Entrepreneurial Action as a Spatiotemporal Process in the Aftermath of Disasters

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Abstract

Received entrepreneurship research suggests that entrepreneurial action helps people and communities in the aftermath of disastrous events. To study this phenomenon, scholars focus on two central themes: 1) entrepreneurial actors (individuals, organizations, or firms in the community) with the right knowledge and motivation possess capabilities determine whether an identified opportunity represents an opportunity for them to exploit so as to alleviate others' sufferings, and 2) the feedback from an exploitation of an existing opportunity significantly influences the recognition and evaluation of subsequent opportunities of helping others. However, contemporary research has examined the first theme while largely ignoring the second one. Addressing this oversight, we develop three graph-theoretic models and operationlize them using the computational social science approach to investigate both the temporal dimension of entrepreneurial action as a process of opportunity identification, evaluation and exploitation over time, and the spatial dimension of entrepreneurial action as a feedback to identify subsequent opportunities among networked actors under disasters.

The first model depicts a simple supply-chain structure where each actor's entrepreneurial action can feed back to his/her spatially interdependent upstream and downstream neighbors. Our model suggests that feedback mechanisms significantly influence actors' entrepreneurial action decisions to alleviate the negative impacts of unanticipated disasters on supply chain performance. Next, we extend the one-dimensional chain structure into a grid network setting in the second model. This model highlights the importance of reciprocal feedback between neighboring actors in facilitating recovery entrepreneurial actions in the aftermath of disasters. Finally, our last model examines the spatiotemporal dynamics of entrepreneurial action over additional network structures, such as small-world and scale-free, determining how information and knowledge feedback circulates in the system facing disastrous events. We show that a shift in the network structure at the spatial dimension changes the number of actors who act entrepreneurially over time.

In sum, we consider entrepreneurial action emerging from the interactions among community members over not only *time* but also *space* in times of disasters. The modeling and analysis extends the action-based entrepreneurship framework into the context of disasters by explicitly specifying dynamic and interactive behavior among community members that are inputs to, and outcomes of, one another in the entrepreneurial process to alleviate the sufferings.

Chapter 1

Introduction

We, human, live in a world that is fraught with dangers and disasters that frequently bring out suffering to a great number of people (Rynes, et al., 2012; Shepherd and Williams, 2014). Despite its centrality to societies and organizations, why and how actors behave in the context of disasters is under-researched. Entrepreneurship research has made the link between entrepreneurial behavior and disaster. The literature suggests that when a community experiences a disaster, the resultant pains or losses can be alleviated via entrepreneurial action (e.g., Dacin et al., 2011; Peredo and Chrisman, 2006; Shepherd, 2015). The act to alleviate the suffering and improve the well-being of one self and others following a disaster is inherently entrepreneurial because it involves risk taking, innovation and recognizing *opportunities* to create value for community members with an uncertain return for the actor(s) (Miller et al., 2012; Shepherd, 2015; Shepherd and Williams, 2014). However, we know little about why and how entrepreneurs compassionately engage in different forms and levels of action in resource devastated environments to bring about relief and well being for themselves and others in response to disaster, the major focus of this thesis.

To contribute to the entrepreneurship-disaster research interface, we develop a formal analysis on how individuals and their community engage in pro-social entrepreneurial action in response to random value destroying events such as natural disasters. We assume that disasters bring about suffering in the community and actors engage in some forms of action to recover from adverse conditions. Our formal modeling approach is grounded in the nascent literature that seeks to study the role and impact of entrepreneurial action in alleviating the suffering of others through an interaction- and community-based perspective (McMullen and Shepherd, 2006; Patzelt and Shepherd, 2011; Shepherd, 2015; Shepherd et al., 2007; Shepherd and Patzelt, 2013). In this thesis, we examine an interaction-based entrepreneurial action process and analyze how different levels of desirability, feasibility, community size, and other factors affect the relationship between actors' entrepreneurial action and the community's collective welfare in response to random value-destroying events.

