short-Term Thinking Tendency	0.002
	(0.013)
Group's Percent Transfers in Stage 1	-0.056***
	(0.015)
Percent of Group that is Male	0.005
	(0.007)
Random Effects	
Standard Deviation Individual	1.081***
	(0.124)
Standard Deviation Group	0.300***
	(0.195)
Intraclass Correlation	0.277

Notes:

1. Standard errors in parentheses. *p<0.05; ** p<0.01, *** p<0.001
2. Omitted categories for comparison: High school degree (level 2)

Figure 2.6: Predicted Probability of a Transfer in Stage 2 by Salience of Inequity & Alter's Reputation



Notes:

1. Analysis of observations in the Reputation and Rank Condition only.
2. High Salience of Inequity is indicated by an actor being among the system's highest givers (e.g., one standard deviation above others in transferring in Stage 1) *and* the among the system's lowest receivers (e.g., in the bottom rank in Stage 1).

DISCUSSION

Generalized reciprocity is a powerful form of cooperation. By relaxing the need for immediate reciprocity, these systems can sustain cooperation among self-interested actors, making complex, higher-level organization possible (Nowak 2006). Systems of generalized reciprocity are thought to be inherently stable due to inertial, self-generating properties that attract new participants and encourage costly contributions without immediate benefits in return (Lévi-Strauss 1969, Molm 1997, Nowak and Sigmund 1998a,b). However, systems of generalized reciprocity are also considered to be fragile because return benefits are not guaranteed and the system relies on continual contributions from multiple members (Molm 1997). Consequently, small lapses in contributions can trigger mass defections and collapse the entire system. We explored the apparent contradiction of stability versus fragility by examining how robust these systems are in the presence of a potentially disruptive force that is commonplace in organizational contexts: performance rankings.

Performance rankings can impede cooperation by intensifying competition among members, revealing inequities in valued outcomes, and reducing motivations to cooperate. Social scientists have not explicitly examined how systems of generalized reciprocity interact with performance rankings. Determining when and under what conditions a system of generalized reciprocity can withstand potentially disruptive forces, such as performance rankings, can make significant contributions to theories of cooperation and may provide guidelines to specific practices that promote continued cooperation over time.

We find that performance rankings are highly disruptive for systems of cooperation. Despite the establishment of strong norms of generalized reciprocity, the introduction of performance rankings tied to differential rewards dramatically reduced rates of cooperation. Not one group that received performance rank information reached the level of cooperation it had attained prior to the interruption. The observed deleterious effect of performance rankings on cooperation is consistent with the findings of research on shifting rates of cooperation associated with perceived resource asymmetries among actors and notions of fairness (Messick and Sentis 1983, Van Lange et al. 2013, Wade-Benzoni et al. 1996).

In particular, groups that were generous prior to the introduction of performance rank experienced large reductions of cooperation after the interruption. This finding is consistent with equity theory (e.g., Adams 1965) and strong reciprocity (Fehr et al. 2002), which assert that the higher the perceived imbalance between contributions and benefits, the higher the perceived unfairness of the system and the stronger an individual’s need to correct this imbalance. Members of generous groups may have especially strong feelings about differences in outcomes.

Without other options, their only choice may be to decline to cooperate (Fehr and Gintis 2007).

The negative impact of performance rankings, especially for the most generous groups, may serve as a warning to organizations that rely on performance rankings as a management strategy. Performance ranking systems are controversial (Rock and Jones 2015) yet commonplace in many different types of organizations, including for-profit corporations, educational institutions, and governmental organizations (Cappelli and Tavis 2016, Dooren et al. 2015). Our findings imply that performance rankings could impair the ability to build social capital (Baker and Dutton 2007) or establish prosocial organizational cultures (Penner et al. 2005). Belmi and Pfeffer's (2015) argument that norms of reciprocity are weaker in organizational contexts lends credence to our findings. They found that individuals were less inclined to cooperate when they visualized themselves in organizational versus personal contexts. Organizational contexts elicited more self-interested, calculative decision-making frames, which reduced willingness to cooperate. If true, then the introduction of performance rankings would exacerbate the tendency for self-interested, calculative action that is already present in organizations.

Our key finding is that displaying prosocial contributions (reputation) is a recovery mechanism that restores systems of cooperation disrupted by performance rankings. Participants who received either rank information or who received reputation and rank information experienced a similar initial drop in cooperation. However, cooperation continued to fall for those with rank information, while the trajectory reversed for those with reputation and rank information and cooperation continued to rise until it reached pre-interruption rates. We attribute this recovery in part to actors having the ability to correct for inequity aversion and find evidence that actors that are at high risk of experiencing inequity aversion are indeed more likely than other actors to cooperate in the presence of highly cooperative alters. The availability of reputation information makes actors more inclined to cooperate in the presence of performance rankings because it provides opportunities to resolve inequity aversion and restore fairness to the system. Participants can reward those who have been generous in the past and punish those who have been stingy by refusing to help them. Findings from case studies of real organizations are consistent with our interpretation of reputation as a mechanism that offsets the harmful effects of performance rankings. For example, IDEO—the design firm lauded for its robust "culture of helping" (Amabile et al. 2014)—combines performance rankings with informal reputations for helpfulness and formal peer reviews (Hargadon and Sutton 1997).

At one level, our key finding underscores the importance of reputation for systems of generalized reciprocity, adding to the stream of research and theory about the positive effects of reputational incentives on cooperation (Alexander 1987, Baker and Bulkley 2014, Fehr and Gächter 2002, Fehr and Gintis 2007, Nowak and Sigmund 1998a,b, Seinen and Schram 2006, Wedekind and Milinski 2000). At a deeper level, however, our key finding implies that reputation is a source of system robustness. In contrast, the mechanism of gratitude—cooperating due to gratefulness for help received—may not be. Prior empirical work (Baker and Bulkley 2014) found that the gratitude effect was stronger than the reputation effect in a system that did not include performance rankings. While we found significant gratitude effects in all four conditions, the gratitude mechanism was unable to withstand the negative impact of the introduction of performance rankings (see Table 2). The introduction of reputation information did not prevent an immediate drop in cooperation (see Figure 2.4), but in the Reputation and Rank condition the system eventually recovered and cooperation returned to pre-interruption levels. Reputation enables a system of cooperation to withstand forces that would otherwise destroy it.

Our study makes several contributions. Broadly, we contribute to theory on the maintenance of systems of cooperation (Baker and Bulkley 2014, Boyd et al. 2010, Marwell and Ames 1979, 1980, Nowak 2006, Nowak and Sigmund 1998a,b, Penner et al. 2005). Most work in this area assumes that once a system is up and running, its inertial properties will perpetuate it over time. We depart from this research by problematizing the assumption that inertial properties are enough to sustain an established system of cooperation. We introduce a robustness lens (Jen 2003, 2005) to the discussion of systems of cooperation by explicitly examining how these systems are maintained in the presence of perturbations. Here, we focused on the introduction of performance rankings as an exogenous perturbation. However, perturbations can be endogenous—disruptions can emerge from the everyday actions that on their face should maintain these systems. For example, acts that increase the mutual benefits associated with cooperation may unintentionally pave the way for a system's collapse by making the payouts associated with defection larger (Stewart and Plotkin 2014). A robustness lens turns the focus toward understanding the role that mechanisms of disruption and recovery play in the maintenance of systems of cooperation. It shifts the conversation from "system maintenance" to "system maintenance in the presence of disruptive forces." In so doing, it provides insights into how and when systems of cooperation are robust to anticipated and unanticipated perturbations.

In examining the effects of performance rankings on cooperative systems we contribute to research that examines the use of rankings (e.g., forced distribution ratings systems) to manage the performance of organizational members (Anderson and Brown 2010, Moon et al. 2016, Rock and Jones 2015). Evidence is mixed regarding whether rankings are beneficial or harmful for organizations (Anderson and Brown 2010). While there is some evidence that rankings help to attract and retain high performers, performance rankings may reduce employees' motivations to perform cooperative, prosocial behaviors (Moon et al. 2016). Since citizenship behaviors directly affect the ability of an organization to catalyze task activities and processes (Borman and Motowidlo 1993), performance rankings may ultimately undercut their expected performance gains (Moon et al. 2016). Our findings provide empirical support for these concerns. We find that performance rankings negatively impact actors' willingness to cooperate over time—even in the presence of strong norms of cooperation.

Finally, we contribute to research on prosocial behavior at the macro-level (Baker and Bulkley 2014, Baker and Dutton 2007, Cross and Parker 2004, Penner et al. 2005). To date, this research has focused on the benefits that systems of generalized reciprocity create in organizations (Bolino and Grant 2016). Because of these perceived benefits, practitioners often recommend these systems to leaders (Cross and Parker 2004). Our research suggests that these systems may be more difficult to implement and maintain than previously thought, especially in the presence of performance rankings, but that recognizing and rewarding the prosocial contributions of organizational members might reduce the negative effects of performance rankings. We find evidence that reputation information helps restore disrupted systems of cooperation, permitting actors to respond to perceptions of inequity by rewarding the cooperative behaviors of others.

MANAGERIAL IMPLICATIONS

One clear implication of our findings is that if managers seek to develop a pay-it-forward culture of helping or other types of cooperative systems they must pay careful attention to the potentially disruptive effects of performance rankings. Despite their inertial properties, these systems are likely to collapse in the presence of performance rankings and other conditions that result in an increase in competition or perceived inequity (e.g., gamification programs and ratings systems). To motivate more geographically dispersed workforces managers are enlisting performance rankings, gamification tools, and ratings systems at increasing rates (Cappelli 2009, Mollick and Rothbard 2014, Webster and Wing-Fai 2017). Relatedly, increased availability of information technology is enabling organizations to continuously monitor employees' activities and report back transparent performance data that is often in the form of a ranking (Bernstein and Li 2017). Together with this research, our findings suggest that systems of cooperation will likely be subject to increasing amounts of potentially disruptive forces and that the maintenance of prosocial organizational cultures may become more difficult in the near future.

However, our findings also point to a way that managers can offset these potentially disruptive forces. Our findings suggest that managers can maintain or restore cooperation, *without* changing the underlying performance appraisal system, by displaying employees' prosocial contributions and offering recognition for prosocial activities. For example, so-called peer-to-peer bonus systems enable employees to recognize and reward other employees' cooperative behaviors (Erez et al. 2015). Other examples include organizational routines in which members publicly express appreciations of helpfulness, acknowledgements in company newsletters of those who go the "extra mile," service awards, and formal performance reviews that explicitly include measures of cooperation (Weinzweig 2010, p. 2012–2014). Employing these strategies may permit organizations to retain the benefits of using comparative performance appraisal systems such as enhanced employee effort, task performance (Moon et al. 2016) and self-policing to avoid unproductive behaviors (Bernstein and Li 2017), without undercutting cooperation.

Two key boundary conditions influence the range of these managerial implications. First, our study invokes a specific type of performance appraisal system. Similar to the types of performance rankings that are commonly employed to manage sales forces (Zoltners et al. 2008, 2011) and the widely-used forced distribution ratings (FDRS) performance appraisal system (Moon et al. 2016), we use a type of zero-sum ranking in our experiment. A zero-sum ranking dictates that actors that are higher in the rankings will have access to benefits at the expense of actors that are lower in the rankings. We used this type of ranking because it maps on to performance comparison pressures that are prevalent in organizational contexts. Even organizations that do not explicitly use a zero-sum performance ranking system often feature some zero-sum competitive elements. For example, if we assume that an organization has a pool of equally talented employees, it is likely that only a select few will be promoted to leadership positions. Further, in the absence of explicit performance rankings, individuals will often infer implicit rankings, which may elicit similar dynamics (Magee and Galinsky 2008, Willer 2009). In our experiment, a zero-sum ranking encapsulates these competitive pressures. Yet, organizations may actively seek to avoid zero-sum performance structures. For example, a hybrid type of performance appraisal system, which combines individual and team performance metrics, may produce less competitive dynamics and hence attenuate the potentially disruptive effects of rankings.

Second, in our experimental design actors had access to perfect information about others' cooperative behaviors (i.e., reputations were accurate and complete). While prior research shows that group members often create accurate evaluations of others' prosocial contributions (Willer 2009), actors could conceivably have access to more or less accurate information about others' cooperative behavior. The larger the group, the more difficult it is to keep track of accurate assessments of others' reputations (Baker and Bulkley 2014, Tennie et al. 2010). Additionally, other biases related to prosocial behaviors and gender dynamics that are prevalent in organizational contexts may affect the accuracy of these assessments. For example, compared to men women may receive less credit for prosocial behaviors because they are assumed to be altruistic in nature (Flynn 2005). Inaccurate reputations may mean that more deserving employees (highly prosocial employees) will not be on the receiving end of efforts to reward reputation and reduce inequity. Future research should explore whether high givers continue to exhibit efforts to reward cooperative others when they themselves are not recognized for their prosocial contributions.

CONCLUSION

Cooperation is essential for social systems ranging from small groups to organizations to international relations. Indeed, complex society would be impossible without it. As (Nowak 2006, p. 1560) put it "[h]umans are the champions of cooperation: From hunter-gather societies to nation-states, cooperation is the decisive organizing principle of human society." Accordingly, identifying how cooperation is maintained among self-interested actors is "one of the fundamental problems in biology and the social sciences" (Egas and Riedl 2008, p. 871). We contribute to research and theory on cooperation by explicitly examining how systems of cooperation fare in the presence of a potentially disruptive force commonly found in organizational contexts: performance rankings.

Using a longitudinal between-groups experimental design that included more than 80 rounds of decision-making, we analyzed how introducing performance rankings affected cooperation. We found that established systems of cooperation could not withstand the introduction of performance rankings. Despite the development of a group norm of generalized reciprocity during a lengthy period of decision-making prior to the interruption, participants who received information about performance rankings were much less likely to cooperate than individuals who did not receive any additional information. In contrast, participants who also received reputation information—information about the relative generosity (stinginess) of others in the past—were more likely to cooperate despite the presence of performance rankings. Our research opens a new avenue of inquiry: the robustness of systems of cooperation. We considered robustness in the presence of one common potentially disruptive force (rankings) but other exogenous and endogenous forces or "shocks" can imperil a system of cooperation. We analyzed the effects of one recovery mechanism (reputation) but other recovery mechanisms likely exist. Future research may identify additional disruptive forces and recovery mechanisms, broadening and deepening our understanding of robust systems of cooperation. Finally, our research supports a growing chorus of concern regarding rankings as performance appraisal systems and suggests that organizations should find ways to recognize and reward the prosocial contributions of their members.

CHAPTER 3

With Cheaters We all Prosper?: Micro-Movements through Rankings and their Implications for System Robustness

Cooperation is essential for effective organizing (Arrow 1974). Yet, cooperation is challenging to maintain over time because it requires individuals to forego opportunities to maximize their self-interests in favor of the collective. As such, understanding how to achieve cooperation inside groups and organizations has long been considered a central area of inquiry in the social sciences (Salvato et al. 2017). Toward this end, scholars have focused on individual characteristics that identify members who are more likely to cooperate, situational characteristics that are likely to provoke prosocial emotions that inspire cooperative behaviors, and the presence of social structures that set and enforce either formal or informal obligations to cooperate (e.g., norms, regulations, and social hierarchy). Of these social structures, social hierarchy and more specifically reputation has received the most attention (Simpson and Willer 2015).

Reputation has long captured the attention of scholars studying cooperation because it serves as a powerful incentive for performing cooperative behaviors. In the context of cooperation, reputation is an individual's record of performing expected levels of cooperative behaviors. This information tends to be comparative in nature (e.g., has a particular individual contributed as much as other members of an organization?). Reputations signal which members of a group are more deserving of the group's scarce resources (Wedekind and Milinski 2000). Groups and organizations naturally seek to reward members who are key contributors and identify and sanction members who free-ride off the cooperative contributions of others (e.g., Rabin 1993; Willer 2009). Reputation rankings display comparative records of cooperative behavior. Therefore, they can serve as cognitive shortcuts, from which group members can determine who is most deserving of scarce resources (Baker and Bulkley 2014) and from which individuals can self-monitor their behavior (Bernstein and Li 2017). Yet, reputation rankings and other hierarchically-based mechanisms for eliciting cooperation may contain a dark side (Pettit et al. 2016). Reputation rankings provide performance comparison information, which can create a unidirectional drive for increased performance vis-à-vis other individuals in the ranking (Festinger 1954). Recent research has demonstrated links between opportunities for reputation gains and losses and the performance of uncooperative behaviors such as cheating and acts of deception (e.g., Garcia et al. 2006; Pettit et al. 2016; Vriend et al. 2017). This work portends that reputation rankings may ultimately be counterproductive for the maintenance of cooperation inside organizations.

Given these mixed findings for the effects of social hierarchy on cooperative behavior, one avenue forward is to examine which factors make rankings as a whole more likely to produce cooperative behaviors and which will produce uncooperative behaviors. A next step would then be to either limit these factors or remove rankings all together. However, this path forward and the recent research that warns of rankings' negative externalities both share a common assumption. *They assume that uncooperative behaviors are uniformly harmful for organizations.* This paper relaxes this assumption. It asks if individuals that exhibit uncooperative behaviors will *also* be more likely to exhibit higher levels of cooperative behaviors in response to pressures stemming from rankings. Evidence that this is the case may indicate that organizations can tolerate the uncooperative behaviors that arise from rankings because they are associated with a concomitant rise in cooperative behaviors.

Answering the question of whether rankings are helpful or harmful for maintaining cooperation inside organizations may be more important now than ever before. The new world of work presents unique challenges for organizations that can make achieving cooperation more difficult. Traditional mechanisms for ensuring cooperation and employee performance may be irrelevant or outdated with non-traditional work arrangements (e.g., virtual teams) as they have the potential to make monitoring, socialization, organizational identification, and face-to-face connections more difficult to achieve. It is important to understand how these changes alter how employees experience work and correspondingly how systems achieve social order amid these transforming experiences (Barley, Bechky, and Milliken 2017).

The new world of work was made possible by a rapid rise in technology. This rise in technology also allows employers to continually monitor employees' activities and report back transparent performance data that employees can use to monitor and adjust their own behaviors (Bernstein and Li 2017). Rankings may be improved by the greater availability and transparency of data. Rankings are traditional mechanisms used to elicit cooperation, but they may take on more relevance in this new world of work as they may be naturally positioned to leverage these advances in technology.

In the present study, I examine one organization's use of rankings to promote voluntary cooperation from its members. Using data from the online community Stack Overflow—a question and answer site for programmers, I examine over 16,000 actors' reputation lifecycles—entire histories moving through a reputation ranking—and their corresponding rates of cooperative and uncooperative behaviors. Prior studies that demonstrate the link between movements in rankings and uncooperative behaviors are typically based in a laboratory, primarily present cooperative and uncooperative behaviors as tradeoffs, and examine this tradeoff at one single point in time (e.g., Garcia et al. 2006; Pettit et al. 2016; Vriend et al. 2016). Examining actors' reputation lifecycles allows for the occurrence of contemporaneous behaviors—actors can be both cooperative and uncooperative. In contrast to prior research, I do not find that either incremental increases in ranking positions or the nearness to gains in rank are associated with increases in cooperative behavior. I do find that incremental increases in rank are associated with a higher likelihood of exhibiting *uncooperative* behavior. However, I find that actors that exhibit uncooperative behavior also exhibit slightly higher rates of cooperation in response to both potential gains and losses in rank. Last, contrary to work on moral licensing (e.g., cleansing), I find that rates of cooperative behavior decrease dramatically after actors are sanctioned for uncooperative behaviors. Jointly these findings suggest that organizations can tolerate negative externalities associated with rankings (uncooperative behaviors) as the members that perform them are also more likely to cooperate, but that sanctioning uncooperative behaviors may limit future rates of cooperation.

This study offers several contributions to the study of organizations. First, it makes two contributions to the expanding literature on the dynamic nature of social hierarchy (e.g., Brion and Anderson 2013; Pettit et al. 2013; Pettit et al. 2016). By using longitudinal data this study repeatedly assesses individuals' responses to potential gains and losses in rank. Extant research tends to examine decision-making at one single point in time and in laboratory settings. In contrast, this study examines actors' cooperative and uncooperative behaviors in a natural organizational setting, allowing this study to capture cumulative social pressures that may not be reliably produced in a laboratory setting. Cumulative pressures, such as repeatedly missing an opportunity for a reputation gain, may elicit different dynamics than one-shot examinations of behavior. Additionally, this study allows for contemporaneous opportunities for cooperative and uncooperative behaviors. Prior studies that show a link between movements in rankings and uncooperative behavior present these behaviors as tradeoffs (e.g., Pettit et al. 2016, Vriend et al. 2016). However, organizations present simultaneous opportunities for cooperative and uncooperative behaviors. By relaxing the assumption that these behaviors produce mutually exclusive options of behavior, this study takes a step toward understanding the system-level net effects of rankings.

Second, this study contributes to research that examines the functionality of social hierarchy in organizations (e.g., Anderson and Brown 2010; Simpson and Willer 2015). As a form of social hierarchy, rankings have been linked with both functional and dysfunctional outcomes for organizations. While they have been associated with benefits such as increased task coordination and improved decision-making, there is growing evidence that rankings may be problematic for achieving cooperation (Anderson and Brown 2010). Accordingly, scholars have called for more research into when reputation rankings are harmful and helpful for organizations (Simpson and Willer 2015). By examining a virtual organization that exists solely because of the voluntary contributions of its members, this study presents a conservative test for the ability of social hierarchy to enhance cooperation.

Last, this study broadly contributes to our understanding of how tools of social order meet challenges associated with the changing nature of work (Barley, Bechky, and Milliken 2017). Rankings have traditionally been used to enhance cooperation inside organizations, but studies show that they create mixed outcomes for organizations. By examining an online community that explicitly uses rankings to motivate cooperative behavior, this study examines how individuals engage with the type of rankings that may be a standing feature of the new world of work—highly transparent rankings that contain perfect information about actors' past performance.