Disasters provide novel contexts that can advance entrepreneurship research. They necessitate a focus on the largely understudied interaction- and community-based perspective of entrepreneurial action (Shepherd, 2015) in the face of adversity. That is, a number of community members (i.e., networked *actors*) – individuals, organizations, or firms – are altered to the occurrence of disastrous events and willing to act entrepreneurially to help the less fortunate and unfortunate. Although the temporal process of entrepreneurial action has been extensively studied (McMullen and Dimov, 2013; Keyhani et al., 2015), entrepreneurship literature overlooks the spatial dynamics of entrepreneurial action in the networked system (i.e., community) where these actors share knowledge and experience with each other through business and social connections, then resulting in the feedback from an existing entrepreneurial action to a subsequent one (Gaimon and Bailey, 2013; Shepherd, 2010). Further little has known on the structure of connections and its implications for entrepreneurship in space-time in the context of disasters (Parker, 2008).

Evidence indicates that entrepreneurs are intimately embedded in a broader community (e.g., business and social networks) and benefit from their connections with other entrepreneurs for the discovery of entrepreneurial opportunities in response to unanticipated disasters (Klepper and Sleeper, 2005; Markman et al., 2005; Parker, 2008; Shepherd, 2015). In other words, network connections facilitate the feedback from exploitation of an existing opportunity to discovery of subsequent opportunities over space and over time. In a community, networked actors continuously modify the identification, evaluation, and exploitation of opportunities based on connected others' behavior. For instance, an actor's entrepreneurial action may increase the feasibility and desirability of subsequent opportunities and provide such information to other actors through network connections (Shepherd and Patzelt, 2013). The role of community is to determine the magnitude of feedback that one's action could possible generate, in terms of how many (i.e., the number of connected others) and how much (i.e., the degree of connections).

Several studies have started to consider entrepreneurial process involving connected actors, including spousal relations (Aldrich and Cliff, 2003), parent-subsidiary organizational structure (Bradley et al., 2011), and strategic alliance (Hora and Dutta, 2013). Those studies, however, only take spatial feedback as an exogenous input to the focal entrepreneur's action, thereby overlooking the strategic interactions between him/her and the community members around (Keyhani et al., 2015; Shepherd and Patzelt, 2013). Therefore, the distinct phenomenon of networked and contagious entrepreneurial-action dynamics over time is still largely unexplained. Studies of graph theory, which is the principal mathematical language for describing the properties of networks, shed light on this underexplored topic.

Graph theory suggests that there are two key aspects of investigating a network (or graph) of interconnected potential entrepreneurial actors: time dynamical property, i.e., behavioral rule, and space dynamical property, i.e., network structure (or "who-connects-to-whom" structure) (Barabási and Albert, 1999; Erdős and Rényi, 1960; Keeling, 1999). The behavioral rule formulates each networked actor's decision on entrepreneurial action – a temporal process of identifying, evaluating and exploiting opportunities for value creation (Keyhani et al., 2015; McMullen and Shepherd, 2006). The network structure identifies an actor's spatial connections, who generate direct feedback on the actor's behaviors (Albert et al., 2000). Thus, community members are arranged following a topological structure and take entrepreneurial actions in the aftermath of disasters, during which an actor's entrepreneurial-action decision both constrains and are constrained by their connections' entrepreneurial-action decisions. The interplay of the temporally and spatially properties in a community creates a dynamic context in which entrepreneurship thrives.

To highlight the underlying dynamism, we employ the computational techniques, cellular automata (CA) and agent based modeling (ABM) (Miller and Page, 2007; Nair et al., 2009), to operationalize the graph theoretic models over time and space dimensions. CA and ABM are organizational research simulation methods that effectively explore the strategic interactions among neighboring actors (e.g., Davis et al., 2007; Harrison et al., 2007; Miller and Page, 2007; Yang and Chandra, 2013). Our work starts from the simple CA method in which actors adopt a common, fixed rule to examine the stylized models. We next construct more complicated ABM method by adding complexity and heterogeneity among actors in the networked system. In this sense, the simulation methods truly pinning down the fundamental spatiotemporal dynamics of entrepreneurial actions. The modeling and analysis extends the action-based entrepreneurship framework into the context of network dynamics and disasters by explicitly specifying dynamic and interactive behavior among networked actors that are inputs to, and outcomes of, one another in the entrepreneurial process to respond value destroying events.