THEORETICAL FRAMEWORK

The importance of maintaining cooperation in organizations cannot be overstated. Cooperation has been described as an essential component of effective organizing and labeled as the ultimate antecedent to organizational life (Axelrod 1984; Kogut and Zander 1992). This importance is due in large part to the many performance outcomes that are associated with high levels of cooperation. Myriad empirical studies have recorded the link between high levels of cooperation and successful group and organizational-level outcomes such as enhanced productivity, better problem-solving, greater levels of innovation and creativity, enhanced work environments, higher levels of job satisfaction, better work relationships, and improved organizational performance (Salvato, Reur, and Battiglani 2017; Smith, Carroll, and Ashford 1995; Tjosvold 1984). Several definitions of cooperation have been put forth while examining this phenomenon. I define cooperation here as the *continual* enactment of an individual behavior that benefits a group. Embedded within this definition is the realization that there are naturally occurring obstacles to cooperation (e.g., social dilemmas) that can undermine actors' willingness to cooperation and that collective action cannot be achieved without the continuation of this willingness to cooperate over time (Ring and Van de Ven 1994; Simpson and Willer 2015).

Cooperation is costly for individual actors because it requires them to expend personal resources to advance collective interests (Axelrod 1984). Costs may expand with repeated cooperation events. While cooperative behaviors enable collective action, they also introduce a collective action problem or social dilemma: individuals can maximize their self-interests by receiving benefits from group membership while free-riding on the cooperative behaviors of others, but this maximization of self-interests leads to suboptimal collective outcomes (e.g., Hardin 1982). A group can only flourish when a critical proportion of its members forego opportunities to maximize their self-interests in favor of the collective's interests. How do groups inspire their members to forego the maximization of their self-interests? How is this inspiration maintained over time?

One explanation can be found in the type of individuals that make up a group and the psychological state in which they are situated. A growing body of work has begun to examine the link between individual characteristics and cooperative behavior. Scholars have emphasized the role of social value orientation and stable preferences in enabling cooperation (e.g., Balliet et al. 2009; van Lange et al. 2013). Prosocial emotions have also been used to explain increasing cooperative behaviors (e.g., Caprara et al. 2012). For example, the emotion of gratitude is linked with higher reports of cooperative behaviors (Emmons and McCullough 2002). Individuals may possess more prosocial personalities (Penner et al. 2005) or prosocial values (Grant 2008; Rioux and Penner 2001). Due to personality differences or stable preferences, individuals may have a baseline proclivity for experiencing prosocial emotions (Grant and Bolino 2016). In this case, the extent to which individuals are likely to experience positive emotions will tend to shape their rates of cooperative behaviors. Alternatively, the situational state—the climate and time surrounding a given situation—may be more or less likely to give rise to positive emotions. For example, providing information about how others will benefit from a cooperative act can create a state that increases prosocial emotions. Grant (2007) shows that fundraising call center employees, whose job it is to secure donations, contribute more efforts to the collective goal when they are provided information about scholarship beneficiaries who directly benefit from their efforts. The bottom line being that this perspective focuses on individual traits and how they affect rates of cooperation.

Another explanation can be found in social forces that help elicit cooperation. These forces can be either informally or formally created by interactions among the members of a group or collective (e.g., Smith, Carroll, and Ashford 1995). Informal cooperation emphasizes the role of socialization through norms and the spontaneous development of voluntary participation that arises from cultural forces that are not due to explicit contractual obligations (e.g., a culture of generalized reciprocity creates a social pressure to pay-forward help when it is received). Norms can be classified as either descriptive (e.g., what most people do in a given situation), or injunctive (e.g., behavioral expectations that are enforced by sanctions) (Cialdini et al. 1990). The threat of punishment for the violation of a norm is a strong predictor of cooperative behavior (Fehr and Gintis 2002), but even the mere perception of what is typical behavior for a group can be enough to invoke cooperative behavior (Simpson and Willer 2015).

Conversely, formal cooperation emphasizes the role of social structures such as hierarchy, rules, and regulations (Smith, Carroll, and Ashford 1995). These social structures are more explicit forms of social control that create and enforce contractual obligations to cooperate. For example, organizations can design team structures that force individuals to work together (Ouichi 1980), and international protocols for climate change can require countries to adhere to emissions regulations (Wijen and Ansari 2007). These more explicit social structures are designed in such a way that the standards for cooperation are made explicit. Members are aware of their responsibilities. Rewards or sanctions for rates of cooperation are more transparent. As opposed to the perspective that focuses on individual characteristics, this perspective emphasizes the role of social factors external to an individual.

A related view combines aspects of both the individualistic and social explanations of cooperation. Known as cooperation theory, Deutch (1949) proposes that individuals who are faced with a simultaneously competitive and cooperative environment (e.g., group membership or another form of collective action) will cooperate to the degree that their individual interests are aligned with the group's interest (Tjosvold 1984). The alignment of self and group interests can occur both informally (e.g., because of cognitive dissonance a person reframes the cost associated with cooperation to that of a gain) and formally (e.g., managers structure an incentive program that actively rewards individuals for group level performance, therein better aligning the individual's interests with that of the collective). This theory asserts that individuals possess diverse individual characteristics that shape baseline preferences and interests and emphasizes that cooperation occurs when these baseline interests are aligned with those of the collective.

This study focuses on the formal force of a social hierarchy (i.e., a ranking) as a control mechanism that is in place to elicit cooperation. I chose this focus for two reasons: 1) the presence of transparent social structures designed to elicit cooperation is on the rise (Bernstein and Li 2017), and 2) debate exists about whether they are helpful or harmful for organizations (Anderson and Brown 2010). With the rise in technological capabilities that reduce the need for in-person interaction, we are arguably in an era of the new world of work, where traditional organizations are giving way to more geographically dispersed, and temporary teams (Barley, Bechky, and Milliken 2017). With geographically distributed teams, more informal methods for ensuring cooperation such as normative pressures achieved through socialization may not be as easy to create. Further, without in-person interaction, it may be more difficult to elicit the positive emotions that create spontaneous cooperation. Instead, managers are turning to more formal types of cooperation-inducing mechanisms such as rankings, badge and ratings systems, and gamification tools to ensure the presence of cooperation (Bernstein and Li 2017). The increase of these methods of social control, and specifically rankings, may be problematic if they give rise to counterproductive externalities that undermine future rates of cooperation. For example, Kitts (2006) shows that rankings provide benefits that are sufficiently valuable, which in turn created the negative externality of rivalry. As a result of this rivalry, actors began sanctioning *cooperative* behaviors, which undermined future rates of cooperation. Accordingly, understanding when reputation rankings are helpful and harmful for the collective's success is an important avenue for future research (Anderson and Willer 2014; Simpson and Willer 2015).

Reputation Rankings and Cooperative Behavior

Social hierarchy is a common way to maintain social order and thereby promotes cooperation inside groups and organizations. A social hierarchy is the explicit or implicit ordering of individuals along a valued social dimension (Magee and Galinsky 2008).[10] A position in a social hierarchy confers material, psychological, and social benefits, wherein individuals in higher positions within the hierarchy receiving a greater portion of benefits. Explicit hierarchies involve some form of transparency whereby actors within these hierarchies can understand their position without the aid of others. Implicit hierarchies involve some form of opacity whereby actors within these hierarchies must seek out others' impressions to understand where they stand in relation to others. Social hierarchy is often studied in one of two forms: status or reputation. Reputation rankings reflect an actor's relative past performance in a specific capacity (Weigelt and Camerer 1988; Benjamin and Podolny 1999). More specifically, reputation rankings order individuals along a valued social dimension based upon their past performance, whereas status orderings arise with collective judgments of an individual's relative

---

[10] While scholars widely recognize that social hierarchy is a ubiquitous feature of social life (Anderson and Brown 2010), the construct of social hierarchy lacks sufficient clarity (Bunderson et al. 2016). Social hierarchy has referred to individuals' varying levels of prestige, power, and status within a social group, as well as the overall rate of inequality between group members (e.g., in steep hierarchies a small set of actors control most of the resources) (see Bunderson et al. 2016 for a review). I have narrowed the focus of this study to one type of social hierarchy—a reputation ranking.

standing in terms of prestige, honor, and deference (Berger, Cohen, and Zelditch 1972; Vriend et al. 2016). This study focuses on reputation rankings as public, transparent records of observable cooperative behaviors.[11,12]

In the context of systems of cooperation, reputation is an assessment of members' relative contributions to the group's goals. Group members are incentivized to cooperate because groups tend to keep track of, reward, and punish individuals according to their rates of cooperative behaviors. For example, Willer (2009) showed that even without the aid of any scorekeeping devices groups were able to accurately keep track of members' rates of cooperation, group members felt pressure to cooperate because they were aware that they were being tracked, and members received social and material rewards in proportion to their rates of cooperation. Numerous economic experiments document groups using reputation information to allocate resources toward more cooperative members (Milinski, Semmann, and Krambeck 2002; Seinen and Schram 2006; Wedekind and Milinski 2000). Actors, aware of this contingent access to benefits, manage their reputations to gain these rewards. While reputation often acts as an incentive to cooperate because it provides justification of benefits from the group, an explicit reward structure does not need to be in place for reputation to induce cooperation. Even without explicit material reward structures, individuals tend to cooperate more in the presence of reputation information (Barclay and Willer 2007; Wedekind and Milinski 2000).

While tracking reputation becomes more difficult in larger groups (Baker and Bulkley 2014), the link between the presence of reputation information and higher cooperative behaviors

[11] While distinct in degree of transparency and point of evaluation, the study of cooperation in relation to reputation and status has given rise to overlapping streams of research, which have demonstrated similar underlying dynamics (Simpson and Willer 2015). Therefore, the theoretical arguments found within this manuscript will be informed by both the status and reputation literatures.

[12] Rankings are a macro-level structure—an ordering of all relevant members on a valued social dimension. In research on the effects of rankings, we are often concerned with individuals' experiences at a specific rank, or their movements to and from a specific ranking position. A single individual's position within a ranking is similar to the concepts of social standing (Doreian 1986) or social rank (Garcia et al. 2006) found in sociology and psychology.

is still present in large groups. For example, this link has been observed in largescale online market places and open-source projects (Anthony et al. 2009; Smith and Kollock 1999). Regardless of the setting, the public nature of reputation information is likely to enhance cooperative behaviors (Lacetera and Macis 2010). Jointly, these studies suggest that the link between reputation information and cooperation is an entrenched phenomenon in society and that individuals will be motivated to cooperate by the potential of a gain in rank and concerns about a loss in rank.

Reputation Rankings and Uncooperative Behavior

While the cooperative-enhancing benefits of social hierarchies are well documented (e.g., Thibault and Kelley 1959; Blau 1968; Hardy and Van Vugt 2006; Magee and Galinsky 2008; Willer 2009; Tai, Narayanan, and McAllister 2012), a growing body of research is highlighting unintended consequences of rankings. Rankings may incentivize uncooperative behaviors (e.g., Garcia et al. 2006; Pettit et al. 2016; Vriend, Jordan, and Janssen 2016). Uncooperative behaviors such as cheating, dishonesty, and sabotoge allow individuals to obtain hierarchical rewards without having to play by “the rules of the game” (Schweitzer et al. 2004; Ordonez et al. 2009). These negative behaviors may arise with reputation rankings because rankings by design create performance comparisons—actors assess their performance vis-à-vis others’ performance. Social comparison theory notes that performance comparisons can create a unique form of pressure that leads to a unidirectional drive to perform better and better (Festinger, 1954). These pressures tend to intensify near qualitatively meaningful standards that hold intrinsic and extrinsic value, such as the top of a ranking (Garcia et al. 2006). Scholars have long been concerned that rankings may create temptations for cheating and other forms of uncooperative behaviors (e.g., Krakel 2007; Lazear 1989). Recent work finds empirical support for these concerns. Vriend, Jordan, and Janssen (2016) find that actors are more likely to hold unethical intentions (e.g., a willingness to sabotage competitors and overstate performance) and exhibit uncooperative behaviors (e.g., deception) when they are in a top rank or close to achieving a top rank.

These pressures may also be pronounced in cases where actors are at risk of losing privileges that come with higher positions in the rankings. Prospect theories of motivation highlight the role of losses and potential losses in inciting behaviors that may undermine cooperation. Dubbed as loss aversion, this theory posits that actors will behave in a risk-adverse manner to preserve gains and a risk-seeking manner to avoid losses (Kahneman and Tversky 1984; Tversky and Kahneman 1991). Cheating and other forms of cooperative behaviors often come with the risk of being caught and punishment. Loss aversion that comes from the threat of losing a position in a ranking may cause actors to become more willing to assume this risk. For example, in a recent study, Pettit et al. (2016) found evidence that actors are more likely to cheat in response to a threat of loss in rank than they are with an opportunity to achieve a gain. Hence, we have evidence that both potential gains and losses in rank can lead to uncooperative behaviors. Consequently, I hypothesize that the closer an actor is to gaining or losing a position in a reputation ranking that is associated with a meaningful privilege, the higher their amount of (*un)*cooperative behaviors.

> **H1a:** The closer an actor is to *gaining* a position in a ranking that is associated with a privilege, the higher their amount of *cooperative* behaviors.
>
> **H1b:** The closer an actor is to *gaining* a position in a ranking that is associated with a privilege, the higher their amount of *<u>un</u>cooperative* behaviors.
>
> **H2a:** The closer an actor is to *losing* a position in a ranking that is associated with a privilege, the higher the likelihood that they will exhibit *cooperative* behaviors.

H2b: The closer an actor is to *losing* a position in a ranking that is associated with a privilege, the higher the likelihood that they will exhibit *<u>un</u>cooperative* behaviors.

Systemic Implications of Reputation Rankings

Why might we expect that actors may be likely to exhibit *both* cooperative and uncooperative behaviors in response to a potential reputation gain or loss? Extant research has thus far been focused on the presence of one effect at the expense of the other, but this research typically examines cooperative and uncooperative behaviors as mutually exclusive options and examines this tradeoff at one single point in time (e.g., Garcia et al. 2006; Vriend et al. 2016; Pettit et al. 2016).[13] This could lead to the assumption that if someone is likely to exhibit uncooperative behaviors then they are equally unlikely to exhibit cooperative behaviors. Yet, it is conceivable that actors inside organizations may have multiple opportunities to exhibit both cooperative and uncooperative behaviors.

The ability to track both types of behaviors may change what we know about the relationship between movements through rankings and (un)cooperative behaviors. Research in moral licensing shows that individuals tend to keep track of their "balance" of uncooperative and cooperative behaviors and act in ways to maintain this balance. Specifically, past practices provide a license to act in ways that contradict prior behavior (Miller and Effron 2010). Accordingly, cooperative behaviors may provide a license to exhibit uncooperative behaviors (Monin and Miller 2001; Sachdeva, Illiev, and Medin 2009; Kouchaki 2011). For example, studies show that people who were asked to recall their past moral acts were more likely to cheat to get higher payoffs in later time periods (e.g., Clot, Grolleau, and Ibanez 2014; Jordan et al. 2011). Correspondingly, actors that exhibit uncooperative behaviors may exercise a form of

[13] Edelman and Larkin's (2015) study, which examines the likelihood that actors will attempt to get ahead in SSRN's most downloaded paper rankings through self-downloads (i.e., cheating), shows actors behaviors over time. However, this setting does not feature ways to track cooperative behaviors.

reverse moral licensing to offset these behaviors. For instance, actors may exhibit cooperative behavior as a way to engage in moral cleansing—committing cooperative acts to boost self-worth after one's moral self-worth has been threatened—to counteract past uncooperative behaviors (Sachdeva, Illiev, and Medin 2009). Ultimately, we may expect that actors will be attuned to the ratio of their past cooperative and uncooperative behaviors and that they will be likely to act in ways that offset imbalances between the two. Further, a willingness to engage in uncooperative behaviors, especially ones that harbor the threat of punishment, suggests that actors that engage in these behaviors may be even more sensitive to the pressures associated with a proximity to a meaningful standard of achievement. Paradoxically, this could lead these actors to engage in *more* cooperative behaviors than actors that do not eventually exhibit uncooperative behaviors.

This could be consequential for organizations because it suggests that the link between reputation rankings and uncooperative behaviors may not be detrimental for a system of cooperation. Actors' cooperative behaviors may outweigh their uncooperative behaviors. Accordingly, I hypothesize that actors that are more prone to uncooperative behaviors will exhibit more cooperative behaviors than actors that never exhibit uncooperative behaviors. Heightened susceptibility to ranking pressures is the mechanism that underlies this expectation. Last, I hypothesize that actors that exhibit uncooperative behaviors will be more likely to exhibit greater rates of cooperative behaviors in future time periods to make up for their uncooperative behavior.

> **H3a:** Actors that are prone to uncooperative behaviors will cooperate more in response to pressures associated with *potential gains* in rakings than actors that never exhibit uncooperative behaviors.

> **H3b:** Actors that are prone to uncooperative behavior will cooperate more in response to pressures associated with *potential losses* in rankings than actors that never exhibit

uncooperative behaviors.

H4: Actors that are sanctioned for uncooperative behavior will exhibit higher rates of cooperation after they are sanctioned.

RESEARCH DESIGN, DATA, AND METHODS

I test these hypothesize in the context of an online community that is built from the voluntary, cooperative contributions of its members. The empirical context is the cooperative and uncooperative behaviors of 3,260,187 members of the Stack Overflow online knowledge sharing community from April 2009 to June 2017. An online community is defined as an aggregation of individuals who share a common interest and interface through an online platform or other computer-mediated mechanism (Hagel and Armstrong 1997; Williams and Cothrel 2000). Stack Overflow is the flagship online community in Stack Exchange—an overarching company that includes over 150 online communities (ranging from topics such as parenting and conspiracy theories to mathematics and biology). Stack Overflow is a question and answering site for professional and enthusiast programmers using multiple programming languages (e.g. C++, java, python, etc.). The site was created in 2008 by founders Jeff Atwood and Joel Spolsky and is the most popular online technological community on the internet with over 5 million active users as of January 2016 (Atwood, 2008). The site is entirely dependent on members' contributions. Knowledge exchange occurs through the posting of questions and other members' responses in the form of answers and edits. The type of knowledge exchange fostered on Stack Overflow is typically of high quality and based in fact rather than advice or opinion—a unique capability that differentiates Stack Overflow from other online communities such as Yahoo Answers, Facebook, and LinkedIn that are focused on networking or other forms of connectivity (e.g., "friending" or "following" members) (Funk 2014).

To maintain the high quality of the site's content, Stack Overflow enlists the help of democratically elected site moderators and a reputation ranking system. [14] Site moderators are members that are elected for life to act as liaisons between the community and the Stack Exchange Company. Their main tasks consist of responding to alerts that a post might need to be removed or altered because it is a form of spam, is offensive, or is in need of other forms of moderator attention.[15] The reputation ranking system is meant to signal the amount that the community trusts a specific community member. According to the founders, the reputation system's explicit purpose is to keep track of members' past contributions and motivate their continued cooperation, so that the site is itself self-sustaining and self-monitoring (Atwood, 2009). Members' reputation points are posted in a public ranking and alongside their user ID for each question, answer, and editing activity. Hence, members' reputation points are consistently visible to the participants and other community members. Reputation points are tied to site-specific privileges (see Table 3.1). Privileges are both a source of power over site content and a source of responsibility for maintaining the site's functioning (e.g., ability to edit content, close and open posts, tag posts as inappropriate, etc.).

Members earn reputation points based on the quality of their contributions to the site, as judged by other members (e.g., by receiving upvotes for high quality contributions and downvotes for low quality contributions). The bulk of reputation points are awarded for an upvoted question (+5), upvoted answer (+10), and an answer that is accepted by the question originator as the best answer (+15) (see Table 3.2 for a breakdown of the Stack Overflow Reputation System). Reputation points can also be lost for low quality contributions. The bulk of reputation points that are lost are for downvoted questions (-2) and answers (-2). It is important

[14] Each of the Stack Exchange online communities uses a version of this reputation ranking system.
[15] A lengthy description of site moderator's duties can be found at https://stackoverflow.com/help/site-moderators. This includes a full list of current site moderators and the site's Theory of Moderation, which all moderators must agree to abide by.

to note that downvoting behaviors cost the member that is downvoting 1 reputation point. Reputations cannot drop below 0. Members do not earn reputation points for accepting their own answers. Finally, point allocations due to the combination of upvoting, downvoting, and suggested edits are capped at 200 points per day for each member.

Table 3.1: Stack Overflow Privileges Based on Reputation Level

Reputation Point Total	Site Privileges (Milestones Bolded)
1	Create Posts (questions and answers)
5	Participate in media (discuss site improvements)
10	**Create wiki posts/Remove new user restrictions**
15	Flag posts for moderator attention /Vote on site documentation
20	Talk in chat rooms
50	Comment on other people’s posts and topic requests
75	Create bounties from your reputation
100	Approve documentation / Create new chat rooms / Collaborate on editing of Wiki Posts
125	Vote Down: Indicate whether questions and answers are not useful
200	**Reduce ads visible on SO to user**
250	View and cast close and reopen votes
500	Access review queues
1,000	**Established User: See vote counts / Create gallery chat rooms only available to some**
1,500	Create tags for site
2,000	Edits to any question and answer are applied immediately (without moderator approval)
2,500	Create tag synonyms to reduce tag proliferation
3,000	Help decide which posts are off-topic or duplicates
5,000	Approve tag wikis made by regular users
10,000	Access moderator tools (e.g., reports, delete questions, reviews)
15,000	Mark questions as protected
20,000	**Trusted User: expanded editing, deleting and undeleting privileges**
25,000	**Access to internal and Google site analytics**

Note: The table is populated from information found at https://stackoverflow.com/help/privileges?tab=all.

Table 3.2: Description of Stack Overflow's Reputation System

Reputation Gains	Reputation Losses
Question is voted up: +5	Question is voted down: -2
Answer is voted up: +10	Answer is voted down: -2
Answer is marked as "accepted": +15 (+2 to acceptor)	Downvoting: -1
Suggested edit is accepted: +2 (up to +1,000 per user)	Placing a bounty on a question: - bounty amount
Awarded a bounty: + full bounty amount	Post receives 6 spam or offensive flags: -100
Site association bonus: +100 (one time for each site)	

Notes:

1. Chart adapted from information provided at https://stackoverflow.com/help/whats-reputation.
2. Members can earn a maximum of 200 reputation points per day through upvotes, downvotes, and suggested edits. Other types of activities (e.g., bounties) are not subject to this reputation cap.
3. Reversal of votes reverse reputation points (e.g., if a member de-selects an upvote, the points the other member earned will be deducted at the end of the day).
4. Members do not earn points from accepting their own answers to their questions.
5. Bounties are tools used by members to draw attention to their questions. A bounty is a non-refundable amount of a member's reputation points that they offer for an answer to their question. A bounty period last for a minimum of one day and a maximum of seven days. After the seventh day if an answer is not selected as the accepted answer, then the answer with the highest votes will be awarded the bounty. More information on bounties can be found at https://stackoverflow.com/help/bounty.
6. Different levels of reputation points unlock site privileges. See Table 1 for a full list of privileges that are tied to reputation points.

Although Stack Exchange reputation rankings are not associated with any traditional material gains (e.g., monetary compensation), some companies report stack overflow reputation as being a helpful criterion for job selection (Johnson 2013), and reputations arguably hold psychological value for members. Stack Exchange Meta Community message boards (sites where members post and answer questions about the functionality and rules of the Stack Overflow site) reveal that these reputations are important and well attended-to by community members. The reputation tag is one of the most popular tags on the Stack exchange Meta site, with over 3,800 questions devoted to the topic. One of the subtopics of interest is how to prevent community members from "cheating" to gain undeserved reputation points. For example, community members express concern for behaviors such as strategically downvoting all answers on a thread that compete with a participant's own answer. Other behaviors that are of concern include repeatedly posting low quality answers as first posts to a thread to increase the likelihood that they are viewed and rudely answering and commenting on answers to gain attention and receive upvotes. The community labels these practices as “rep-farming.” These practices are viewed with great disdain by the site’s members and several threads on the meta sites are devoted to ameliorating these practices.

Rep-farming is an example of behaviors that are uncooperative for the site’s functioning and ultimate goal (to maintain a high caliber, open-source knowledge community). To limit uncooperative behaviors and maintain high levels of quality, the site’s founders introduced a “penalty box” to sanction members for performing uncooperative behaviors (Atwood, 2009). The penalty box on Stack Exchange operates in a manner similar to a penalty box in hockey. Members are “put on a time out” for an amount of time that is commensurate with their level of violations (determined by the site’s moderators). Offenses that can put users in the penalty box include: disruptive behavior such as voting irregularities, intentionally spamming the community on repeated occasions, repeatedly disregarding community norms, trolling, and generally bad community behavior (Atwood 2009). Stack Overflow refers to penalty box events as periods of suspension. While suspended, users’ reputations are set to 1. They cannot post questions, answers, or comments and they do not have the ability to gain reputation. Although Stack Exchange does not have a “hall of shame” where information on who is suspended is easily accessible and publicly displayed, it is possible to see this information by querying a public sequel database that records which individuals are suspended at any given moment.

Several features of this context make Stack Overflow an attractive dataset to test hypotheses surrounding the effects of reputation rankings in systems of cooperation. First, Stack Overflow explicitly uses the reputation ranking system to motivate cooperative behavior form its site members (Atwood 2008). Similar to sales rankings, leader boards, badge and reputation systems used in many organizations to motivate higher levels of productivity and other forms of cooperative behavior in organizations (Cappelli 2009, Mollick and Rothbard 2014, Webster and Wing-Fai 2017), Stack Overflow created the reputation ranking system to recognize members for their cooperative contributions to the site. Furthermore, the digitized nature of the Stack Overflow setting provides complete and accurate records of members' daily changes in reputation. The completeness of reputation assessments and members' cooperative behaviors are less reliably inferred from non-digitized contexts, which may rely on biased or inaccurate assessments made by supervisors or other organizational members (Moon et al. 2016). Jointly, these two features allow me to reliably examine how individuals' movements in a reputation ranking affect the amount of cooperative contributions they make on the site. Put simply, with these complete records I am able to more accurately assess whether reputation rankings accomplish what they intend to—motivate continued cooperative contributions over time.

Second, Stack Overflow systematically records and penalizes uncooperative behaviors. Uncooperative and or unethical behaviors tend to be difficult to record or infer in field research and therefore tend to be assessed through anonymous surveys and or experiments—both of which have their limitations. Surveys may suffer from the underreporting of uncooperative behaviors and laboratory experiments are often devoid of the consequences that occur in actual organizations. Accordingly, this context is advantageous for examining whether and how reputation rankings incite uncooperative behaviors because it features accurate and complete records of individuals' actual uncooperative behaviors inside an organization.

Third, the longitudinal nature of the dataset facilitates the examination of members' behaviors over time. Hence, it permits me to examine trends in individuals' contributions in response to periodic movements through a reputation ranking. As opposed to other studies of cheating and deceptive behavior in response to a change in rank position which examine one single decision that is in the form of a tradeoff—enacting either cooperative or uncooperative behaviors (e.g., Garcia et al. 2006; Pettit et al. 2016, Vriend et al. 2016) the nature of this data permits me to both examine simultaneous and repeated opportunities for cooperative and uncooperative behaviors. An analysis of which can offer additional insights into the joint effects of rankings on both cooperative and uncooperative behaviors over time.

Sampling Procedure

The sampling frame for this study includes all Stack Overflow members whose data appeared in Stack Overflow's public release of data in June 2017. The data for these users spans the time frame of August 1, 2008 through June 15, 2017. This data was then matched with non-public data received from the Stack Exchange Company that included daily changes in reputation and information about suspension events. All data was de-identified prior to analysis. The public data release contained records of 3,454,985 unique individuals who had contributed at least one question or answer during their tenure.[16] These individuals were matched with 64 million records of reputation changes. Of these individuals, 2,520,088 were excluded because they had less than two reputation changes during their tenure, leaving a total of 934,897 individuals. These individuals were matched with 10,164 records of suspension. Ten percent of individuals were suspended more than once, with a maximum of 24 entries.

The nature of these data creates two problems for analysis that must be addressed. First, relative to the number of members in a community, suspension constitutes a "rare" event. In cases where the positive outcomes (ones) are significantly fewer than the negative case (zeros),

[16] Stack Overflow has a much larger number of community members who are registered to use the site (e.g., over 5 million registered users as of January 2017). However, a large portion of these registered members do not post questions or answers to the site. This study is confined to active users.

logistic regression coefficients can be biased (King and Zeng 2001). Second, the size of the data makes computation costly. Even collapsing these individuals' behaviors at the week level (compared to daily accounts) significantly increases the computational power required for variable construction. Both of these potential problems can be addressed by adopting a choice-based or case-control based sampling procedure (King and Zeng 2001). This procedure preserves all positive outcomes (ones) and randomly draws from all non-positive outcomes (zeros) to fill in the sample. Using this method, I formed a sample that included all individuals who entered the penalty box at least one time (n=6,301), and then randomly sampled from individuals who never entered the penalty box to fill in the sample (n=6,301). Individuals' behaviors are examined at the level of the week. I am concerned with measuring how changes in reputation affect cooperative and uncooperative behaviors over time. Therefore, I constructed a panel dataset with individual-week as the unit of analysis. The panel is unbalanced. Individuals enter the dataset with their first record of a change in reputation. Tables 3.3-3.7 show the distributions of observations based on milestone rank. Actors are in a milestone rank category if they are at risk of achieving that milestone rank. For example, category M1 consists of all observations where an actor has not yet reached milestone rank M1.

Examining the distribution of observations of actors occupying different ranks, one outlier rank is highly visible (10% of the way to the first milestone). When actors first enter the dataset they start at one reputation point, which is 10% toward the first milestone. Since this point likely reflects actors' beginning reputation points, I drop this category from the analysis (*n=702,935).* Similarly, I drop observations that are at the very top of the ranking—those who have exceeded the final milestone because these actors are not at risk of gaining a milestone rank (*n=20,190).* For a comparison of the distribution of observations by percent of milestone rank achieved see Figures 3.1 and 3.2. This resulted in a final sample of 8,514 individuals and 1,281,811 individual-week observations. On average, there are 225 observations (weeks) per individual.

Figure 3.1: Frequency of Observations at Percent of the Way to the Next Milestone on Original Sample

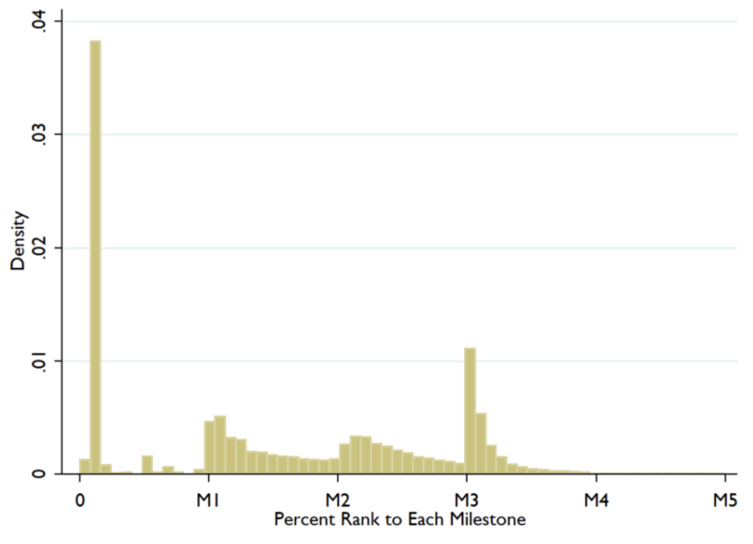
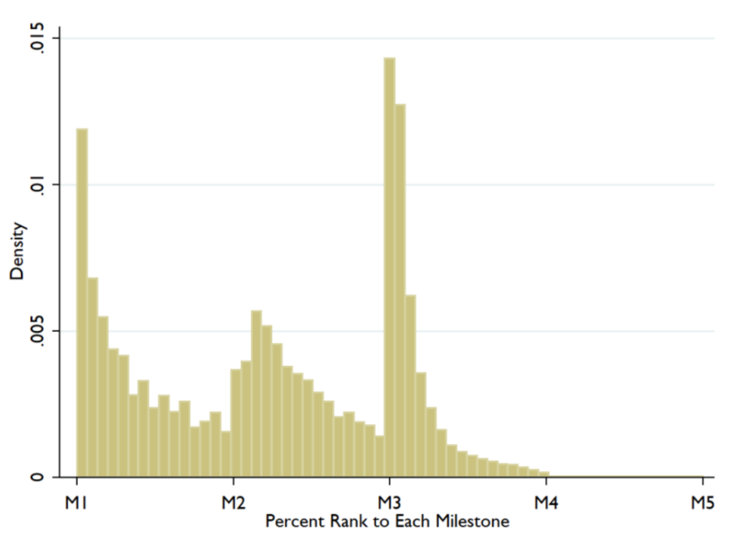


Figure 3.2: Frequency of Observations at Percent of the Way to the Next Milestone after Removing Bottom and Top Milestones Categories



Notes for Figures 3.1 & 3.2:

1. "M" Stands for Ranking Milestone Level. Actors receive significant new privileges at each milestone.
2. All observations of actors at risk of achieving rank milestone 1 were eliminated due to an outlier of observations clustered at a reputation of 1 (10% of the way to the first milestone). This is the reputation people start with.
3. All observations of actors that exceeded the final rank milestone 5 were eliminated because there is no more ranking milestone to achieve.

Table 3.3: Number of Observations in Each Milestone

Milestone Category	M1	M2	M3	M4	M5	M6
Reputation	<10	>=10 <200	>=200 <1,000	>=1,000 < 20,000	>=20,000 <25,000	>25,000
Number of Observations	702,935	476,523	413,896	384,787	6,605	20,190

Table 3.4: Number of Observations of Suspensions in Each Milestone Rank

Milestone Category	M1	M2	M3	M4	M5	M6
Reputation	<10	>=10 <200	>=200 <1,000	>=1,000 < 20,000	>=20,000 <25,000	>25,000
Number of Observations	703	1,898	2,695	1,527	15	76

Table 3.5: Number of Observations with High Risk of Proximity Gain (10%) in Each Milestone Rank

Milestone Category	M1	M2	M3	M4	M5	M6
Reputation	<10	>=10 <200	>=200 <1,000	>=1,000 < 20,000	>=20,000 <25,000	>25,000
Number of Observations 90-100% of Next Milestone	43,307	117,711	116,651	26,989	2,393	---
Number of Observations 50-89%	6,805	20,131	19,213	3,062	567	---

Table 3.6: Number of Observations with High Risk of Proximity Loss (10%) in Each Milestone Rank

Milestone Category	M1	M2	M3	M4	M5	M6
Reputation	<10	>=10 <200	>=200 <1,000	>=1,000 < 20,000	>=20,000 <25,000	>25,000
Number of Observations 0%-10% of Next Milestone	---	204,521	223,190	132,089	2,863	---
Number of Observations 11%-49% of Next Milestone	---	134,160	54,842	222,647	782	---

Table 3.7: Number of Observations with Reputation Changes (From Week to Week)

Milestone Category	M1	M2	M3	M4	M5	M6
Number of Observations Same	700,415	470,554	402,286	338,539	3,315	
Number of Observations Gain	2,382	5,470	10,687	44,889	3,246	
Number of Observations Loss	138	499	923	1,359	44	

MEASURES

Dependent Variables. There are two main dependent variables in my dataset: 1) count of cooperative behaviors, and 2) count of uncooperative behaviors. Both are calculated at the level of a week. Cooperative behavior is defined as any behavior that the group under study defines as appropriate, group-enhancing behavior. At Stack Overflow, cooperative behavior is defined as the posting of genuine questions and answers to the website. Accordingly, I operationalize *Cooperative behavior* as the total number of question and answer posts for a given individual in week *t.* To examine whether changes in reputation lead to uncooperative behaviors, I defined my second dependent variable, *Uncooperative behaviors*, as a binary variable that took the value of 1 if an individual was suspended for a negative reason in week *t*. In my data, individuals were suspended for one of 6 reasons: 1) Failure to learn over time (e.g., continually asking programming specific questions in a meta forum site, the purpose of which is to discuss community improvements), 2) Voting irregularities (e.g., strategically downvoting a competitor's answer), 3) Promoting oneself (e.g., spamming the site with promotional ads), 4) Plagiarism (e.g., stealing someone else's answer and posting it as one's own to answer a similar question), 5) A need to cool down (e.g., individual often posts negative, disruptive comments that spark anger and discontent), and 6) Network-wide suspension (e.g., as determined by site moderators when behavior is bad enough to warrant a suspension across all Stack Exchange communities). I count all but the first reason (failure to learn over time), as a negative reason for suspension. Of the 10,614 suspension events, 93.13% qualify as negative reasons, and 3.32% were missing a reason. This resulted in a final set of 9,539 suspension events. Figure 3.3 displays the percent of suspension events by reason. Figure 3.4 displays the distribution of these events over the years 2009-2017 (by quarter-year). Table 3.8 lists all constructs, variables, and their operationalizations.

Figure 3.3: Distribution of Reasons for Suspension

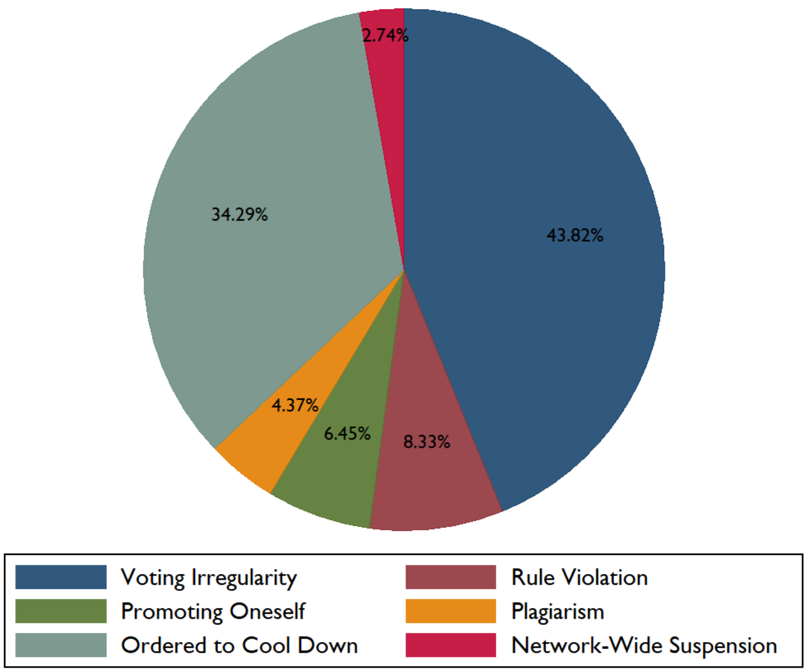
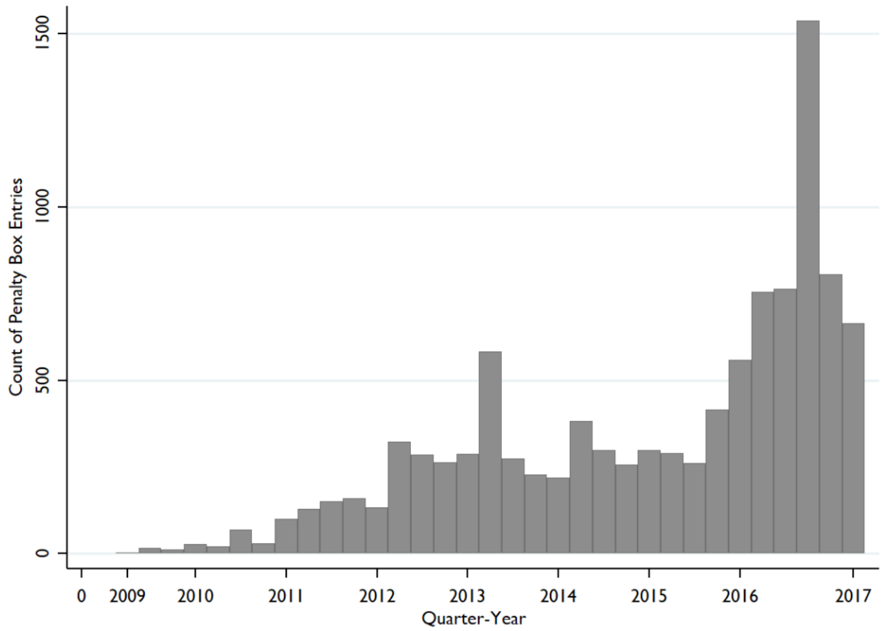
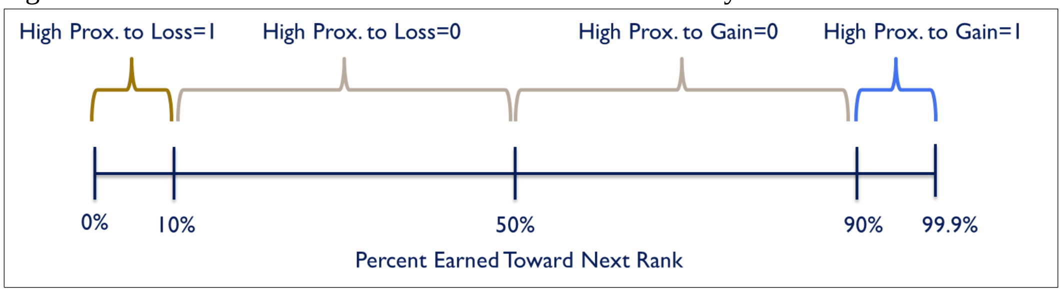


Figure 3.4: Number of Suspension Events by Quarter-Year (Q1-2009-Q2-2017)



Independent Variables. In this study, I am interested in capturing how movements through a ranking affect rates of cooperative and uncooperative behavior. I operationalize the pressures associated with these movements in three ways. First, I calculate a continuous measure of the percent of the way the actor is to achieving the next milestone rank. *Percent of next milestone rank achieved*, is calculated as the percent of reputation points that are needed to achieve the next milestone ranking that an actor has earned. This measure restarts at 0% once the actor is in a new milestone rank category. Second, I created a measure that reflects whether an actor is close to achieving the next milestone rank. *Proximity to gain* is a dichotomous variable where 1=the individual is 90% or more of the way to achieving the next milestone rank and 0=the individual is less than 90%, but more than 50% of the way there. Third, I created a measure that reflects when an actor is close to losing their current milestone rank. *Proximity to loss* is a dichotomous variable where 1=the individual is only 10% or less above a milestone rank and 0=the individual is greater than 10%, but less than 50% of the way to the next milestone.[17] In operationalizing these variables I made the assumption that individuals are more focused on a potential gain in rank when they are above 50% of the way toward the next ranking threshold and are more focused on a potential loss when they are below 50% of the way to the next ranking threshold (see Figure 3.5 for a visualization of the measures).

Figure 3.5: Visualization of Measures that Calculate Proximity to Rank Gains and Losses



Hypothesis 3 compares individuals who are more prone to uncooperative behavior (i.e., individuals who are more susceptible to ranking threshold pressures) with individuals who never exhibit uncooperative behaviors. Individuals who had an inclination toward uncooperative behavior were represented by an indicator variable: 1=was suspended at some point during their tenure.

I include controls that may influence the rate of cooperative and uncooperative behaviors. Amount of recognition from peers, *Count of upvotes received* during a given week, could be associated with increases in both cooperative and uncooperative behaviors. Recognition could increase confidence, which could lead to increases in cooperative behaviors or overconfidence, which could lead to increases in uncooperative behaviors. Similarly, both constructs could be

[17] As robustness checks I examined proximity to a gain at 20% and 30% proximity to the rankings. I also examined the predictors of logged reputation point total and a “gain mindset” (>=50%) vs. “loss mindset” (<50%). Results are mixed, suggesting that the effect is not uniform within categories (see appendix for these additional models).

associated with being called out by peers for low quality, *Count of downvotes received* during a given week. Lack of recognition could increase rates of both cooperative and uncooperative behaviors. Individuals could increase cooperative behaviors to prove others wrong, or turn to uncooperative behaviors out of frustration when they have not been recognized. More recent posting activity could indicate higher motivations to move up in the ranking, which could in turn be associated with increases in both cooperative and uncooperative behaviors. *Days Since Last Activity* is measured as the number of days since the last post, calculated during the final day for week *t-1*. Last, I include a control for the amount of time an individual has been a member on the site, which could be associated with familiarity with community norms and experience with posting. *Tenure on Site* is measured as the number of days between the individual's account origination date and the last date in week *t-1*.

Analytical Strategy

Two model specifications were used to explore how movements through rankings are associated with rates of cooperative and uncooperative behaviors. Given the longitudinal nature of the date and the fact that cooperative behavior is measured as a count of posts which takes only non-negative integer values, I first used a panel poisson regression model (xtpoisson) with fixed effects for the individual. The number of cooperative behaviors is highly skewed. Count data is often highly skewed, making poission models the standard approach for analyzing panel count data (Allison 2009; Ferguson et al. 2016; Somaya, Williamson, & Lorinkova, 2008). For hypotheses that examined the occurrence of uncooperative behavior I used a panel logistic regression model (xtlogit). All models used actor fixed effects, which accounts for any unobserved heterogeneity between actors by calculating within-actor estimates for the coefficients (Hausman, Hall, and Griliches 1984).