1.1 Motivation and structure

Following the lead of the entrepreneurship and graph theory literatures, we formally explore the dynamic interplay between spatial feedback process rooted in network structure and temporal entrepreneurial action process under uncertainty among community members. In particular, we consider entrepreneurial opportunities arising from the value-changing uncertainty (e.g., natural and man-made disasters). We investigate the occasions to see the emergence of entrepreneurial action in space-time in the following ways (see Table 1.1 for a summary).

In Chapter 3, we explore a one-dimensional chain structure of community and examine the opportunity exploitation in times of extreme environmental events. While natural and man-made disasters disproportionately impact the business landscape, little is known how they influence the process of opportunity identification, evaluation and exploitation among community members. Herein, we consider disasters creating recovery "opportunities" for potential economic, social and environmental value creation. In the context of disasters, somebody needs to recognize the presence of an recovery opportunity, evaluate the situation and decide whether to launch a recovery action, and eventually engage in or disengage from the recovery activities. We develop a one-dimensional supply-chain model to examine the effectiveness of popular recovery activities to address disruptions caused by unpredicted disasters. The central theme of this chapter is to examine the pursuit of recovery opportunities in times of extreme environmental events. Our analysis shows that a supply chain recovers best if member firms adopt a radical, rapid, costly recovery strategy that immediately resolves the disruption. This observation is robust to various resource consumption requirements. We apply our methodology in the case of Taiwan's 2011 food contamination scandal and provide managerial insights.

In Chapter 4, we conceptualize the notation of altruistic entrepreneurship and operationalize it as opportunity beliefs with different degrees of altruistic reciprocity that actors use to pursue entrepreneurial opportunities amid disasters in a two-dimensional square lattice (i.e., grid) structure of community. A CA model is developed to investigate the impact of different opportunity beliefs on the community value creation. Our simulations suggest that altruistic opportunity beliefs are associated with higher value creation in times of disasters than non-altruistic opportunity beliefs, especially when actors adopt an aggressive opportunity-evaluation rule. This work extends the theory of entrepreneurial action into the context of disaster by specifying its link with reciprocal altruism.

In Chapter 5, we explore the spatiotemporal dynamics of entrepreneurial action over several network structures. They are square lattice networks, pack networks, ring lattice networks, random graphs, small-world networks, and scale-free networks, each determining how information and knowledge feedback circulates in the systems. Our modeling and analysis show that a shift in the network structure at the spatial dimension changes the number of actors who act entrepreneurially over time. And such direct impact is moderated by the actors' opportunity-recognition belief (i.e., whether a third-person opportunity arising from spatial feedback is present) and the degree of feedback against friction under market imperfection. Our work provides a formal foundation of action-based entrepreneurship framework. Chapter 6 extends the findings in the context of both value-adding (e.g., technological advancement) and value-destroying events. The simulation results suggest that scale-free networks are better at fostering entrepreneurial actions under uncertainty.

Table 1.1: Structure

Chapter	**Research objectvies**	**Network configuration of community**	**Computational technique**
3	This chapter examines the robustness of different types of entrepreneurial actions (i.e., recovery activities) to alleviate the disruptions in the community caused by unanticipated disasters.	Chain	cellular automata
4	This chapter explores the effectiveness of various opportunity beliefs on taking entrepreneurial actions to create collective values for a community in the aftermath of disasters.	Square lattice	cellular automata
5 & 6	This chapter investigate the role of network structures on exploring and exploiting entrepreneurial opportunities for a community's collective value creation under uncertainty.	Square lattice Pack Ring lattice Random Small-world Scale-free	agent-based modeling

The thesis is organized as follows. Chapter 2 reviews the literatures on entrepreneurial action process, graph theory, and computational social science. Chapters 3, 4, and 5 presents the three behavioral models and computational analysis to explore the entrepreneurial dynamics in space-time. Chapter 6 summarizes our finding and propose a synthesized model of entrepreneurial action under various types of uncertainty. We make our conclusions in Chapter 7.