Table 3.8: Description of Constructs and Variables in Chapter 3

Construct	Variable	Definition	Level
Cooperative Behavior (DV)	Count of posts	Count of questions and answers in week *t*	Week
Uncooperative Behavior (DV)	Suspension occurred in week	1=suspension started in week *t*	Week
Proximity to Gain	Percent of next milestone rank achieved	Calculates the percent of the way the actor is to their next ranking milestone. This continuous measure restarts at 0% when the actor is at a new milestone. The measure varies from 0 to 99.99 and is calculated for week *t-1*.	Week
Proximity to Gain-2	Proximity to gain	1=10% or less to go to ranking threshold (i.e., earned 90% or more of the points needed to get to next ranking threshold) in week *t-1*	Week
Proximity to Loss	Proximity to loss	1=10% or less to go to dip below last earned ranking threshold (i.e., at max 10% of the way to the next ranking threshold) in week *t-1*	Week
Inclination Toward Uncooperative Behavior	Will eventually exhibit uncooperative behavior	1=exhibits uncooperative behavior at least once during tenure on the site	Individual
Severity of Offense	Days suspended	Number of days listed for suspension at time suspension began	Week
Time Period After Sanction	Time period occurs after suspension ends	1=observation occurred after suspension ends	Week
Controls			
Total Activity	Total activity	Count of total cooperative and uncooperative events in week *t-1*	Week
Recency of Activity	Days since last active	Count of days since last posted on the site based on the last date in week *t-1*	Week
Experience with Site	Tenure on site	Count of days since joining the site based on the last date in week *t-1*	Week
Recognized for High Quality Contributions	Count of Upvotes Received	Count of upvotes received from other site members in week *t-1*	Week
Called Out for Low Quality Contributions	Count of Downvotes Received	Count of downvotes received from other site members in week *t-1*	Week

RESULTS

Table 3.9 displays descriptive statistics separated by whether the actor was eventually suspended. On average actors across the two sub-samples had the same level of site tenure (around 2.45 years), but actors who were at some point suspended in their tenure were on average more active and had higher reputations. To offset this discrepancy, models that examine the likelihood of uncooperative behavior (suspension) control for total activity in the prior week. I operationalized pressures associated with a potential gain in rank in two ways: 1) as the percent of the next rank that has been earned (0-100%) and 2) whether the actor is at least 90% of the way to the next rank. I will first discuss the effects associated with potential gains in rank and then will discuss the effects associated with potential losses in rank.

Table 3.10 displays results for models that examine ranking pressures as the percent of the next milestone rank that is achieved (a continuous measure from 0 to 99.9%). Table 3.11 displays results for models that examine ranking pressures as being at least 90% of the way to a gain in rank (referred to as “proximity to gain”). As would be expected, receiving upvotes—public recognition of a job well done—is positively associated with more future cooperative behaviors and negatively associated with uncooperative behaviors (suspension). Interestingly, receiving downvotes is positively associated with both cooperative and uncooperative behaviors. Across all models, longer stretches of inactivity are associated with lower rates of both cooperative and uncooperative behaviors, suggesting that total activity influences both cooperative and uncooperative behavior. In fact, Model 2 (Table 3.10) and Model 6a (Table 3.11) both show that total activity in the prior week is associated with a higher likelihood of suspension.

Table 3.9: Summary Statistics for Chapter 3

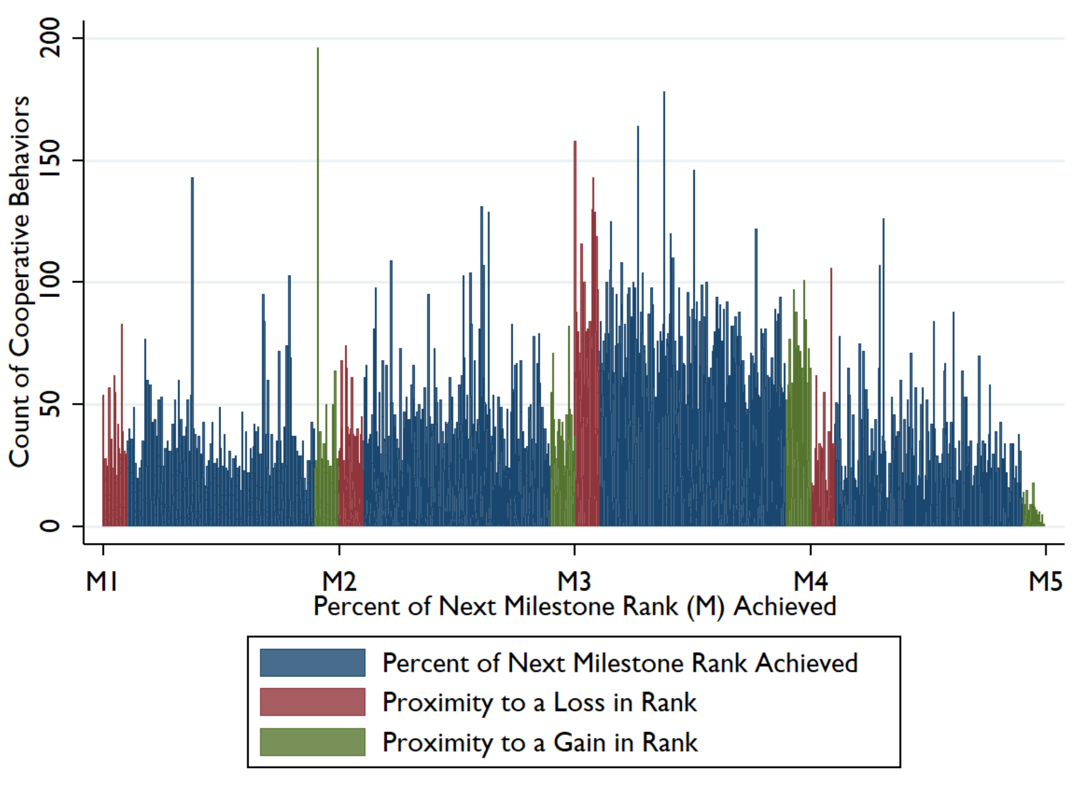
Variable	Obs.	Mean	SD	Min.	Max.
Actors who were never suspended	**981,214**				
Count of Cooperative Behaviors	987,750	0.156	1.297	0	154
Reputation	986,677	584.763	4651.352	0	>25,000*
Percent of Next Milestone Earned	977,949	20.356	21.864	0	99.995
Proximity to Rank Gain	131,510	0.132	0.334	0	1
Proximity to Rank Loss	345,344	0.423	0.494	0	1
Count of Upvotes Received	981,214	0.397	2.779	0	302
Count of Downvotes Received	981,214	0.018	0.2016	0	31
Days Since Last Active	981,214	381.116	452.552	0	3134
Tenure on Site (days)	981,214	897.940	640.408	0	>2,000*
Total Activity	981,214	0.153	1.298	0	154
Actors who were suspended at some point in their tenure	**1,011,214**				
Count of Cooperative Behaviors	1,017,186	0.856	4.111	0	234
Suspension event in a given week	1,017,186	0.007	0.082	0	1
Reputation	1,016,331	2591.775	13,308.09	0	>25,000*
Percent of Next Milestone Earned	994,431	28.165	26.919	0	99.989
Proximity to Rank Gain	222,883	0.144	0.351	0	1
Proximity to Rank Loss	623,415	0.314	0.464	0	1
Count of Upvotes Received	1,011,214	1.797	9.672	0	677
Count of Downvotes Received	1,011,214	0.114	0.606	0	67
Days Since Last Active	1,011,214	190.769	299.658	0	2423
Tenure on Site (days)	1,011,214	867.676	599.562	0	>2,000*
Total Activity	1,011,214	0.864	4.125	0	234
Obs. Occurred Suspension Finished	1,017,186	0.630	0.483	0	1

Notes:

1. (*) To preserve the anonymity of Stack Overflow's members, the maximum values for reputation and tenure on the site are not reported.
2. Summary statistics are for the full sample (before milestone categories M1 and M6 were eliminated).
3. Unit of analysis is actor-week
4. All independent variables are lagged
5. Proximity to Rank Gain values are only calculated for rank percentages above 49%--when it is assumed that this pressure will be more pronounced than a pressure of a loss, 1=90% or more of the way to the next ranking threshold.
6. Proximity to Rank Loss values are only calculated for rank percentages below 50%--when it is assumed that this pressure will be more pronounced than a pressure of a gain, 1=10% or less of the way to the next ranking threshold.

Hypothesis 1a predicts that potential rank gains will be associated with increases in cooperative behavior. I do not find support for this hypothesis with either operationalization of potential rank gains. There is no significant effect of percent of the next milestone rank that is achieved on cooperative behavior (Model 1, Table 3.10) and proximity to a rank gain (being at least 90% of the way to the next rank) is associated with a slight decrease in cooperative behavior (Model 5a, Table 3.11). Given all other variables are held constant, actors that are close to a rank gain are expected to have an incident rate of only 0.892 times as great as actors that are not close. From these results it would appear as if rankings do not positively influence rates of cooperation. Supplemental analyses reveal that there are significant positive effects associated with movements through the ranking, but that these depend on how high actors are in the overall ranking (across all milestone categories). Figure 3.6 displays a descriptive plot of the frequency of cooperative behaviors by the percent of next milestone rank that is achieved. From a visual assessment of the relationship between ranking category and cooperation it appears that actors at risk of achieving the 2rd and 3rd milestones cooperate more in response to increases in the percent of rank achieved toward the next milestone.

Figure 3.6: Frequency of Cooperative Behaviors by the Percent of Next Milestone Rank Achieved



Supplemental analyses find some support for this impression (see Appendix). Controlling for all other factors, the negative effect of percent of rank achieved on cooperative behavior is less pronounced in higher areas of the ranking (e.g., milestones 3-5), compared with lower categories in the ranking (milestone 2). Additional supplemental analyses show that a gain mindset (e.g., being at least 50% of the way toward the next threshold) as compared to a loss mindset is associated with both higher rates of cooperative and uncooperative behavior (see Appendix). Ultimately, this shows that while actors are in different subsets of the ranking, they may experience different pressures and react differently than they did in other subsets of the ranking.

Figure 3.7: Marginal Effects of Category Membership and the Effect of Percent of Next Milestone Achieved on Rates of Cooperative Behavior

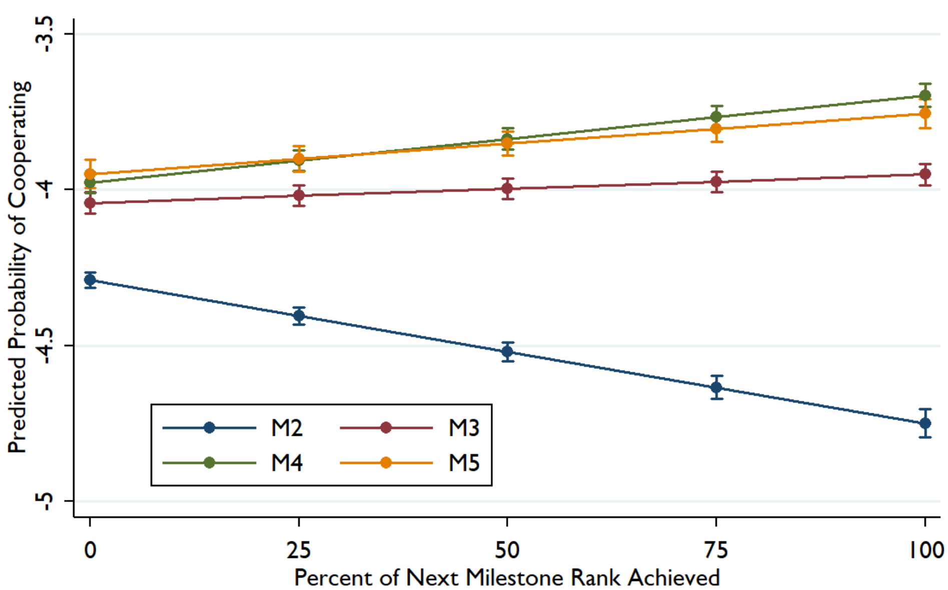
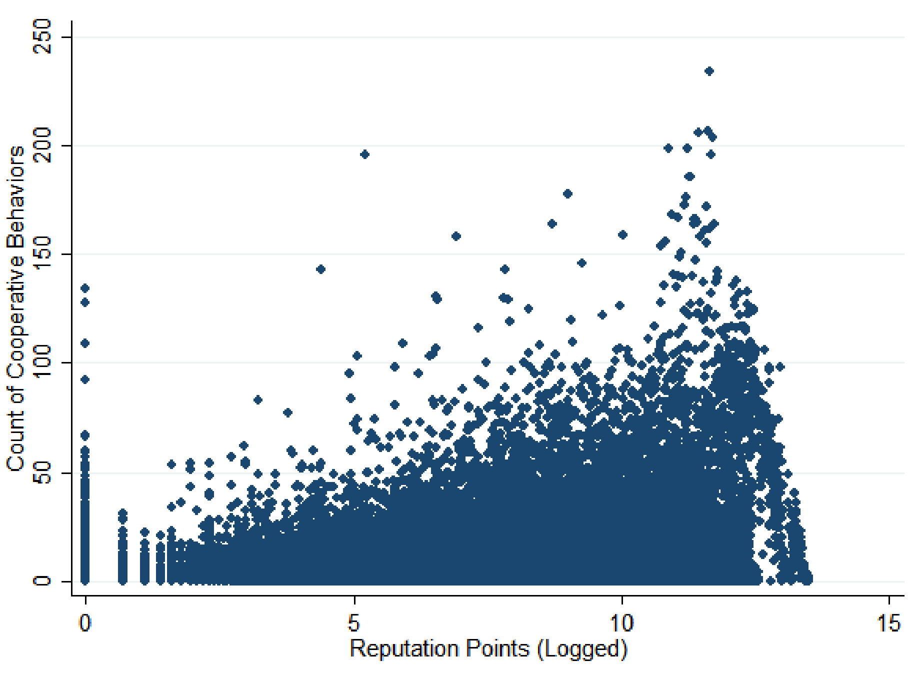


Figure 3.8: Count of Cooperative Behaviors by Logged Reputation Points for All Milestone Ranks



Hypothesis 1b predicts that potential rank gains will be associated with increases in <u>un</u>cooperative behavior. I find support for this hypothesis with the operationalization of ranking pressures as the percent of next rank that is earned (Model 2, Table 3.10). If an actor were to increase his rank by one percentage point, his incident rate ratio for suspension would increase by a factor of 1.004, with everything else held constant. However, there is no significant relationship between an actor being at least 90% of the way to the nearest rank and suspension (Model 6a, Table 3.11). Jointly this may suggest that more incremental movements forward in a ranking create pressures that lead to increases in uncooperative behaviors, rather than just nearness to a gain in rank.

Hypothesis 2a predicts that proximity to a <u>loss</u> in rank will be associated with increases in cooperative behaviors. Compared with actors that are higher than 10% of the way from the most recently earned rank, actors that are at risk of a loss in rank are expected to have an incident rate 1.21 times greater for cooperative behavior, all other factors held constant. Hence, I find strong support for hypothesis 2a; threats of loss in rank are associated with higher rates of *cooperative* behavior. Interestingly, I do not find support for hypothesis 2b. I find that the proximity to a loss in rank is associated with a *decrease* in the likelihood that an actor will be suspended. Compared with actors that are further than 10% of the way from the most recently earned rank, actors that are closer to a loss in rank are 18% less likely to be suspended (Model 6b, Table 3.11). This result is inconsistent with prior research, which reports that actors will be likely to cheat to avoid a status loss even when they are provided with an alternative, legitimate option to increase their position (e.g., Pettit et al. 2016). My findings suggest the opposite effect—that actors would be more likely to exhibit cooperative behaviors to avoid a loss.

To test hypothesis 3a, I compare the effect of potential rank gains on the rates of cooperation for actors that are never suspended to those who are at some point suspended in their tenure (i.e., they are more prone to uncooperative behavior)[18]. Hypothesis 3a predicts that actors who are more prone to uncooperative behavior will display higher average rates of cooperative behavior in response to potential gains in rank. I find support for this hypothesis across both operationalizations of potential gains in rank. The percent earned to the nearest rank is associated with a slight decrease in cooperative behaviors for those who do not enter the penalty box (β= *-0.001, p<0.001*), but is associated with a slight increase in cooperative behaviors for those who eventually enter the penalty box (β= *0.001, p<0.001)* (Model 3a, Table 3.10).[19] The operationalization of potential rank gains as at least 90% of the way toward a rank gain shows a similar trend. Although both proximity to a gain is negatively associated with cooperative behaviors for both actors that are eventually suspended and actors that are never suspended, this effect is lower in degree for actors that are more prone to uncooperative behavior (β= *-0.098,*

[18] Models that examine hypotheses 3a&3b only examine actors' behavior before their first suspension period.
[19] While these differences are small, coefficients from these models are statistically significantly different (X^2= *76.882, p<0.001*).

p<0.001 vs. β= -0.142, p<0.001) (Models 7a and 7b, Table 3.11). These findings suggest that actors that are more prone to uncooperative behaviors are on average just as cooperative, if not slightly more cooperative than actors that are never suspended.

Table 3.10: Likelihood of Behavior by Percent of Milestone Rank Achieved

	Model 1: Count of cooperative behaviors	Model 2: Likelihood of suspension	Model 3a: Count of coop. behaviors of actors who are *never* suspended	Model 3b: Count of coop. behaviors of actors who are *eventually* suspended
Perc. of Milestone Rank Achieved	0.000	0.004**	-0.001**	0.001***
	(0.000)	(0.001)	(0.000)	(0.00)
Milestone Category 3	0.320***	0.821***	0.145***	0.547***
	(0.007)	(0.066)	(0.012)	(0.012)
Milestone Category 4	0.343***	1.144***	0.018	0.641***
	(0.009)	(0.105)	(0.019)	(0.017)
Milestone Category 5	0.304***	0.639	0.019	0.669***
	(0.014)	(0.463)	(0.033)	(0.030)
Count of Upvotes Received	0.021***	-0.023***	0.030***	0.021***
	(0.000)	(0.004)	(0.000)	(0.000)
Count of Downvotes Received	0.080***	0.156***	0.058***	0.051***
	(0.001)	(0.012)	(0.004)	(0.002)
Days Since Last Active	-0.013***	-0.0133***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.00)	(0.000)
Tenure on Site	-0.001***	-0.004***	-0.001***	-0.000***
	(0.000)	(0.00)	(0.00)	(0.000)
Total Activity		0.089***		
		(0.004)		
Actor Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	1,083,199	670,559	418,298	98,811
Number of Actors	7,718	5,149	2,610	2,562

Notes:
1. *p<.05, **p<0.01, ***p<0.001
2. Standard errors are in parentheses.
3. Model 1 reports results from a Panel Poisson Regression model with actor fixed effects. Model 2 reports results from a Panel Logistic Regression model with actor fixed effects.
4. All independent variables are lagged (calculated at week *t-1*).
5. All observations that occurred before the first milestone was reached were eliminated from the sample due to an outlier rank (see Figure 3.1 Percent of Way to Next Milestone).
6. All observations that occurred after the final milestone was reached were eliminated from the sample. A plausible denominator to construct the percent ranking measure could not be determined.
7. All observations in which individuals were suspended in week *t-1* were dropped because individuals cannot accrue reputation points while they are suspended box (*n=145,041*).
8. The comparison category for milestone rank category is milestone category 2.
9. Model 3b examines the behavior of actors that were suspended in the time period *before* their first entry.

Hypothesis 3b predicts that actors who are more prone to uncooperative behavior will cooperate more in response to potential losses in rankings than actors who never exhibit uncooperative behaviors. I do not find support for this hypothesis. Instead, I find that actors that are never suspended are much more likely to cooperate in response to potential losses in rank than those who are more prone to uncooperative behaviors ($\beta=0.256$, $p<0.001$ vs. $\beta=0.066$, $p<0.001$) (Models 7c and 7d, Table 3.11).

Last, hypothesis 4 predicts that actors that were suspended will be exhibit higher rates of cooperation after their suspension to make up for their past uncooperative behaviors. I find the opposite to be the case (see Table 3.12). Suspension is associated with an incident rate of cooperating that is 33% lower than rates of cooperation prior to the suspension.

Table 3.11: Effects of High Proximity to Gaining or Losing Milestone Ranks

	Model 5a: Count of coop. behaviors	Model 5b: Count of coop. behaviors	Model 6a: Likelihood of suspension	Model 6b: Likelihood of suspension	Model 7a: Count of coop. behaviors of actors who are _never_ suspended	Model 7b: Count of coop. behaviors of actors who are _eventually_ suspended	Model 7c: Count of coop. behaviors of actors who are _never_ suspended	Model 7d: Count of coop. behaviors of actors who are _eventually_ suspended
Proximity to Gain	-0.114***		0.142		-0.142***	-0.098***		
	(0.009)		(0.113)		(0.022)	(0.021)		
Proximity to Loss		0.187***		-0.187***			0.256***	0.066***
		(0.005)		(0.061)			(0.011)	(0.011)
Milestone Category 3	0.996***	0.353***	1.090***	0.760***	0.982***	1.046***	0.095***	0.664***
	(0.015)	(0.009)	(0.134)	(0.090)	(0.026)	(0.026)	(0.016)	(0.003)
Milestone Category 4	1.859***	0.067***	1.113***	1.011***	1.863***	1.732***	-0.338***	0.431***
	(0.019)	(0.012)	(0.224)	(0.139)	(0.040)	(0.036)	(0.024)	(0.022)
Milestone Category 5	1.923***	-0.209***	0.313	-0.183	1.892***	1.909***	-0.424***	0.150***
	(0.024)	(0.019)	(0.777)	(0.732)	(0.058)	(0.053)	(0.044)	(0.045)
Count of Upvotes Received	0.013***	0.026***	-0.021*	-0.022***	0.017***	0.014***	0.032***	0.024***
	(0.000)	(0.000)	(0.010)	(0.005)	(0.001)	(0.001)	(0.000)	(0.000)
Count of Downvotes Rec.	0.0449***	0.0821***	0.129***	0.161***	0.0483***	0.032***	0.056***	0.023***
	(0.002)	(0.001)	(0.026)	(0.015)	(0.009)	(0.005)	(0.004)	(0.000)
Days Since Last Active	-0.010***	-0.013***	-0.011***	-0.012***	-0.005***	-0.008***	-0.008***	0.066***
	(0.000)	(0.00)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
Tenure on Site	-0.002***	-0.001***	-0.005***	-0.004***	-0.002***	-0.000***	-0.001***	-0.011***
	(0.000)	(0.00)	(0.000)	(0.000)	(0.000)	(0.00)	(0.000)	(0.000)
Total Activity			0.095***	0.087***				
			(0.011)	(0.005)				
Actor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	242,710	792,011	79,382	398,069	82,931	23,597	308,160	72,793
Number of Actors	4,254	6,945	1,400	3,616	1,093	1,199	2,301	2,137

Notes:
1. *p<.05, **p<0.01, ***p<0.001

Notes Continued from Table 3.11:

2. Standard errors are in parentheses.
3. All models use Panel Poisson Regression with actor fixed effects.
4. All independent variables are lagged (calculated at week *t-1*).
5. Proximity to Rank Loss does not have any values in before the first milestone is achieved because there is no risk of losing any privileges once actors are in the lowest stage of rank.
6. All observations in which individuals were suspended in week *t-1* were dropped because individuals cannot accrue reputation points while in the penalty box.
7. Proximity to Rank Loss does not have any values in before the first milestone is achieved because there is no risk of losing any privileges once actors are in the lowest stage of rank.
8. Models 3b and 3d examine the behavior of actors that were more prone to uncooperative behavior in the time period *before* their first suspension.
9. Wald tests confirm that the coefficients across models are statistically significantly different.

Table 3.12: Comparing Rates of Cooperation Pre and Post Suspension

	Model 4: Count of coop. behaviors of actors who are <u>*eventually*</u> suspended
Post Suspension	-0.400***
	(0.006)
Milestone Category 3	0.460***
	(0.008)
Milestone Category 4	0.565***
	(0.010)
Milestone Category 5	0.518***
	(0.014)
Count of Upvotes Received	0.020***
	(0.000)
Count of Downvotes Received	0.077***
	(0.001)
Days Since Last Active	-0.015***
	(0.00)
Tenure on Site	-0.001***
	(0.000)
Actor Fixed Effects	Yes
Number of Observations	664,903
Number of Actors	5,108

Notes for Table 3.12:

1. *p<.05, **p<0.01, ***p<0.001
2. Standard errors are in parentheses.
3. Model uses Panel Poisson Regression with actor fixed effects.
4. All observations in which individuals were in the penalty box in week *t-1* were dropped because individuals cannot accrue reputation points while they are suspended.

DISCUSSION

Scholars have long considered rankings to be powerful drivers of cooperative behavior (e.g., Thibault and Kelley 1959; Blau 1968; Tai, Narayanan, and McAllister 2012). Rankings and other forms of social hierarchy act as cognitive shortcuts, which allow groups to reward cooperative behavior and sanction uncooperative behavior (Baker and Bulkley 2014). However, rankings may also have a dark side. Recent research shows that pressures associated with potential gains or losses in rank can lead to increases in uncooperative behaviors such as cheating and deception (Pettit et al. 2016; Vriend et al. 2016). Negative behaviors such as these may undermine the legitimacy of rankings and trigger negative behaviors in others. Hence, multiple scholars have called for more research that helps determine when rankings are beneficial or harmful for efforts to achieve cooperation (Anderson and Brown 2010; Anderson and Willer 2014; Pettit et al. 2016; Simpson and Willer 2015).

This study seeks to answer this call by relaxing the assumption that actors are making tradeoffs between cooperative and uncooperative behaviors. This allows me to explore whether actors that exhibit uncooperative behaviors also exhibit higher rates of cooperative behaviors than actors who always "play by the rules". In other words, it explores whether rankings produce a "net-positive" effect for systems. A finding to this effect may suggest that organizations could tolerate the dark side of rankings to realize the full measure of their cooperation-enhancing effects. By exploring how everyday movements through a ranking create psychological pressures that sometimes trigger uncooperative behavior, this study examines reputation rankings as an endogenous perturbation to the system of cooperation. By examining a large sample of actors over extended periods of time in their actual organization, it seeks to identify how pervasive uncooperative behaviors are and whether they may be offset by the cooperation enhancing effects of rankings. Ultimately, it seeks to understand whether uncooperative behaviors may be a tolerable byproduct of a robust system of cooperation, or one that managers must actively seek to eliminate.

Determining whether uncooperative behaviors such as cheating can be a symptom of a robust system of cooperation can make contributions to both theory and practice. Theoretically it advances our understanding of whether rankings are ultimately helpful or harmful for maintaining cooperation. In practice it helps inform debate surrounding the use of rankings as performance appraisal systems inside organizations. Some organizations (e.g., Amazon and GE) are actively working to eliminate rankings systems in an effort to improve organizational cultures (Cappelli and Tavis 2016). This study helps us better understand whether active effort to remove rankings is an effective strategy or a case of "throwing the baby out with the bathwater."

Are movements in rankings associated with increases in uncooperative behavior? I find evidence that this may be the case. The higher an actor's percent achieved toward the next milestone ranking, the higher the likelihood that they will be suspended. This is consistent with prior research that theorizes that rankings create a unidirectional drive upward (Festinger 1954), which increases pressures associated with performance (Garcia et al. 2006). Inconsistent with this same research, I do not find that this effect is heightened by the proximity to a gain or loss in rankings. High proximity to a gain in rank was not associated with increases in the likelihood of suspension and surprisingly proximity to a loss was associated with a *decrease* in the likelihood of suspension. This finding runs counter to recent findings that report higher rates of cheating in response to threats of status loss (e.g., Pettit et al. 2016). Contrary to Pettit et al.'s (2016) finding that actors prefer to cheat to avoid status loss, even when presented with an opportunity to avoid this loss by cooperating, I find that not only are actors *less* likely to enact uncooperative behavior to preserve their ranking position, they are *more* likely to cooperate. I find that on average actors who have high proximity to a loss (less than 10% away from the most recently earned ranking), are more likely to cooperate than actors who are further ahead in the ranking. Jointly, these findings suggest that the potentially problematic outcomes associated with rankings are only associated with upward movements through the ranking.

Uncooperative behaviors primarily become problematic for systems of cooperation when they detract from rates of cooperation. For example, the tragedy of the commons effect highlights how the absence of voluntary cooperative behaviors can erode a system of cooperation (Hardin 1982). Similarly, in the context of online communities and other organizations that subsist off voluntary contributions, a rise in uncooperative behaviors becomes problematic when it is at the expense of cooperative behaviors. If instead actors who respond to movements in ranking with uncooperative behaviors are *also* more likely to respond with cooperative behaviors, this may suggest that systems of cooperation can be robust to the negative externalities of ranking systems because actors' cooperative behaviors outweigh their uncooperative behaviors. My findings find support for this line of theorizing. I find that actors who are more prone to uncooperative behaviors exhibited slightly higher rates of cooperation than actors who never exhibited uncooperative behaviors. Contrary to prior research that frames cooperative and uncooperative behaviors as tradeoffs (e.g., Garcia et al. 2006; Pettit et al. 2016; Vriend et al. 2016); this finding implies that actors do not necessarily think of cooperative and uncooperative behaviors as mutually exclusive options. Instead, actors may be inclined to exhibit both. From a system-level perspective this matters. Single acts can trigger a cascade of similar behaviors in others. Consequently, every cooperative act has the potential to matter a great deal for the maintenance of the system as a whole.

In this vein, it is interesting to think of the role sanctions play in the maintenance of cooperation. One of the mechanisms through which rankings help enhance cooperation is by facilitating the punishment of uncooperative behavior. Indeed, when group members have the opportunity to impose sanctions on non-cooperators the group often converges to perfect rates of cooperation (Fehr and Gachter 2000). Hence, some scholars describe punishment as the ultimate mechanism for sustaining cooperation (e.g., Boyd et al. 2010; Fehr and Gintis 2007; Putterman 2010). However, these same scholars also recognize that it is often costly (either materially or socially) to punish other actors. Further, without coordinated efforts among punishers, punishment often fails as a mechanism to ensure cooperation (Janssen et al. 2010). The advent of more transparent rankings systems offers one way to counteract this problem—actors can police themselves. For example, in a field experiment Bernstein and Li (2017:13) find that employees who received transparent data about their performance were more likely to adjust their behavior on their own, which suggests that a transparent ranking can "act as a surrogate for managers." Rankings that reflect past cooperative acts may produce similar results. Research in moral cleansing (e.g., Sachdeva, Illiev, and Medin 2009) suggests that actors that exercise uncooperative behaviors will perform cooperative behaviors to atone for these uncooperative behaviors and preserve their self-concept as a productive member of the community. I do not find evidence of moral cleansing in this context. On average actors that are more prone to uncooperative behaviors have much lower rates of cooperation once they re-enter the system after their suspension. This suggests that punishment may harbor an unforeseen consequence for the system—it could reduce the likelihood that these members return to their previously high levels of cooperation.

Last, I examined the overall potential for a ranking to act as a cooperation-enhancing mechanism. I do not find a general trend between gains in rank and increases in cooperative behaviors. Instead, I find that threats of loss in rank are the only strong predictors of cooperative behavior. At first glance, this appears to be inconsistent with prior research that extolls the cooperation-enhancing effects of rankings (e.g., Thibault and Kelly 1959; Tai, Narayanan, and McAllister 2012; Willer 2009). However, supplemental analyses revealed that this effect is present, but that it varies based on the overall ranking category. Overall, actors tended to exhibit higher rates of cooperation in response to increases in reputation when they are in the middle of the full ranking system, compared to the bottom and top of the rankings. This finding is consistent with the theory of middle-status-conformity (e.g., Phillips and Zuckerman 2001), which posits that actors in the middle of rankings are more likely to conform to standards of behavior to advance their positions within a hierarchy.

In summary, these finding suggest that upward movements through rankings create pressures that increase the likelihood that actors will perform uncooperative behaviors, but that these pressures also increase the likelihood that these actors will perform cooperative behaviors. At the level of an individual this suggests that certain types of trajectories through rankings may make some actors more susceptible to the performance pressures associated with rankings. At the level of a system this suggests that systems of cooperation can be maintained even though rankings produce pressures that can perturb systems of cooperation. Ultimately uncooperative behaviors are not harbingers of failing systems of cooperation, but instead may be symptoms of robust cooperation.

This study offers several contributions. First, it contributes to dynamic perspectives of rankings (e.g,, Brion and Anderson, 2013; Pettit et al. 2010; Pettit et al. 2016) by examining actors' lifecycles in a ranking system. To date, most of the research that examines rankings from a dynamic perspective occurs in a laboratory setting and examines behaviors for limited periods of time. In contrast, this study examines repeated observations of actors in their actual organizational setting, where pressures that arise from movements in the ranking may accumulate over time. This study focused on how the direction of movements (upward and downward) in rankings affected rates of cooperative and uncooperative behavior. Future research could focus on other types of movements and their implications for actors and systems of cooperation. For example, high frequency in movements may change how the direction of movement affects actors within rankings. This study showed that movements upward in a ranking may lead to increases in uncooperative behaviors. However, it is possible that frequent movements upward might provide actors with confidence that they will reach higher ranks and therein reduce performance comparison pressures and rates of uncooperative behavior.

This study further contributes to dynamic perspectives of rankings by relaxing the assumption that actors face a tradeoff between cooperative and uncooperative behaviors (e.g., Garcia et al. 2006; Pettit et al. 2016; Vriend et al. 2016). Relaxing this assumption permits the examination of how movements through a ranking affect the likelihood that actors will simultaneously exhibit both types of behaviors[20]. In so doing, it offers insights into the net effects of rankings for systems of cooperation. It shows that the pressures that rankings produce may increase the likelihood of uncooperative behavior, but that they also increase the likelihood that actors will behave in ways that counteract this uncooperative behavior. With an eye toward

[20] Discarding the tradeoff framework also illuminates another antecedent related to cooperation. Prior research often assumes that the inverse of cooperation is choosing to not cooperate (e.g., defecting from the norm of cooperation). This may limit the scope of studies of cooperation. A focus on cooperation as a tradeoff between cooperation and defection assumes that actors are aware of potential opportunities to cooperate. As a result of this assumption, the absence of cooperation may be interpreted as a choice to defect from norms of cooperation. However, it is conceivable that the absence of cooperation may instead be due to a lack of awareness of potential opportunities to cooperate. Under these conditions interventions to restore cooperation could vary greatly (e.g., creating awareness of opportunities versus reshaping responses to norms). Future research may benefit from examining cooperation as a two-stage model, wherein the first stage reflects an antecedent process that triggers a decision about cooperation (e.g., awareness of an opportunity or actively searching out an opportunity to cooperate).

system level dynamics (e.g., aggregation, diffusion, and behavioral cascades), this study identifies micro-movements in rankings that have implications for systems of cooperation. Our understanding of how these micro-movements impact systems of cooperation would be greatly enhanced by simulations that show how these dynamics play out at the system level. Such an approach would help us understand whether actors' cooperative behaviors truly offset their uncooperative behaviors.

Second, this study adds to our understanding of the functional benefits of hierarchy in organizations (e.g., Anderson and Brown 2010; Anderson and Willer 2014). Extant research presents mixed results and has called for more research that explains what determines whether a ranking system is helpful or harmful. By examining a virtual organization that exists solely because of the voluntary contributions of its members, this study presents a conservative test for the ability of social hierarchy to enhance cooperation. In this study I found evidence of both helpful and potentially harmful effects of rankings. This work shows how different types of movements *within* rankings can switch whether a ranking is helpful or harmful for organizations. In addition to asking which conditions make the hierarchy as a whole more likely to be helpful or harmful for organizations, this study suggests that it may be helpful to explicitly examine factors that alter individuals' experiences inside rankings. Additionally, it suggests that rankings will naturally produce negative externalities that should be explicitly managed.

Last, this study offers insights into how rankings may fit into the changing nature of work (e.g., Barley, Bechky, and Milliken 2017). Online communities are examples of new organizational structures that comprise the New World of Work. Online communities allow actors to connect virtually to share knowledge, exchange ideas, collaborate and learn (Hagel and Armstrong 1997). They display several characteristics that are concomitant with the changing nature of work: an increase in technologically mediated work, reduced face-to-face interaction, geographically dispersed community members, and lower barriers for entering and exiting the organization. Each of these characteristics may negatively impact the maintenance of systems of cooperation because they can decrease the power of normative pressures to cooperate, reduce actors' identification with organizational goals, and decrease the power of social relations (e.g., social closure) for enforcing cooperation. This study examined how movements through rankings affected the likelihood that individuals would continue to cooperate despite these characteristics. As a next step, it would be interesting to explicitly examine the relative power of these interpersonal mechanisms for maintaining cooperation in the new world of work.

While this study offers several contributions, it also features some limitations that shape the expanse of these contributions. Consistent with ranking theory (e.g., Garcia et al. 2006; Pettit et al. 2016), I measure threats to rank as an actor being only 10% or less above a ranking position. In so doing, I assume that actors will be concerned with a loss in rank when they are in this position. This is a reasonable assumption because actors do lose the privileges that are associated with a rank position if they dip back below the milestone threshold. However, the archival nature of this data does not permit me to confirm whether or not actors actually experience threats associated with a loss in rank. It is conceivable that they could be focused on their most recent achievement and therefore may be cooperating more because they feel that they are a valued member of the community. Future work could explicitly survey members of these communities to determine how they experience different ranking positions, therein confirming or transforming the nature of the insights found in this study.

Additionally, the scope of this study is defined in part by the type of uncooperative behaviors that arise in rankings. I examine whether uncooperative behaviors can be offset by increases in cooperative behaviors, arguing that this may produce a net positive effect for the system as a whole. Embedded in this argument is the assumption that these behaviors are rather benign—that they won't negatively impact other actors to a degree that would decrease their future rates of cooperation. With the new world of work, this may very well be the case. The size of the online community (millions of members) and the fact that information about uncooperative behaviors is not easily accessible makes it less likely that other actors will know enough about uncooperative behaviors to be negatively impacted by them. This may not be the case in other contexts. In other contexts actors may have easy access to information about others' uncooperative behaviors. More malicious forms of uncooperative behavior may affect others more negatively. For example, performance comparison pressures have been tied to the sabotage of other actors' performance (Tesser and Smith 1980; Poortvliet 2013). In surveys of sales teams at a Chinese telecommunications company, Lam et al. (2011) found that lower performing employees harmed higher performing employees (e.g., interfered with their performance and treated them with disrespect) and this adversely affected their team's overall performance. It is conceivable that due to the availability of information about uncooperative behaviors or the level of harm they cause others increases in cooperative behaviors may not be able to offset uncooperative behaviors.

CONCLUSION

Prior research shows that rankings can be helpful and harmful for maintaining cooperation. Rankings can incentivize cooperation by facilitating the reward of cooperative behaviors and the punishment of uncooperative behaviors. However, rankings may also heighten performance comparison pressures, which in turn may incite uncooperative behaviors such as cheating to get ahead in the rankings. By relaxing the assumption that actors view cooperative and uncooperative behaviors as tradeoffs, this study allows for the possibility that actors may exercise higher rates of cooperative behaviors to offset their cooperative behaviors. I find evidence to this effect, suggesting that organizations may be able to tolerate the negative externalities rankings produce because they produce a net-positive affect on cooperation.

CHAPTER 4

Understanding How Rankings Affect Systems of Cooperation

This dissertation began with the observation that the changing nature of work may be altering how employees experience and interact with mechanisms that are meant to achieve social order. Social order is achieved when a group sets and maintains standards of behavior that benefit the group. Society as a whole can be thought of as an exercise in achieving social order—a composite set of individuals solidified around common goals (Durkheim 2005). At its roots, maintaining social order is fundamentally a question about how to achieve cooperation among self-interested individuals. Scholars have long been occupied by this question.

Beginning with Hobbe's (1998) description of mankind's pure state of nature as "every man against every man", multiple efforts have been made to identify mechanisms that suppress self-interests and encourage cooperation. In contrast to perspectives that emphasize individual-level predictors such as prosocial personalities, emotions, motivations, and value orientations, sociological perspectives view cooperation as being heavily influenced by forces outside of the individual such as norms, social hierarchy, and the structure of relations between individuals (Simpson and Willer 2015). This dissertation proceeds along similar lines by examining how norms (generalized reciprocity) and social hierarchy (reputation rankings) maintain levels of cooperation inside organizations. I add to this conversation on social order by examining these mechanisms with a robustness lens (Jen 2005). A robustness lens seeks to understand how social systems maintain performance in the face of exogenous and endogenous perturbations (i.e., potentially disruptive forces). I seek to understand how these mechanisms maintain systems of cooperation in the presence of one potentially disruptive force: rankings. Rankings can create performance comparison pressures that have the potential to undercut motivations to cooperate (Garcia et al. 2013). While it is widely recognized that rankings and other forms of social hierarchy are a standard feature of organizational life (Anderson and Brown 2010), scholars have yet to explicitly examine whether and how these mechanisms sustain cooperation in the presence of rankings.

This dissertation begins to fill this gap by examining rankings as exogenous and endogenous perturbations to systems of cooperation. First, I examined rankings as an exogenous perturbation to systems of cooperation by exploring how established systems of cooperation fare after the introduction of rankings. A sudden introduction of social hierarchy can occur in several contexts—for example, when an entrepreneurial venture begins to scale up by hiring employees, or an organization switches from a flatter organizational structure (e.g., holocracy) to a steeper hierarchical structure. Chapter 2 asks whether systems of generalized reciprocity are naturally able to withstand the potentially disruptive forces that rankings produce, or if they are likely to be disrupted. And, if they become disrupted, which mechanisms can restore cooperation. I find that systems of cooperation are in fact disrupted by the introduction of rankings, but that the simultaneous introduction of information about actors' prosocial contributions can restore disrupted systems. Robust cooperation can be achieved in the presence of rankings, but only if information about actors' prosocial reputations is also a feature of the system's design.

Second, I examined rankings as an endogenous perturbation to systems of cooperation by exploring how rankings can produce pressures that may unintentionally undermine cooperation when they are used to maintain systems of cooperation. Rankings have long been used by groups (both formally and informally) to maintain cooperation. Knowledge of an implicit ranking of contributions keeps people cooperating (Willer 2009). The use of rankings as a formal mechanism to elicit cooperation is growing. It is a standing feature of many large, geographically dispersed, virtual organizations such as online communities, open-source collaboration projects, and electronically based markets. For example, Restivo and van de Rijt (2012) show that the reputation badge system used by Wikipedia helps elicit higher amounts of cooperative actions such as posting and editing. Chapter 3 asks what it is about actors' experiences in rankings that increases the likelihood that they produce potentially disruptive pressures (i.e., uncooperative behaviors) and whether the presence of these uncooperative behaviors has the power to undermine the maintenance of the system of cooperation as a whole. I find that upward movements in a ranking are more likely to produce uncooperative behavior, but actors that exhibit this behavior cooperate more than actors that do not exhibit this behavior. This suggests that rankings can be used to achieve robust cooperation because there is a net-positive effect of rankings at the system-level.

Together, these studies show that rankings *do* in fact perturb systems of cooperation. As exogenous perturbations, rankings may be especially problematic for systems of cooperation that are maintained by normative social structures. Generalized reciprocity is a strong norm that has been described as the most effective mechanism for creating stable systems of cooperation (e.g., Nowak 2006). I found that the introduction of rankings was highly disruptive for systems of cooperation, but that as endogenous perturbations rankings did not appear to be as problematic for systems of cooperation. Future work on systems of generalized reciprocity may benefit from examining systems of generalized reciprocity that originate *alongside* rankings, making rankings endogenous perturbations. The presence of rankings may impair the ability of systems of generalized reciprocity to take off. Conversely, systems of generalized reciprocity may coevolve with rankings—adjusting for social comparison pressures by mindfully steering help in the direction of non-competitive others. Prior research provides evidence to this effect. Doyle et al. (2017) show that the higher the status distance between an ego and an alter (with the ego holding the more favorable position), the more help the ego will provide an alter. At the system level this may result in tightly connected clusters of helping, rather than a wider, more circular system that connects more diverse actors. It is unclear which type of system of cooperation would be more robust over time. Future research can disentangle whether rankings are more disruptive to systems of cooperation when they are exogenous or endogenous and explore how each of the interpersonal mechanisms for maintaining cooperation (norms and social relations) interact with each type.