Chapter 2

Literature Review

This chapter reviews the key literatures on two substantive areas, entrepreneurship and pro-social motivation, and two methodological areas, graph theoretic model and computational social science. Specifically, the substantive literatures provide theoretical foundations to rationalize an interaction- and community-based entrepreneurial action process to alleviate the pains and losses after disasters. And the methodological literatures help us formalize those theoretical arguments to explore possible insights.

2.1 Entrepreneurship

2.1.1 Entrepreneurial action framework

Entrepreneurship requires actions. Following Shepherd and Patzelt (2013) and McMullen and Shepherd (2006), the model of entrepreneurial action includes three steps: interpreting environment to identify opportunities for someone (i.e., third-person opportunity), evaluating the feasibility and desirability of an identified opportunity to determine whether it is the opportunity for oneself (i.e., first person opportunity), and engaging or disengaging from action by mobilizing resources and efforts with uncertain outcomes and payoffs (i.e., entrepreneurial action).

The entrepreneurial action literature has extensively explored this entrepreneurial process. Table 2.1 summarizes the possible sources from which an entrepreneurial opportunity may arise. Actors that have the right the knowledge and motivation are able to identify

Table 2.1: Exemplar studies on entrepreneurial opportunity recognition

Sources	**Definitions**
Change in supply	– *Technological change* (McMullen and Shepherd, 2006; Schumpeter, 1934; Shane and Venkataraman, 2000) – *Lead user attributes*: Individuals "whose goal fulfilment is hampered by technological performance bottlenecks" and have the ability to develop "techonolgocal solutions by themselves" (Autio et al., 2013, p.1352) – *Technological probing*: The activity that "users open new discussion threads to signal and frame a new issue, problem, call for advance, or area of exploration" (Autio et al., 2013, p.1353)
Change in demand	– *Prior knowledge* of markets, of customer problems, and of ways to serve customers (Ardichvili et al., 2003) – *Prior knowledge* of customer problems and potential *financial reward* (Shepherd and DeTienne, 2005) – *Entrepreneurial education* (e.g., on underserved markets or of how to produce a particular product) (Mũnoz C. et al., 2011)
Human capital	– *General human capital* (basic skills) and *Specific human capital* (industry-related or technically related skills) (Corbett, 2007)
Environmental sustainability	– *Sustainable entrepreneurship*: "The discovery, creation, and exploitation of opportunities to create future goods and services that sustain the natural and/or communal environment and provide development gain for others" (Patzelt and Shepherd, 2011, p.632; Shepherd and Patzelt, 2011) – *Knowledge of the natural/communal environment*: problems in the natural and communal environment (or market failure); triple bottom line – economic gain, environmental gain, and social gain; understanding the market for natural resourcesrenewable and non-renewable resources; education in forestry, oceanography, and tourism (Patzelt and Shepherd, 2011; Shepherd and Patzelt, 2011) – *Perceptions of threat of the natural/communal environment*: threats to needs for competence, relatedness, and autonomy (Patzelt and Shepherd, 2011) – *Altruism*: "An altruistic motivation arises when individuals experience empathy and sympathy for others" (Patzelt and Shepherd, 2011, p.640)
Operations efficiency	– *Operational entrepreneurship*: "The selection and management of transformation processes for recognizing, evaluating, and exploiting opportunities for potential value creation" (Shepherd and Patzelt, 2013, p.1416)