Additionally, these studies confirmed that robustness can be achieved through different system-level features and dynamics. Systems of cooperation are robust when they maintain levels of cooperation despite the presence of perturbations. Systems of cooperation can be robust to reputation rankings when they include mechanisms that feature recovery mechanisms. In Chapter 2, systems of generalized reciprocity were robust to ranking pressures when they supplied actors with information about others' contributions to the system. This information has the potential to restore systems of cooperation because it permits actors to restore equity and increase the perceived fairness of a system. With this information actors can reward cooperators and punish non-cooperators. Systems of cooperation are also robust when they are unaffected by perturbations. Chapter 3 showed that systems of cooperation can be robust to ranking pressures because the negative externalities they create do not necessarily undermine actors' future rates of cooperation. At the aggregate this should produce a net-positive effect for systems of cooperation. In this case, a separate recovery mechanism is unnecessary and may in fact be counterproductive. Despite extensive research documenting the cooperation-enhancing effects of punishment (Fehr and Gachter 2002; Fehr and Gintis 2007), I found that the sanctioning of actors' uncooperative behaviors negatively affected their future rates of cooperation. As a system-level characteristic, the punishment of uncooperative behavior may only enhance robustness when actors within systems of cooperation are aware of others' uncooperative behaviors, otherwise it may detract from it. Therefore, some system-level features may enhance robustness in certain contexts, but not others. Future research should examine how other system-level characteristics shape the effectiveness of mechanisms that maintain cooperation. Characteristics such as the tenure and diversity of the systems' members, size of the system, and the ambiguity surrounding performance measures (e.g., the accuracy of the information that places people in rankings) may alter rates of cooperative and uncooperative behaviors. For example, in the context of Stack Overflow (which is home to over 150 content-specific communities), sites with higher ambiguity (e.g., the parenting advice and conspiracy theory communities) may feature higher rates of uncooperative behaviors than sites with lower ambiguity (e.g., mathematics). Due to the higher ambiguity about what characterizes a good contribution on these sites (by nature of their content), actors may be more likely to feel that their ranking does not accurately reflect their true performance levels. Under these conditions actors may be more likely to perform uncooperative behaviors to get ahead in the rankings. Although each of these communities features an identical ranking system to motivate cooperative contributions, their unique system-level characteristics may alter the dynamics they engender.

This dissertation makes three overarching contributions to the study of organizations. First, it examines cooperation as a social system. A social systems perspective examines the interrelations between actions—how past actions shape future actions. In understanding how past actions condition future actions, a social systems view necessitates an investigation of both interpersonal mechanisms that carry social forces between actors (e.g., norms), and intrapersonal mechanisms that shape how actors respond to these forces (e.g., personal motivations) (Asch 1959). Examining cooperation as a social system contributes to research on cooperation by merging research that focuses on intrapersonal mechanisms that explain cooperation such as individual characteristics, prosocial values, and motivations (for a review see Smith, Carroll, and Ashford 1995), with research that focuses on interpersonal mechanisms that explain cooperation such as norms, hierarchy, and relations (for a review see Simpson and Willer 2015). These research streams primarily operate in parallel, with little in the way of active, explicit exchange (Simpson and Willer 2015). By merging the two, a systems view has the potential to provide new insights at the cross-section of these perspectives. For instance, social relations are known to be highly effective interpersonal mechanisms for eliciting cooperation. Actors that are more central in a social network tend to contribute more to the collective (Baldassarri 2014). But, it is still unclear why this is the case. Intrapersonal mechanisms such as prosocial orientation, or the experience of prosocial emotions such as levels of commitment could help explain this effect (Simpson and Willer 2015).

Second, this dissertation adopts a dynamic perspective of rankings to further our understanding of how systems of cooperation are maintained alongside rankings. Static views of rankings assume stable psychological experiences of rankings. Dynamic views of rankings explore how actors' movements through rankings trigger different psychological experiences of rankings, revealing different pressures that may elicit new behaviors from the same set of actors over time. For example, middle-status conformity theory posits that actors within the middle of a ranking will be more likely to conform to standards of behavior (e.g., expectations for cooperation toward a collective goal) in the hopes of achieving a higher rank (Phillips and Zuckerman 2001). Rapid movements upward in a ranking may heighten the impression that higher rank is achievable, thereby engendering more cooperation from these actors relative to actors that move more slowly through a ranking.

Last, by explicitly focusing on the maintenance of cooperation in the presence of potentially disruptive forces, this dissertation imports a robustness lens from the study of complex systems in the natural and engineering sciences. A robustness lens focuses on the maintenance of performance and functionality in the face of exogenous and endogenous perturbations (Jen 2003). Such an approach has the power to differentiate between mechanisms that maintain levels of cooperation under stable, predictable, and ideal conditions, from those that maintain cooperation in the presence of potentially disruptive pressures. For example, norms of generalized reciprocity encourage actors to pay forward help they have received under the guise that if they need help in the future it will be available to them. This can trigger a cascade of help among the members of an organization. The removal of large portion of a system's members (e.g., through high turnover), could halt these cascades of helping behaviors. Turnover replaces actors that have received help—actors that feel grateful and experience an urge to help others—with actors that have yet received help. Consequently, the original actors that remain may continually inject help into a system, but may ultimately not receive benefits from the system. Such a system is likely to deteriorate over time (Molm 1997). Understanding how systems of cooperation interact with perturbations such as high rates of turnover has the potential to illuminate a new set of mechanisms that can produce longer-lasting cooperation.

CONCLUSION

There is perhaps no line of inquiry that is more fundamental for the study of organizations, and social life more broadly, than understanding how cooperation is maintained over time among self-interested actors. Cooperation is not only a key element for building effective organizations, but is also the substrate from which society as a whole has emerged. This dissertation focuses on how systems of cooperation are maintained in the presence of rankings. Rankings and other forms of social hierarchy are arguably ubiquitous features of social life. As such, they are potentially unavoidable sources of perturbations for systems of cooperation. By focusing on how to maintain systems of cooperation in the presence of rankings, this dissertation highlights mechanisms that make systems of cooperation more robust to pressures associated with rankings. Robustness has critical implications for both theory and practice as this lens illuminates strategies that position organizations to achieve long-term performance despite the occurrence of failure, environmental uncertainty, rapid change, and increasing complexity.

APPENDIX

Supplemental Tables and Figures

Table A.1: Mixed-Effects Logistic Regression: (Reputation Condition Only)

	Model 1	Model 2	Model 3
Fixed Effects			
Level 1: Decision Rounds Post-Interruption (*n*=2,740)			
Ego's Percent Gratitude	0.065***	0.071***	0.065***
	(0.012)	(0.0123)	(0.012)
Ego's Percent Generosity	0.058***	0.060***	0.057***
	(0.006)	(0.006)	(0.007)
Increasing Decision Rounds	-0.006	-0.006	-0.006
	(0.005)	(0.006)	(0.006)
Alter's Reputation for Transferring in Stage 1	0.054***	-0.017	0.059***
	(0.003)	(0.010)	(0.004)
Level 2: Individual (Ego) (*n*=136)			
Short-term Thinking Tendency (CRT)	-0.004	-0.004	-0.006
	(0.005)	(0.005)	(0.006)
Male	-0.480	-0.574	-0.505
	(0.361)	(0.415)	(0.445)
Age (mean-centered)	-0.065	-0.070	-0.096
	(0.041)	(0.046)	(0.051)
Education: Some College (dummy)	0.329	0.498	0.409
	(0.352)	(0.405)	(0.436)
Education: Bachelor's Degree (dummy)	0.212	0.076	0.343
	(0.503)	(0.569)	(0.625)
Education: Post-Doc (dummy)	0.104	0.012	-0.319
	(0.839)	(0.946)	(1.032)
Level 3: Groups (*n*=18)			
Group's Average Short-Term Thinking Tendency	0.0086	0.011	0.048
	(0.018)	(0.019)	(0.026)
Percent of Group that is Male	0.0068	0.012	0.019
	(0.008)	(0.008)	(0.012)
Group's Percent Transfers in Stage 1	-0.092***	-0.172***	
	(0.016)	(0.021)	
Group's Percent Transfers in Stage 1 x Alter's Rep.		0.001***	
		(0.000)	
Group was Stingy in Stage 1			3.874***
			(0.784)
Group was Generous in Stage 1			-4.337***
			(0.915)
Group was Stingy in Stage 1 x Alter's Rep.			-0.025***
			(0.006)
Group was Generous in Stage 1 x Alter's Rep.			0.044***
			(0.001)
Random Effects			
Standard Deviation Individual	0.027***	0.052	0.634***
	(0.037)	(1.712)	(0.270)
Standard Deviation Group	1.396***	1.634***	1.751***
	(0.165)	(0.196)	(0.226)

Note: Standard errors in parentheses. *p<0.05; ** p<0.01, *** p<0.001. Omitted category: Group with average transferring

Table A.2: Chp. 2 Mixed-Effects Logistic Regression: Table 2 with Rank as the Omitted Category for Comparison (All Conditions represented as Odds Ratios)

	Model 3
Fixed Effects	
Level 1: Decision Rounds Post-Interruption	
Ego's Percent Gratitude	1.019***
	(0.005)
Ego's Percent Generosity	1.050***
	(0.002)
Increasing Decision Rounds	0.999
	(0.002)
Level 2: Individual (Ego)	
Male	0.943
	(0.114)
Age (mean-centered)	0.991
	(0.011)
Education: Some College (dummy)	1.008
	(0.124)
Education: Associate's Degree (dummy)	1.429
	(0.809)
Education: Bachelor's Degree (dummy)	0.918
	(0.151)
Education: Post-Doc (dummy)	1.311
	(0.366)
Short-term Thinking Tendency (CRT)	0.999
	(0.002)
Level 3: Groups	
Group's Average Short-Term Thinking Tendency	0.996
	(0.005)
Group's Percent Transfers in Stage 1	0.990
	(0.006)
Percent of Group that is Male	0.998
	(0.003)
No Additional Information Condition	2.772***
	(0.502)
Reputation Information Condition	2.337***
	(0.422)
Reputation and Rank Information Condition	1.865***
	(0.322)
Random Effects	
Standard Deviation Individual	0.303***
	(0.083)
Standard Deviation Group	0.954***
	(0.056)
Intraclass Correlation	0.233
Number of Observations (Post-Interruption Decisions)	11,496
Number of Individuals (Ego)	574
Number of Groups	74

Notes: Standard errors in parentheses. *p<0.05; ** p<0.01, *** p<0.001. Omitted category: Rank Condition

Table A.3: Chp.3 Effects of High Proximity to Gaining the Next Milestone Rank (20% Away from change in rank)

	Model 5a: Count of coop. behaviors	Model 5b: Count of coop. behaviors	Model 6a: Likelihood of suspension	Model 6b: Likelihood of suspension	Model 7a: Count of coop. behaviors of actors who are *never* suspended	Model 7b: Count of coop. behaviors of actors who are *eventually* suspended	Model 7c: Count of coop. behaviors of actors who are *never* suspended	Model 7d: Count of coop. behaviors of actors who are *eventually* suspended
Proximity to Gain	-0.084**		-0.005		-0.090**	-0.061***		
	(0.007)		(0.089)		(0.016)	(0.016)		
Proximity to Loss		0.132**		-0.079			0.244**	-0.022*
		(0.005)		(0.056)			(0.010)	(0.010)
Milestone Category 3	0.989**	0.347**	1.094**	0.753**	0.974**	1.045***	0.091**	0.663***
	(0.015)	(0.009)	(0.134)	(0.090)	(0.026)	(0.026)	(0.016)	(0.017)
Milestone Category 4	1.842**	0.115**	1.178**	0.896**	1.838**	1.725***	-0.308**	0.495***
	(0.019)	(0.012)	(0.222)	(0.134)	(0.040)	(0.036)	(0.023)	(0.022)
Milestone Category 5	1.893**	-0.151**	0.368	-0.318	1.855**	1.888***	-0.411**	0.240***
	(0.024)	(0.019)	(0.787)	(0.730)	(0.057)	(0.052)	(0.044)	(0.045)
Count of Upvotes Received	0.013**	0.023**	-0.021*	-0.021**	0.017**	0.014***	0.032**	0.022***
	(0.001)	(0.000)	(0.010)	(0.005)	(0.001)	(0.001)	(0.000)	(0.000)
Count of Downvotes Rec.	0.045**	0.082**	0.129**	0.161**	0.049**	0.031***	0.053**	0.066***
	(0.002)	(0.001)	(0.027)	(0.015)	(0.009)	(0.005)	(0.004)	(0.003)
Days Since Last Active	-0.010**	-0.013**	-0.011**	-0.012**	-0.005**	-0.008***	-0.008**	-0.011***
	(0.000)	(0.00)	(0.001)	(0.000)	(0.000)	(0.000)	(0.00)	(0.00)
Tenure on Site	-0.001**	-0.002**	-0.005**	-0.003**	-0.002**	-0.000	-0.001**	0.000***
	(0.00)	(0.00)	(0.002)	(0.000)	(0.00)	(0.00)	(0.00)	(0.000)
Total Activity			0.094**	0.086**				
			(0.011)	(0.005)				
Actor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	242,710	792,011	79,382	398,069	82,931	159,779	308,160	72,793
Number of Actors	4,254	6,945	1,400	3,616	1,093	3,161	2,301	2,137

Table A.4: Chp.3 Effects of High Proximity to Gaining the Next Milestone Rank (30% Away from change in rank)

	Model 5a: Count of coop. behaviors	Model 5b: Count of coop. behaviors	Model 6a: Likelihood of suspension	Model 6b: Likelihood of suspension	Model 7a: Count of coop. behaviors of actors who are *never* suspended	Model 7b: Count of coop. behaviors of actors who are *eventually* suspended	Model 7c: Count of coop. behaviors of actors who are *never* suspended	Model 7d: Count of coop. behaviors of actors who are *eventually* suspended
Proximity to Gain	-0.076***		0.083		-0.010	-0.138***		
	(0.006)		(0.084)		(0.015)	(0.015)		
Proximity to Loss		0.112***		-0.060			0.140***	0.040***
		(0.005)		(0.060)			(0.011)	(0.011)
Milestone Category 3	1.023***	0.332***	1.093***	0.764***	1.000***	1.083***	0.100***	0.656***
	(0.015)	(0.010)	(0.135)	(0.092)	(0.027)	(0.027)	(0.017)	(0.017)
Milestone Category 4	1.870***	0.140***	1.187***	0.896***	1.852***	1.783***	-0.176***	0.457***
	(0.019)	(0.012)	(0.220)	(0.132)	(0.040)	(0.036)	(0.023)	(0.022)
Milestone Category 5	1.912***	-0.114***	0.404	-0.312	1.851***	1.923***	-0.228***	0.187***
	(0.024)	(0.019)	(0.783)	(0.731)	(0.057)	(0.053)	(0.044)	(0.045)
Count of Upvotes Received	0.013***	0.025***	-0.019*	-0.020***	0.017***	0.013***	0.032***	0.023***
	(0.000)	(0.000)	(0.010)	(0.005)	(0.001)	(0.001)	(0.000)	(0.000)
Count of Downvotes Rec.	0.046***	0.082***	0.128***	0.161***	0.070***	0.031***	0.054***	0.066***
	(0.002)	(0.001)	(0.027)	(0.015)	(0.009)	(0.005)	(0.004)	(0.003)
Days Since Last Active	-0.010***	-0.013***	-0.011***	-0.012***	-0.005***	-0.009***	-0.008***	-0.011***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure on Site	-0.001***	-0.001***	-0.005***	-0.004***	-0.002***	0.000	-0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Activity			0.094***	0.086***				
			(0.011)	(0.005)				
Actor Fixed Effects								
Number of Observations	242,193	774,490	78,641	394,735	82,632	23,479	293,005	71,840
Number of Actors	4,233	6,830	1,387	3,587	1,087	1,178	2,201	2,126

Notes for Tables A.3 & A.4

1. *p<.05, **p<0.01, ***p<0.001
2. Standard errors are in parentheses.
3. All models except for Model 2 use Panel Poisson Regression with actor fixed effects. Model 2 uses Panel Logistic Regression with actor fixed effects.
4. All independent variables are lagged (calculated at week *t-1*).
5. All observations in which individuals were in the suspended in week *t-1* were dropped because individuals cannot accrue reputation points while they are suspended.
6. Models 3b and 3d examine the behavior of actors that are more prone to uncooperative behavior in the time period *before* their first suspension.

Table A.5: Chp.3 Effects of Reputation Value (logged) on Cooperative Behavior

	Model 1: Count of coop. behaviors	Model 2: Likelihood of suspension	Model 3a: Count of coop. behaviors of actors who are *never* suspended	Model 3b: Count of coop. behaviors of actors who are *eventually* suspended
Reputation Points Logged	-0.421**	-0.266**	-0.512**	-0.404***
	(0.002)	(0.021)	(0.003)	(0.004)
Milestone Category 3	1.082**	1.124**	1.097**	1.303***
	(0.008)	(0.071)	(0.014)	(0.014)
Milestone Category 4	1.607**	1.475**	1.716**	1.867***
	(0.010)	(0.105)	(0.020)	(0.012)
Milestone Category 5	1.809**	0.925*	2.173**	2.083***
	(0.015)	(0.470)	(0.035)	(0.032)
Count of Upvotes Received	0.0236**	-0.019**	0.033**	0.023***
	(0.000)	(0.004)	(0.000)	(0.000)
Count of Downvotes Rec.	0.076**	0.156**	0.047**	0.053***
	(0.001)	(0.0120)	(0.004)	(0.001)
Days Since Last Active	-0.013**	-0.013**	-0.008**	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure on Site	-0.001**	-0.00358**	-0.001**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Activity		0.0856**		
		(0.004)		
Actor Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	1,083,201	670,752	418,298	98,812
Number of Actors	7,718	5,150	2,610	2,562

Notes:

1. *p<.05, **p<0.01, ***p<0.0012.
2. Standard errors are in parentheses.
3. Models 1 and 3 use Panel Poisson Regression with actor fixed effects. Model 2 uses Panel Logistic Regression with actor fixed effects.
4. All independent variables are lagged (calculated at week t-1).
5. All observations in which individuals were suspended in week t-1 were dropped because individuals cannot accrue reputation points while they are suspended
6. Model 3b examines the behavior of actors that are prone to uncooperative behavior in the time period *before* their first suspension.

Table A.6: Chp.3 Models Showing Effect of Interaction Between Ranking Milestone Category and Percent of Milestone Rank Achieved on Cooperative Behavior

	Model 1: Count of coop. behaviors
Percent of Rank Achieved	-0.005**
	(0.000)
Milestone Category 3	0.249**
	(0.012)
Milestone Category 4	0.314**
	(0.012)
Milestone Category 5	0.341**
	(0.021)
M3*Percent Rank Achieved	0.006**
	(0.000)
M4*Percent Rank Achieved	0.007**
	(0.000)
M5*Percent Rank Achieved	0.007**
	(0.000)
Count of Upvotes Received	0.021**
	(0.000)
Count of Downvotes Rec.	0.080**
	(0.001)
Days Since Last Active	-0.014**
	(0.00)
Tenure on Site	-0.001**
	(0.000)
Actor Fixed Effects	Yes
Number of Observations	1,039,895
Number of Actors	7,347

Notes:

1. *p<.05, **p<0.01, ***p<0.0012.
2. Standard errors are in parentheses.
3. Models 1 uses a Poisson Regression with actor fixed effects.
4. All independent variables are lagged (calculated at week t-1).
5. All observations in which individuals were suspended in week t-1 were dropped because individuals cannot accrue reputation points while they are suspended.

Table A.7: Chp.3 Models Showing Effect on Cooperative Behavior

	Model 1: Count of coop. behaviors	Model 2: Likelihood of suspension	Model 3a: Count of coop. behaviors of actors who are *never* suspended	Model 3b: Count of coop. behaviors of actors who are *eventually* suspended
Gain Mindset	0.050**	0.325**	0.110**	0.132**
	(0.004)	(0.046)	(0.009)	(0.009)
Milestone Category 3	0.522**	1.024**	0.386**	0.778**
	(0.008)	(0.072)	(0.014)	(0.014)
Milestone Category 4	0.608**	1.368**	0.405**	0.939**
	(0.010)	(0.107)	(0.020)	(0.018)
Milestone Category 5	0.571**	0.365	0.377**	0.981**
	(0.014)	(0.478)	(0.034)	(0.031)
Count of Upvotes Received	0.021**	0.031**	0.030**	0.021**
	(0.000)	(0.002)	(0.000)	(0.000)
Count of Downvotes Rec.	0.078**	0.202**	0.057**	0.050**
	(0.001)	(0.012)	(0.004)	(0.002)
Days Since Last Active	-0.014**	-0.013**	-0.008**	-0.012**
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure on Site	-0.001**	-0.004**	-0.001**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Actor Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	1,030,523	630,144	378,548	95,303
Number of Actors	7,267	4,765	2,285	2,358

Notes:

1. *p<.05, **p<0.01, ***p<0.0012.
2. Standard errors are in parentheses.
3. Models 1 and 3 use Panel Poisson Regression with actor fixed effects. Model 2 uses Panel Logistic Regression with actor fixed effects.
4. Gain mindset = 1 if percent of next rank achieved is >=50%
5. All independent variables are lagged (calculated at week t-1).
6. All observations in which individuals were suspended in week t-1 were dropped because individuals cannot accrue reputation points while they are suspended.
7. Model 3b examines the behavior of actors that are prone to uncooperative behavior in the time period *before* their first suspension.

Figure A.1: Count of Cooperative Behaviors by Reputation Points for Milestone Rank Category 2

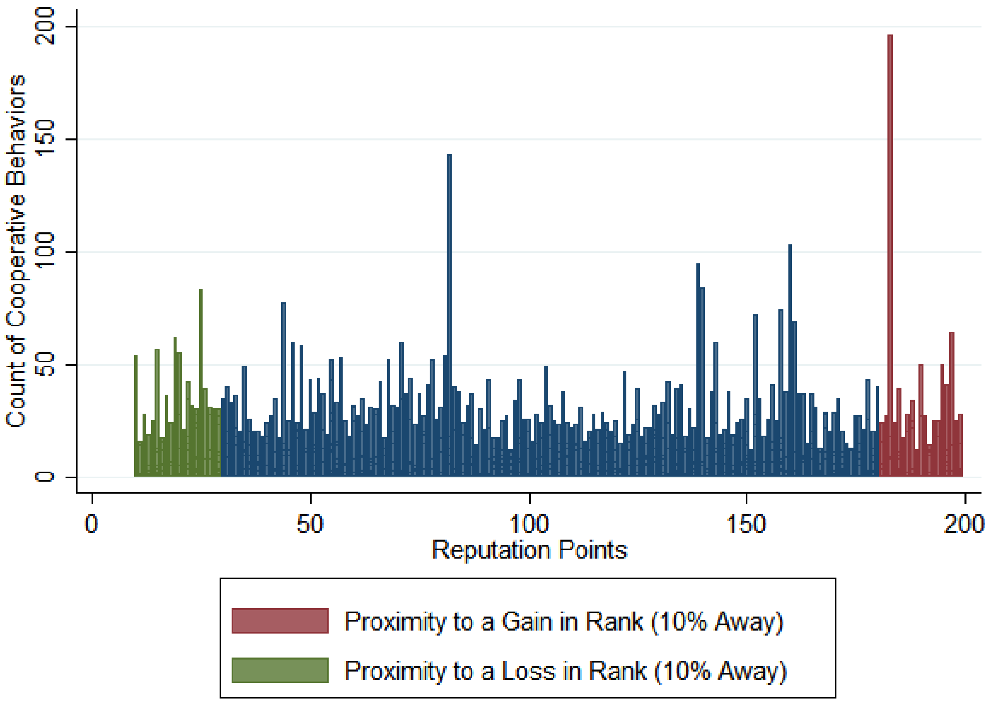


Figure A.2: Count of Cooperative Behaviors by Reputation Points for Milestone Rank Category 3

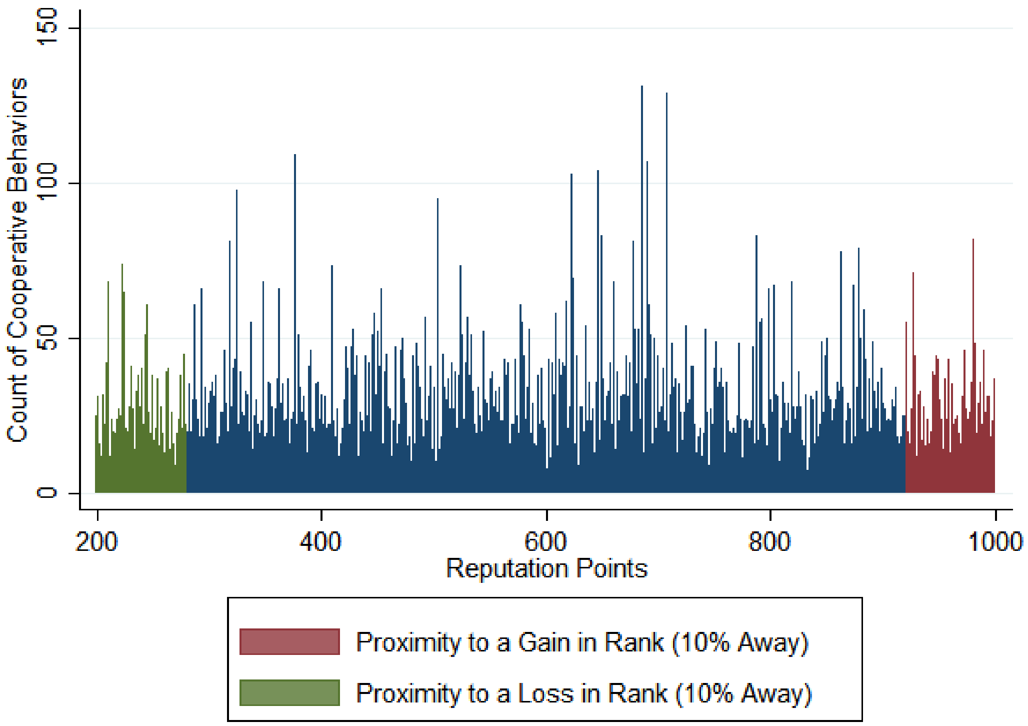


Figure A.3: Count of Cooperative Behaviors by Reputation Points for Milestone Rank Category 4

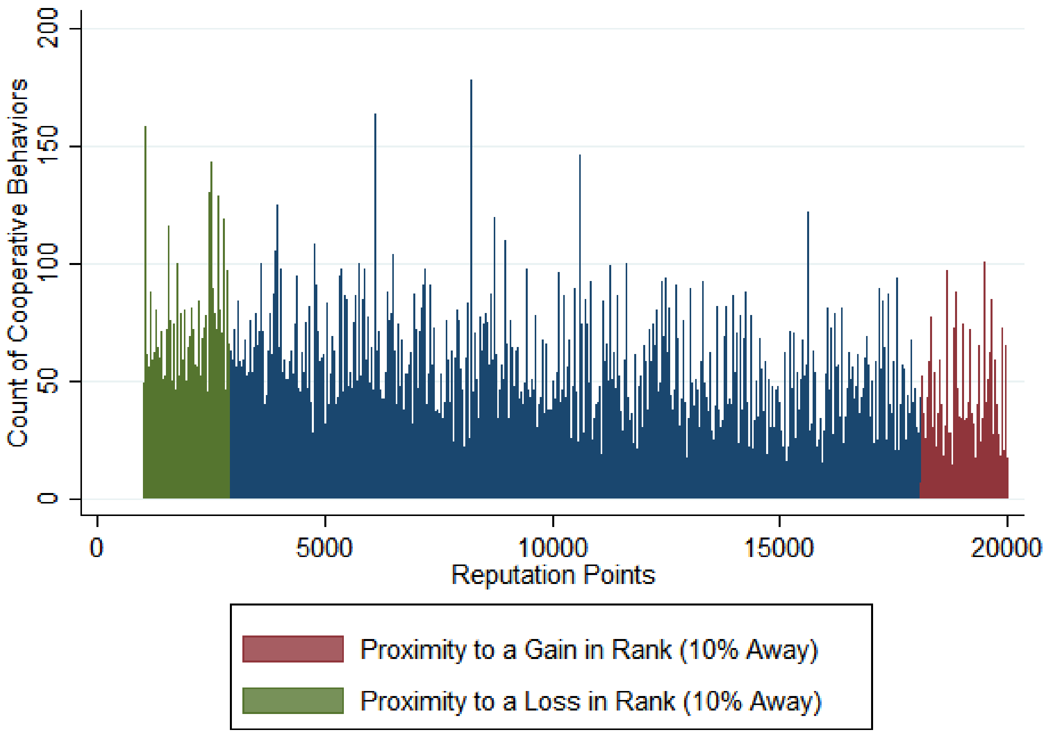
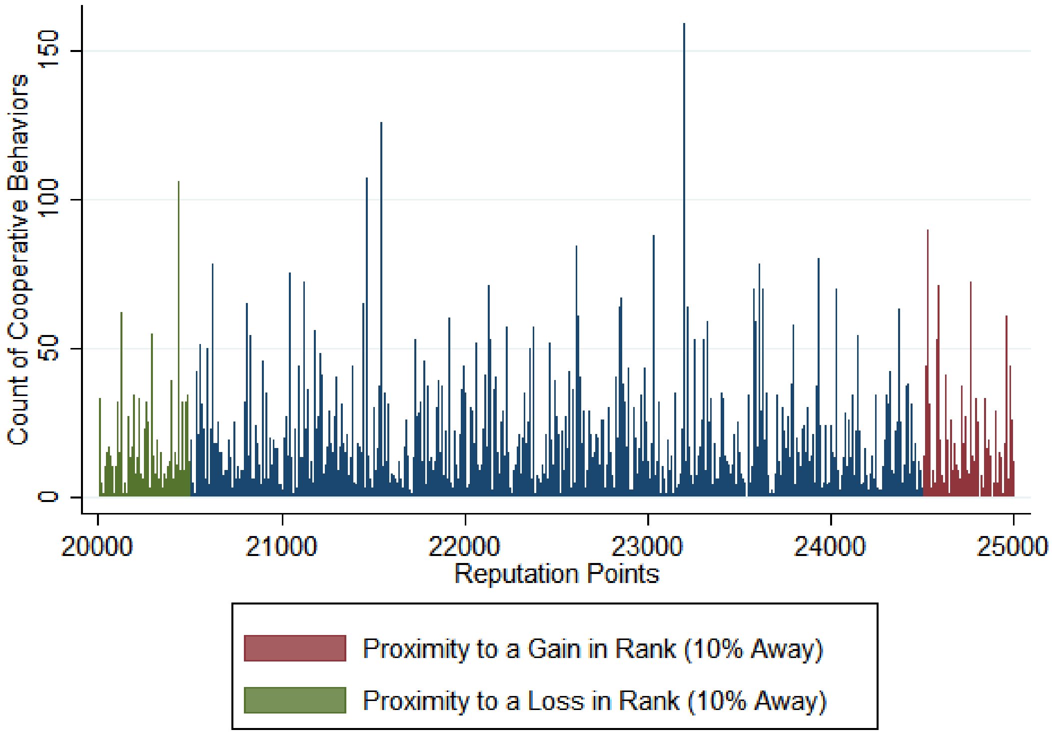


Figure A.4: Count of Cooperative Behaviors by Reputation Points for Milestone Rank Category 5



REFERENCES

Adams, JS (1965) "Inequity in Social Exchange." 267–99 in *Advances in Experimental Pyschology*, vol. 2, edited by L. Berkowitz. New York: Academic Press.

Adler PS, Kwon SW (2002) Social Capital: Prospects for a New Concept. *ACAD MANAGE REV* 27(1):17–40.

Alexander RD (1987) *The Biology of Moral Systems* (Transaction Publishers).

Allison, P. D. (2009). *Fixed effects regression models* (Vol. 160). SAGE publications.

Amabile T, Fisher CM, Pillemer J (2014) IDEO's Culture of Helping. *Harvard Business Review* 92(1–2):54–61.

Anderson C, Brown CE (2010) The functions and dysfunctions of hierarchy. *Research in Organizational Behavior* 30:55–89.

Anderson, C., & Willer, R. (2014). Do status hierarchies benefit groups? A bounded functionalist account of status. In *The psychology of social status* (pp. 47-70). Springer, New York, NY.

Andreoni J, Harbaugh W, Vesterlund L (2003) The Carrot or the Stick: Rewards, Punishments, and Cooperation. *American Economic Review* 93(3):893–902.

Anthony, D., Smith, S. W., & Williamson, T. (2009). Reputation and reliability in collective goods: The case of the online encyclopedia Wikipedia. *Rationality and Society*, *21*(3), 283-306.

Armstrong JS, Collopy F (1996) Competitor Orientation: Effects of Objectives and Information on Managerial Decisions and Profitability. *Journal of Marketing Research* 33(2):188–199.

Arrow, K. J. (1974). *The limits of organization*. WW Norton & Company.

Asch SE (1959) A perspective on social psychology. *Psychology: A study of a science* 3:363–383.

Ashford, S. J., George, E., & Blatt, R. (2007). 2 old assumptions, new work: The opportunities and challenges of research on nonstandard employment. *The Academy of Management Annals*, *1*(1), 65-117.

Axelrod R, Hammond RA, Grafen A, Day T (2004) Altruism via kin-selection strategies that rely on arbitrary tags with which they coevolve. *Evolution* 58(8):1833–1838.

Axelrod R, Keohane RO (1985) Achieving Cooperation under Anarchy: Strategies and Institutions. *World Politics* 38(1):226–254.

Axelrod RM (1984) *The evolution of cooperation* (Basic Books, New York).

Axelrod RM (1997) *The Complexity of Cooperation: Agent-based Models of Competition and Collaboration* (Princeton University Press).

Baker WE, Dutton J (2007) Enabling positive social capital in organizations. Ragins BR, Dutton, Jane, eds. *Exploring positive relationships at work: Building a theoretical and research foundation*. (Lawrence Erlbaum, Mahwah, N.J.), 325–346.

Baker WE, Bulkley N (2014) Paying It Forward vs. Rewarding Reputation: Mechanisms of Generalized Reciprocity. *Organization Science* 25(5):1493–1510.

Balliet, D., Parks, C., & Joireman, J. (2009). Social value orientation and cooperation in social dilemmas: A meta-analysis. *Group Processes & Intergroup Relations*, *12*(4), 533-547.

Barclay, P., & Willer, R. (2007). Partner choice creates competitive altruism in humans. *Proceedings of the Royal Society of London B: Biological Sciences*, *274*(1610), 749-753.

Barghouti, N. S. (1992). Supporting cooperation in the Marvel process-centered SDE. *ACM SIGSOFT Software Engineering Notes*, *17*(5), 21-31.

Barley, S. R., Bechky, B. A., & Milliken, F. J. (2017). The changing nature of work: Careers,identities, and work lives in the 21st century. *Academy of Management Discoveries*, *3*(2), 111-115.

Barnard CI (1938) 1968. *The functions of the executive*.

Barrett S (2016) Coordination vs. voluntarism and enforcement in sustaining international environmental cooperation. *PNAS* 113(51):14515–14522.

Baron, J. N., Davis-Blake, A., & Bielby, W. T. (1986). The structure of opportunity: How promotion ladders vary within and among organizations. *Administrative Science Quarterly*, 248-273.

Bartlett MY, DeSteno D (2006) Gratitude and Prosocial Behavior: Helping When It Costs You. *Psychol Sci* 17(4):319–325.

Belmi P, Pfeffer J (2015) How “Organization” Can Weaken the Norm of Reciprocity: The Effects of Attributions for Favors and a Calculative Mindset. *ACAD MANAGE DISCOVER* 1(1):36–57.

Bendersky, C., & Hays, N. A. (2012). Status conflict in groups. *Organization Science*, *23*(2), 323-340.

Benjamin, B. A., & Podolny, J. M. (1999). Status, quality, and social order in the California wine industry. *Administrative science quarterly*, *44*(3), 563-589.

Berger, J., Cohen, B. P., & Zelditch Jr, M. (1972). Status characteristics and social interaction. *American Sociological Review*, 241-255.

Bernstein ES, Li S (2017) Seeing Where You Stand: From Performance Feedback to Performance Transparency. *ACAD MANAGE PROC* 2017(1):14752.

Blake PR, McAuliffe K (2011) “I had so much it didn’t seem fair”: Eight-year-olds reject two forms of inequity. *Cognition* 120(2):215–224.

Blau PM (1968) The Hierarchy of Authority in Organizations. *American Journal of Sociology* 73(4):453–467.

Bolino MC (1999) Citizenship and Impression Management: Good Soldiers or Good Actors? *ACAD MANAGE REV* 24(1):82–98.

Bolino MC, Grant AM (2016) The Bright Side of Being Prosocial at Work, and the Dark Side, Too: A Review and Agenda for Research on Other-Oriented Motives, Behavior, and Impact in Organizations. *Academy of Management Annals* 10(1):599–670.

Borman W, Motowidlo S (1993) Expanding the criterion domain to include elements of contextual performance. *Personnel selection in organizations; San Francisco: Jossey-Bass*:71–98.

Boyd R, Gintis H, Bowles S (2010) Coordinated Punishment of Defectors Sustains Cooperation and Can Proliferate When Rare. *Science* 328(5978):617–620.

Brion, S., & Anderson, C. (2013). The loss of power: How illusions of alliance contribute to powerholders' downfall. *Organizational Behavior and Human Decision Processes, 121*(1), 129-139.

Brosnan SF, Schiff HC, Waal FBM de (2005) Tolerance for inequity may increase with social closeness in chimpanzees. *Proceedings of the Royal Society of London B: Biological Sciences* 272(1560):253–258.

Brosnan SF, de Waal FBM (2003) Monkeys reject unequal pay. *Nature* 425(6955):297–299.

Bryan JH, London P (1970) Altruistic behavior by children. *Psychological Bulletin* 73(3):200–211.

Cappelli P (2009) What's old is new again: Managerial ?talent? in an historical context. *Research in Personnel and Human Resources Management*. Research in Personnel and Human Resources Management. (Emerald Group Publishing Limited), 179–218.

Cappelli, P., & Keller, J. R. (2013). Classifying work in the new economy. *Academy of Management Review*, *38*(4), 575-596.

Cappelli P, Tavis A (2016) The Future of Performance Reviews. *Harvard Business Review*. Retrieved (August 25, 2017), https://hbr.org/2016/10/the-performance-management-revolution.

Caprara, G. V., Alessandri, G., & Eisenberg, N. (2012). Prosociality: The contribution of traits, values, and self-efficacy beliefs. *Journal of personality and social psychology*, *102*(6), 1289.

Cascio, W. F. (2000). Managing a virtual workplace. *The Academy of Management Executive*, *14*(3), 81-90.

Davis, G. F. (2016). *The vanishing American corporation: Navigating the hazards of a new economy*. Berrett-Koehler Publishers.

Durkheim, E. (2005). *Suicide: A study in sociology*. Routledge.

Charlesworth WR, La Freniere P (1983) Dominance, friendship, and resource utilization in preschool children's groups. *Ethology and Sociobiology* 4(3):175–186.

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of personality and social psychology*, *58*(6), 1015.

Clot, S., Grolleau, G., & Ibanez, L. (2014). Smug alert! Exploring self-licensing behavior in a cheating game. *Economics Letters*, *123*(2), 191-194.

Connelly, B. L., Tihanyi, L., Crook, T. R., & Gangloff, K. A. (2014). Tournament theory: Thirty years of contests and competitions. *Journal of Management*, *40*(1), 16-47.

Cook KS, Rice E (2003) Social Exchange Theory. Timothy J. Owens, John DeLamater, eds. *Handbook of Social Psychology*. (Kluwer Academic Publishers ; Plenum Publishers, New York), 53–76.

Cross RL, Parker A (2004) *The Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations* (Harvard Business Review Press).

Dawes CT, Fowler JH, Johnson T, McElreath R, Smirnov O (2007) Egalitarian motives in humans. *Nature* 446(7137):794–796.

DeSteno D, Monica Y. Bartlett, Jolie Baumann, Lisa A. Williams, Leah Dickens (2010) Gratitude as moral sentiment: Emotion-guided cooperation in economic exchange. *Emotion* 10(2):289–293.

Deutsch M (1949) An experimental study of the effects of co-operation and competition upon group process. *Human relations* 2(3):199–231.

Dooren WV, Bouckaert G, Halligan J (2015) *Performance Management in the Public Sector* (Routledge).

Doyle, S. P., Lount Jr, R. B., Wilk, S. L., & Pettit, N. C. (2016). Helping others most when they are not too close: Status distance as a determinant of interpersonal helping in organizations. *Academy of Management Discoveries*, *2*(2), 155-174.

Dufwenberg M, Gneezy U, Güth W, Van Damme E (2001) Direct vs indirect reciprocity: an experiment. *Homo Oeconomicus* 18:19–30.

Eckel CC, Grossman PJ (1998) Are Women Less Selfish Than Men?: Evidence From Dictator Experiments. *The Economic Journal* 108(448):726–735.

Eckel CC, Grossman PJ (2008) Chapter 113 Men, Women and Risk Aversion: Experimental Evidence. *Handbook of Experimental Economics Results* 1:1061–1073.

Edelman, B., & Larkin, I. (2014). Social comparisons and deception across workplace hierarchies: Field and experimental evidence. *Organization Science*, *26*(1), 78-98.

Egas M, Riedl A (2008) The economics of altruistic punishment and the maintenance of cooperation. *Proceedings of the Royal Society of London B: Biological Sciences* 275(1637):871–878.

Ekeh PP (1974) *Social exchange theory: the two traditions* (Harvard University Press).

Emmons, R., Michael E. McCullough (2003) Counting blessings versus burdens: An experimental investigation of gratitude and subjective well-being in daily life. *Journal of Personality and Social Psychology* 84(2):377–389.

Engelmann D, Fischbacher U (2009) Indirect reciprocity and strategic reputation building in an experimental helping game. *Games and Economic Behavior* 67(2):399–407.

Erez A, Schilpzand P, Leavitt K, Woolum AH, Judge TA (2015) Inherently Relational: Interactions between Peers' and Individuals' Personalities Impact Reward Giving and Appraisal of Individual Performance. *ACAD MANAGE J* 58(6):1761–1784.

Falk A, Fischbacher U (2006) A theory of reciprocity. *Games and Economic Behavior* 54(2):293–315.

Fehr E, Bernhard H, Rockenbach B (2008) Egalitarianism in young children. *Nature; London* 454(7208):1079–83.

Fehr E, Fischbacher U, Gächter S (2002) Strong reciprocity, human cooperation, and the enforcement of social norms. *Hum Nat* 13(1):1–25.

Fehr E, Gächter S (2002) Altruistic punishment in humans. *Nature* 415(6868):137–140.

Fehr E, Gintis H (2007) Human Motivation and Social Cooperation: Experimental and Analytical Foundations. *Annual Review of Sociology* 33(1):43–64.

Fehr E, Schmidt KM (1999) A Theory of Fairness, Competition, and Cooperation. *Q J Econ* 114(3):817–868.

Ferguson, A. J., Cohen, L. E., Burton, M. D., & Beckman, C. M. (2016). Misfit and milestones: Structural elaboration and capability reinforcement in the evolution of entrepreneurial top management teams. *Academy of Management Journal*, *59*(4), 1430-1450.

Festinger, L. (1954). A theory of social comparison processes. *Human relations*, *7*(2), 117-140.

Feinberg, M., Willer, R., & Schultz, M. (2014). Gossip and ostracism promote cooperation in groups. *Psychological Science*, *25*(3), 656-664.

Fischbacher U (2007) z-Tree: Zurich toolbox for ready-made economic experiments. *Exp Econ* 10(2):171–178.

Flynn FJ (2003) What have you done for me lately? Temporal adjustments to favor evaluations. *Organizational Behavior and Human Decision Processes* 91(1):38–50.

Flynn FJ (2005) Identity Orientations And Forms Of Social Exchange In Organizations. *ACAD MANAGE REV* 30(4):737–750.

Frederick S (2005) Cognitive Reflection and Decision Making. *Journal of Economic Perspectives* 19(4):25–42.

Funk, R. J. (2014). *Essays on Collaboration, Innovation, and Network Change in Organizations* (Doctoral dissertation, University of Michigan).