Sources	Definitions
Learning & Cognition	– *Alertness*: the abstract talent and unique knowledge that leads to the discovery of an opportunity (Kirzner, 1973; Gaglio and Katz, 2001; Gaglio, 2004; Gaimon and Bailey, 2013) – *Counterfactual thinking*: "thinking in a way that is contrary to existing facts" (Gaglio, 2004, p.539) – *Exploration alliances*: join with the motivation to discover something new (Rothaermel and Deeds, 2004) – *Spinoff*: "entrants founded by employees of firms in the same industry" (Klepper and Sleeper, 2005, p.1291) – *Cognitive learning*, *Behavioral learning*, and *Action learning* (Lumpkin and Lichtenstein, 2005) – *Pattern recognition*: comparing the opportunity prototypes of experienced and novice entrepreneurs (Baron and Ensley, 2006) – *Information acquisition* (comprehension over apprehension) and *Information transformation* (extension over intention, promotion over prevention) (Corbett, 2007) – *Entrepreneurial cognition*: "the mental process of overcoming ignorance to inform a third-person opportunity belief" (Shepherd et al., 2007, p.76) – *Knowledge spillover* (Acs et al., 2009) – *Prevention focus*: paying attention to prevention-relevant outcomes, such as threats to the organization (instead of opportunities for the organization) (McMullen et al., 2009) – *Self-compassion* (self-kindness, common humanity, mindfulness) (Shepherd and Cardon, 2009) – *Opportunity-recognition beliefs* (Grégoire et al., 2010) – *Opportunity-image*: potential value (desirability), knowledge relatedness (feasibility), window of opportunity (environment), and number of potential opportunities available (environment) (Mitchell and Shepherd, 2010) – *Self-image*: fear of failure (vulnerability) and entrepreneurial self-efficacy (capability) (Mitchell and Shepherd, 2010) – *Business ownership experience* of an experienced entrepreneur (Ucbasaran et al., 2009) – *Appliance portfolio scope & depth* (Hora and Dutta, 2013)
Network design	– *Formal business networks*: "enables entrepreneurs to share good and bad practice can improve efficiency and social welfare" (Parker, 2008, p.627) – *Network ties*: access to capital and intangible resources (e.g., information, advice, and emotional support) (Hoang and Antoncic, 2003; Jack, 2010) – *Family embeddedness* (Aldrich and Cliff, 2003)

them (e.g., Shepherd et al., 2007; Shepherd, 2010). They next determine whether a third-person opportunity is indeed for oneself and make action decisions in terms of its *feasibility* given the actors' knowledge, skills, and capabilities, and of its *desirability* given the actors' motivation (e.g., Haynie et al., 2009, Phan and Chambers, 2013), see Table 2.2 for a review.

Table 2.2: Exemplar studies on entrepreneurial opportunity evaluation and exploitation

Factors	**Definitions**
Risk perception	– *Overconfidence*: the failure to know the limits of one's knowledge (Keh et al., 2002) – *Belief in the law of small numbers*: the use of a small sample to draw from conclusions (Keh et al., 2002) – *Planning fallacy*: the failure to consider past experiences in similar situations because predictions induce a future orientation (Keh et al., 2002) – *Illusion of control*: the overemphasis on one's ability and skills to control events and people (Keh et al., 2002) – *Entrepreneurial cognition*: "the mental process of reducing doubt to inform a first-person opportunity belief" (Shepherd et al., 2007, p.76)
Profit-maxmization	*Timing of exploitation* theory: "entrepreneurs go through exploration activities to reduce their ignorance and eventually shift their attention to exploitation in order to accrue revenues." (Choi et al., 2008, p.336) – *Optimal stopping* in a POMDP (partially observed Markov decision process) with costly information (Lévesque and Maillart, 2008) – *Entrepreneurial rent*: the economic rents attributable to an entrepreneurial action (Keyhani et al., 2015)
Network design	– *Community attention*: attention received from others in his/her community that facilities insights on unrealised user needs (Autio et al., 2013) – *Community spanning*: participation in several communities (Autio et al., 2013)