Garcia SM, Tor A, Gonzalez R (2006) Ranks and Rivals: A Theory of Competition. *Pers Soc Psychol Bull* 32(7):970–982.

Gittell, J. H., Cameron, K., Lim, S., & Rivas, V. (2006). Relationships, layoffs, and organizational resilience: Airline industry responses to September 11. *The Journal of Applied Behavioral Science*, *42*(3), 300-329.

Hagel, J., & Armstrong, A. G. (1997). Net gain. *Harvard Business School Press, Boston*.

Hardy, C. L., & Van Vugt, M. (2006). Nice guys finish first: The competitive altruism hypothesis. *Personality and Social Psychology Bulletin*, *32*(10), 1402-1413.

Hausman, J. A., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship.

Henderson, A. D., & Fredrickson, J. W. (2001). Top management team coordination needs and the CEO pay gap: A competitive test of economic and behavioral views. *Academy of Management Journal*, *44*(1), 96-117.

Hobbes, T. (1998). On the citizen (de cive). *ders.: Man and Citizen (De Homine and De Cive)*, *3*, 87-386.

Garcia, S. M., Tor, A., & Gonzalez, R. (2006). Ranks and rivals: A theory of competition. *Personality and Social Psychology Bulletin*, *32*(7), 970-982.

Garcia, S. M., Tor, A., & Schiff, T. M. (2013). The psychology of competition: A social comparison perspective. *Perspectives on Psychological Science*, *8*(6), 634-650.

Glass GV, Willson VL, Gottman JM (2008) *Design and Analysis of Time-Series Experiments* (IAP).

Gouldner AW (1960) The norm of reciprocity: A preliminary statement. *American sociological review*:161–178.

Grant, A. M. (2007). Relational job design and the motivation to make a prosocial difference. *Academy of management review*, *32*(2), 393-417.

Grant, A. M. (2008). Does intrinsic motivation fuel the prosocial fire? Motivational synergy in predicting persistence, performance, and productivity. *Journal of applied psychology*, *93*(1), 48.

Greenberg J (1987) A Taxonomy of Organizational Justice Theories. *ACAD MANAGE REV* 12(1):9–22.

Greiner B, Vittoria Levati M (2005) Indirect reciprocity in cyclical networks. *Journal of Economic Psychology* 26(5):711–731.

Grossman RL, Sabala M, Gu Y, Anand A, Handley M, Sulo R, Wilkinson L (2008) *Discovering Emergent Behavior From Network Packet Data: Lessons from the Angle Project*

Gulati R, Wohlgezogen F, Zhelyazkov P (2012) The Two Facets of Collaboration: Cooperation and Coordination in Strategic Alliances. *Academy of Management Annals* 6(1):531–583.

Hardin R (1982) *Collective Action* (Resources for the Future).

Hargadon A (2003) *How Breakthroughs Happen: The Surprising Truth about how Companies Innovate* (Harvard Business Press).

Hargadon A, Sutton RI (1997) Technology Brokering and Innovation in a Product Development Firm. *Administrative Science Quarterly* 42(4):716–749.

Heisig JP, Schaeffer M, Giesecke J (2017) The Costs of Simplicity: Why Multilevel Models May Benefit from Accounting for Cross-Cluster Differences in the Effects of Controls. *American Sociological Review* 82(4):796–827.

Janssen, M. A., Holahan, R., Lee, A., & Ostrom, E. (2010). Lab experiments for the study of social-ecological systems. *Science, 328*(5978), 613-617.

Jen E (2003) Stable or robust? What's the difference? *Complexity* 8(3):12–18.

Jen E (2005) *Robust Design: A Repertoire of Biological, Ecological, and Engineering Case Studies* (Oxford University Press).

Johnson, Phillip (2013). http://www.itworld.com/article/2707360/it-management/your-stack-overflowreputation-can-help-get-you-hired---by-stack-overflow.html

Jones GR, George JM (1998) The Experience and Evolution of Trust: Implications for Cooperation and Teamwork. *The Academy of Management Review* 23(3):531–546.

Kahneman D, Knetsch JL, Thaler RH (1991) Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *The Journal of Economic Perspectives* 5(1):193–206.

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American psychologist*, *39*(4), 341.

King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political analysis*, *9*(2), 137-163.

Kitts JA. 2006. Collective action, rival incentives, and the emergence of antisocial norms. *Am. Sociol. Rev.* 71:235–59

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science*, *3*(3), 383-397.

Kollock P (1993) "An Eye for an Eye Leaves Everyone Blind": Cooperation and Accounting Systems. *American Sociological Review* 58(6):768–786.

Kollock P (1998) Social Dilemmas: The Anatomy of Cooperation. *Annual Review of Sociology* 24(1):183–214.

Kräkel, M. (2007). Doping and cheating in contest-like situations. *European Journal of Political Economy*, *23*(4), 988-1006.

Krishnan, R., & Kozhikode, R. K. (2015). Status and corporate illegality: Illegal loan recovery practices of commercial banks in India. *Academy of Management Journal*, *58*(5), 1287-1312.

Kouchaki, M. (2011). Vicarious moral licensing: the influence of others' past moral actions on moral behavior. *Journal of personality and social psychology*, *101*(4), 702.

Lacetera, N., & Macis, M. (2010). Do all material incentives for pro-social activities backfire? The response to cash and non-cash incentives for blood donations. *Journal of Economic Psychology*, *31*(4), 738-748.

LaPorte, T. R. (1994). A strawman speaks up: Comments on The Limits of Safety. *Journal of contingencies and crisis management*, *2*(4), 207-211.

LaPorte, T. R., & Consolini, P. M. (1991). Working in practice but not in theory: theoretical challenges of" high-reliability organizations". *Journal of Public Administration Research and Theory: J-PART*, *1*(1), 19-48.

Lazear, E. P. (1999). Personnel economics: Past lessons and future directions presidential address to the society of labor economists, San Francisco, May 1, 1998. *Journal of Labor Economics*, *17*(2), 199-236.

Leimar O, Hammerstein P (2001) Evolution of cooperation through indirect reciprocity. *Proceedings of the Royal Society of London B: Biological Sciences* 268(1468):745–75

Ledyard J (1995) Public Goods: A survey of experimental research. J. Kagel, A. Roth, eds. *Handbook of Experimental Economics*. (Princeton University Press, Princeton, N.J.).

Lengnick-Hall, C. A., Beck, T. E., & Lengnick-Hall, M. L. (2011). Developing a capacity for organizational resilience through strategic human resource management. *Human Resource Management Review*, *21*(3), 243-255.

Lévi-Strauss C (1969) *The Elementary Structures of Kinship* (Beacon Press).

Lindahl WE, Winship C (1994) A logit model with interactions for predicting major gift donors. *Res High Educ* 35(6):729–743.

Linden A (2015) Conducting interrupted time-series analysis for single-and multiple-group comparisons. *Stata Journal* 15(2):480–500.

Linden A, Adams JL (2011) Applying a propensity score-based weighting model to interrupted time series data: improving causal inference in programme evaluation. *Journal of Evaluation in Clinical Practice* 17(6):1231–1238.

Luhmann, N. (1995). *Social systems*. Stanford University Press.

Magee JC, Galinsky AD (2008) Social Hierarchy: The Self- Reinforcing Nature of Power and Status. *Academy of Management Annals* 2(1):351–398.

Major B (1994) From Social Inequality to Personal Entitlement: the Role of Social Comparisons, Legitimacy Appraisals, and Group Membership. Zanna MP, ed. *Advances in Experimental Social Psychology*. (Academic Press), 293–355.

Malinowski, B. 1922. Argonauts of the Western Pacific. George Routledge & Sons, London

Marwell G, Ames RE (1979) Experiments on the Provision of Public Goods. I. Resources, Interest, Group Size, and the Free-Rider Problem. *American Journal of Sociology* 84(6):1335–1360.

Marwell G, Ames RE (1980) Experiments on the Provision of Public Goods. II. Provision Points, Stakes, Experience, and the Free-Rider Problem. *American Journal of Sociology* 85(4):926–937.

Martin J (1981) Relative Deprivation: A theory of distributive injustice for an era of shrinking resources. Larry L. Cummings, Barry M. Staw, eds. *Research in organizational behavior*. (JAI Press, Greenwich, C.T.).

McCullough ME, Kimeldorf MB, Cohen AD (2008) An Adaptation for Altruism: The Social Causes, Social Effects, and Social Evolution of Gratitude. *Curr Dir Psychol Sci* 17(4):281–285.

Merton, R. K. (1968). *Social theory and social structure*. Simon and Schuster.

Messick D, Sentis KP (1983) Fairness, preference, and fairness biases. David M. Messick, Karen S. Cook, eds. *Equity theory: Psychological and sociological perspectives*. (Praeger, New York), 61–94.

Milinski M, Semmann D, Krambeck HJ (2002) Reputation helps solve the ‘tragedy of the commons.’ *Nature* 415(6870):424–426.

Mollick E, Rothbard N (2014) *Mandatory Fun: Consent, Gamification and the Impact of Games at Work* (Social Science Research Network, Rochester, NY).

Molm LD (1997) *Coercive Power in Social Exchange* (Cambridge University Press).

Molm LD, Collett JL, Schaefer DR (2006) Conflict and Fairness in Social Exchange. *Soc Forces* 84(4):2331–2352.

Molm LD, Collett JL, Schaefer DR (2007) Building Solidarity through Generalized Exchange: A Theory of Reciprocity. *American Journal of Sociology* 113(1):205–242.

Monin, B., & Miller, D. T. (2001). Moral credentials and the expression of prejudice. *Journal of personality and social psychology*, *81*(1), 33.

Moon SH, Scullen SE, Latham GP (2016) Precarious curve ahead: The effects of forced distribution rating systems on job performance. *Human Resource Management Review* 26(2):166–179.

Mulligan JR, Bull Schaefer RA (2011) A New Hope for Rank and Yank. *Journal of Leadership & Organizational Studies* 18(3):385–396.

Murnighan JK, Saxon MS (1998) Ultimatum bargaining by children and adults. *Journal of Economic Psychology* 19(4):415–445.

Nowak MA (2006) Five Rules for the Evolution of Cooperation. *Science* 314(5805):1560–1563.

Nowak MA, Roch S (2007) Upstream reciprocity and the evolution of gratitude. *Proceedings of the Royal Society of London B: Biological Sciences* 274(1610):605–610.

Nowak MA, Sigmund K (1998) Evolution of Indirect Reciprocity by Image Scoring. *Nature* 393(6685):573–577.

Nowak MA, Sigmund K (1998) The Dynamics of Indirect Reciprocity. *Journal of Theoretical Biology* 194(4):561–574.

Nowak MA, Sigmund K (2005) Evolution of Indirect Reciprocity. Retrieved (August 28, 2017), http://pure.iiasa.ac.at/7763/.

Ordóñez, L. D., Schweitzer, M. E., Galinsky, A. D., & Bazerman, M. H. (2009). Goals gone wild: The systematic side effects of overprescribing goal setting. *The Academy of Management Perspectives, 23*(1), 6-16.

Ostrom E (2010) Polycentric systems for coping with collective action and global environmental change. *Global Environmental Change* 20(4):550–557.

Ostrom E, Burger J, Field CB, Norgaard RB, Policansky D (1999) Revisiting the Commons: Local Lessons, Global Challenges. *Science* 284(5412):278–282.

Ouchi, W. G. (1980). Markets, bureaucracies, and clans. *Administrative science quarterly*, 129-141.

Paikoff RL, Savin-Williams RC (1983) An exploratory study of dominance interactions among adolescent females at a summer camp. *J Youth Adolescence* 12(5):419–433.

Parsons, T. (1991). *The social system*. Psychology Press.

Penner LA, Dovidio JF, Piliavin JA, Schroeder DA (2005) Prosocial Behavior: Multilevel Perspectives. *Annual Review of Psychology* 56(1):365–392.

Pettit NC, Doyle SP, Lount RB, To C (2016) Cheating to get ahead or to avoid falling behind? The effect of potential negative versus positive status change on unethical behavior. *Organizational Behavior and Human Decision Processes* 137:172–183.

Pettit, N. C., Yong, K., & Spataro, S. E. (2010). Holding your place: Reactions to the prospect of status gains and losses. *Journal of Experimental Social Psychology*, *46*(2), 396-401.

Pfeffer, J., & Cohen, Y. (1984). Determinants of internal labor markets in organizations. *Administrative Science Quarterly*, 550-572.

Pfeiffer T, Rutte C, Killingback T, Taborsky M, Bonhoeffer S (2005) Evolution of cooperation by generalized reciprocity. *Proceedings of the Royal Society of London B: Biological Sciences* 272(1568):1115–1120.

Phillips, D. J., & Zuckerman, E. W. (2001). Middle-status conformity: Theoretical restatement and empirical demonstration in two markets. *American Journal of Sociology*, *107*(2), 379-429.

Podolny, J. M., & Phillips, D. J. (1996). The dynamics of organizational status. *Industrial and Corporate Change*, *5*(2), 453-471.

Poortvliet PM (2013) Harming Others' Task-Related Efforts. *Social Psychology* 44(6):373–379.

Puranam, P., Alexy, O., & Reitzig, M. (2014). What's "new" about new forms of organizing?. *Academy of Management Review*, *39*(2), 162-180.

Putnam RD (2000) Bowling Alone: America's Declining Social Capital. *Culture and Politics*. (Palgrave Macmillan, New York), 223–234.

Putterman, L. (2010). Cooperation and punishment. *Science*, *328*(5978), 578-579.

Queller DC (1985) Kinship, reciprocity and synergism in the evolution of social behaviour. *Nature* 318(6044):366–367.

Rabe-Hesketh S, Skrondal A (2008) *Multilevel and Longitudinal Modeling Using Stata, Second Edition* (Stata Press).

Restivo, M., & Van De Rijt, A. (2012). Experimental study of informal rewards in peer production. *PloS one*, *7*(3), e34358.

Rabin M (1993) Incorporating Fairness into Game Theory and Economics. *The American Economic Review* 83(5):1281–1302.

Rand DG, Nowak MA, Fowler JH, Christakis NA (2014) Static network structure can stabilize human cooperation. *PNAS* 111(48):17093–17098.

Range F, Horn L, Viranyi Z, Huber L (2009) The absence of reward induces inequity aversion in dogs. *PNAS* 106(1):340–345.

Rankin DJ, Taborsky M (2009) Assortment and the Evolution of Generalized Reciprocity. *Evolution* 63(7):1913–1922.

Ring PS, van de Ven AH (1994) Developmental Processes of Cooperative Interorganizational Relationships. *The Academy of Management Review* 19(1):90–118.

Rioux, S. M., & Penner, L. A. (2001). The causes of organizational citizenship behavior: a motivational analysis. *Journal of applied Psychology*, *86*(6), 1306.

Rock D, Jones B (2015) Why More and More Companies Are Ditching Performance Ratings. *Harvard Business Review*.

Salvato C, Reuer J, Battigalli P (2017) Cooperation Across Disciplines: A Multilevel Perspective on Cooperative Behavior in Governing Interfirm Relations. *Academy of Management Annals*:annals.2014.0001.

Santos FC, Pacheco JM, Lenaerts T (2006) Evolutionary dynamics of social dilemmas in structured heterogeneous populations. *PNAS* 103(9):3490–3494.

Savin-Williams RC (1976) An Ethological Study of Dominance Formation and Maintenance in a Group of Human Adolescents. *Child Development* 47(4):972–979.

Schweitzer, M. E., Ordóñez, L., & Douma, B. (2004). Goal setting as a motivator of unethical behavior. *Academy of Management Journal*, *47*(3), 422-432.

Sachdeva, S., Iliev, R., & Medin, D. L. (2009). Sinning saints and saintly sinners: The paradox of moral self-regulation. *Psychological science*, *20*(4), 523-528.

Seinen I, Schram A (2006) Social status and group norms: Indirect reciprocity in a repeated helping experiment. *European Economic Review* 50(3):581–602.

Shadish WR, Cook TD, Campbell DT (2002) *Experimental and Quasi-experimental Designs for Generalized Causal Inference* (Houghton Mifflin).

Siegel, P. A., & Hambrick, D. C. (2005). Pay disparities within top management groups: Evidence of harmful effects on performance of high-technology firms. *Organization Science*, *16*(3), 259-274.

Sigmund K, Hauert C, Nowak MA (2001) Reward and punishment. *PNAS* 98(19):10757–10762.

Simpson B, Harrell A, Melamed D, Heiserman N, Negraia DV (2017) The Roots of Reciprocity: Gratitude and Reputation in Generalized Exchange Systems. *Am Sociol Rev*:0003122417747290.

Simpson, B., & Willer, R. (2015). Beyond altruism: Sociological foundations of cooperation and prosocial behavior. *Annual Review of Sociology*, *41*, 43-63.

Smith KG, Carroll SJ, Ashford SJ (1995) Intra- and Interorganizational Cooperation: Toward a Research Agenda. *ACAD MANAGE J* 38(1):7–23.

Smith, M. A., & Kollock, P. (Eds.). (1999). *Communities in cyberspace*. Psychology Press.

Somaya, D., Williamson, I. O., & Lorinkova, N. (2008). Gone but not lost: The different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal*, *51*(5), 936-953.

Stewart AJ, Plotkin JB (2014) Collapse of cooperation in evolving games. *PNAS* 111(49):17558–17563.

Strayer FF, Strayer J (1976) An Ethological Analysis of Social Agonism and Dominance Relations among Preschool Children. *Child Development* 47(4):980–989.

Sudhir K, Roy S, Cherian M (2016) Do Sympathy Biases Induce Charitable Giving? The Effects of Advertising Content. *Marketing Science* 35(6):849–869.

Sutcliffe, K. M., & Vogus, T. J. (2003). Organizing for resilience. *Positive organizational scholarship*, 94-110.

Tai, K., Narayanan, J., & McAllister, D. J. (2012). Envy as pain: Rethinking the nature of envy and its implications for employees and organizations. *Academy of Management Review*, *37*(1), 107-129.

Tennie C, Frith U, Frith CD (2010) Reputation management in the age of the world-wide web. *Trends in Cognitive Sciences* 14(11):482–488.

Tesser A, Smith J (1980) Some effects of task relevance and friendship on helping: You don't always help the one you like. *Journal of Experimental Social Psychology* 16(6):582–590.

Thibault, JW, Kelley, HH (1959) The social psychology of groups. New York: Wiley.

Tjosvold D (1984) Cooperation Theory and Organizations. *Human Relations* 37(9):743–767.

Tjosvold D, Wong ASH, Chen NYF (2014) Constructively Managing Conflicts in Organizations. *Annual Review of Organizational Psychology and Organizational Behavior* 1(1):545–568.

Tversky A, Kahneman D (1991) Loss Aversion in Riskless Choice: A Reference-Dependent Model. *Q J Econ* 106(4):1039–1061.

Van Lange PAM, Joireman J, Parks CD, Van Dijk E (2013) The psychology of social dilemmas: A review. *Organizational Behavior and Human Decision Processes* 120(2):125–141.

Vohs KD, Noelle Nelson, Catherine Rawn (2009) Why Do Choices Tax Self-Regulatory Resources? Three Tests of Candidates to Explain Decision Fatigue. *ACR North American Advances* NA-36.

Vriend T, Jordan J, Janssen O (2016) Reaching the top and avoiding the bottom: How ranking motivates unethical intentions and behavior. *Organizational Behavior and Human Decision Processes* 137:142–155.

Wade-Benzoni KA, Tenbrunsel AE, Bazerman MH (1996) Egocentric Interpretations of Fairness in Asymmetric, Environmental Social Dilemmas: Explaining Harvesting Behavior and the Role of Communication. *Organizational Behavior and Human Decision Processes* 67(2):111–126.

Walsh, J. P., Meyer, A. D., & Schoonhoven, C. B. (2006). A future for organization theory: Living in and living with changing organizations. *Organization Science*, *17*(5), 657-671.

Walster E, Walster GW, and Berscheid E (1978) Equity: Theory and Research. *eweb:22046*. Retrieved (August 22, 2017),

Webster J, Wing-Fai L (2017) Introduction: creativity, knowledge and innovation in virtual work. *New Technology, Work and Employment* 32(1):1–11.

Wedekind C, Milinski M (2000) Cooperation Through Image Scoring in Humans. *Science* 288(5467):850–852.

Weick, K. E. (1987). Organizational culture as a source of high reliability. *California management review*, *29*(2), 112-127.

Weick KE, Roberts KH (1993) Collective Mind in Organizations: Heedful Interrelating on Flight Decks. *Administrative Science Quarterly* 38(3):357–381.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2008). Organizing for high reliability: Processes of collective mindfulness. *Crisis management*, *3*(1), 31-66.

Weigelt, K., & Camerer, C. (1988). Reputation and corporate strategy: A review of recent theory and applications. *Strategic management journal*, *9*(5), 443-454.

Weinzweig A (2010) *A Lapsed Anarchist's Approach to Building a Great Business: Zingerman's Guide to Good Leading, Part 1* (Zingerman's Press).

West SA, Griffin AS, Gardner A (2007) Social semantics: altruism, cooperation, mutualism, strong reciprocity and group selection. *Journal of Evolutionary Biology* 20(2):415–432.

West SA, Griffin AS, Gardner A (2007) Evolutionary Explanations for Cooperation. *Current Biology* 17(16):R661–R672.

Wijen F, Ansari S (2007) Overcoming Inaction through Collective Institutional Entrepreneurship: Insights from Regime Theory. *Organization Studies* 28(7):1079–1100.

Willer R (2009) Groups Reward Individual Sacrifice: The Status Solution to the Collective Action Problem. *American Sociological Review* 74(1):23–43.

Williams, R. L., & Cothrel, J. (2000). Four smart ways to run online communities. *MIT Sloan Management Review*, *41*(4), 81.

Zinko R, Ferris GR, Humphrey SE, Meyer CJ, Aime F (2012) Personal reputation in organizations: Two-study constructive replication and extension of antecedents and consequences. *Journal of Occupational and Organizational Psychology* 85(1):156–180.

Zoltners AA, Sinha P, Lorimer SE (2008) Sales Force Effectiveness: A Framework for Researchers and Practitioners. *Journal of Personal Selling & Sales Management* 28(2):115–131.

Zoltners AA, Sinha PK, Lorimer SE (2011) How to manage forced sales rankings. *Harvard Business Review Blog*.