Factors	Definitions
Learning & Cognition	– *Exploitation alliances*: "join existing competencies across organizational boundaries in order to generate synergies" (Rothaermel and Deeds, 2004, p.205) – *Perceived knowledge of customer demand*, *perceived development of enabling technologies*, *perceived capability of the management team*, and *perceived stakeholder support* (Choi and Shepherd, 2004) – *Resource relatedness*: relatedness of the entrepreneurs' human capital (e.g., existing knowledge, skills, ability, resources) (Haynie et al., 2009) – *Coporate entrepreneurship*: perceived top management support, perceived work discretion, perceived rewards and reinforcements, perceived time availability, and perceived flexible organizational boundaries (Hornsby et al., 2009) – *Entrepreneurial self-efficacy* (Chen et al., 1998; Fitzsimmons and Douglas, 2011) – *Perceived desirability* (Douglas and Shepherd, 2002; Fitzsimmons and Douglas, 2011)
Operations efficiency	– *Technology commercialisation*: "the translation of technological capabilities into beneficial products and services that increase profit and/or social welfare" (Krishnan, 2013, p.1443) – *Product/service design* (Loch and Terwiesch, 2005; Joglekar and Lévesque, 2013) – *Product/service integration* with one or more complementary technologies (Anderson Jr. and Parker, 2013) – *Operational capabilities* (Tatikonda et al., 2013)

Feedback from exploiting an existing opportunity in discovering subsequent opportunities plays a significant role in this dynamic entrepreneurial process (Shepherd and Patzelt, 2013). The feedback may take two possible forms: (1) a temporal process that one actor's current entrepreneurial action may change his/her ability and ability and motivation to evaluate subsequent opportunities (McMullen and Dimov, 2013), and (2) a spatial process that other actors' entrepreneurial actions can enhance his/her recognition of subsequent opportunities (Shepherd, 2010). In this sense, entrepreneurship is a spatiotemporal process of identification, evaluation, and exploitation of opportunities for potential value creation arising from direct and indirect interactions among potential actors networked with each other.

To recognize opportunities in a networked system, spatial feedback directs actors' attention to possible entrepreneurial spillover from others. Actors raise their awareness of entrepreneurial action launched by a connected actor that disrupts the existing market and equilibrium. By doing so, they are likely to discover opportunities for potential value creation and receive forward-looking benefits of entrepreneurial spillover flowing from the connected actor (Gaimon and Bailey, 2013; Shepherd and Patzelt, 2011). Examples include a new venture spinoff from a parent firm (Klepper and Sleeper, 2005), a technology startup with knowledge transferred from labs and universities (Keyhani et al., 2015; Markman et al., 2005), and a novice entrepreneur inspired by and learned from an experienced entrepreneur (Parker, 2008; Phan and Chambers, 2013). Thus, in a networked system, opportunities may take the forms of possible spillover fed back from other actor's entrepreneurial action.

Actors next evaluate an identified opportunity on its feasibility, i.e., knowledge and abilities to capture the entrepreneurial spillover, if any, in the presence of market imperfection, and desirability, i.e., the spillover from a connected actor is positive to his/her own value creation (Haynie et al., 2009; McMullen and Shepherd, 2006). They have to overcome frictions arising from imperfection in the economy, such as transactional costs and barriers to trade (e.g., Chatain and Zemsky, 2011), to actually get access to the value spilled over from a neighboing entrepreneur. Such friction gives advantage to some actors over others for entrepreneurial rent (Keyhani et al., 2015), which creates barriers to spillover and diminishes the degree of feedback. Yet the spillover does not always take the form of positive value creation to connected others. Rather, it is possible that an entrepreneur brings damage to the networked system, such as overexploitation of public goods and being environmentally unfriendly (e.g., Santos et al., 2008; Shepherd et al., 2013). This negative feedback, intuitively, is not desirable to his/her connected actors who would suffer additional potential costs for exploitation. In the long term, the actor self is likely to be punished by receiving no valuable spatial feedback from connections (Nowak, 2006; Ohtsuki et al., 2006).

As a result, actors' interdependent entrepreneurial-action decisions lead to the spatiotemporal dynamics of entrepreneurship. A number of actors acting entrepreneurially, i.e., entrepreneurs, create values to self and others and promote the identification of subsequent opportunities in the networked system (Shepherd and Patzelt, 2013). That is, we conceptualize the role of feedback in the action-based entrepreneurship framework as a facilitator of opportunity identification, evaluation, and exploitation for value creation in a networked system in which potential entrepreneurial actors are embedded.

2.1.2 Entrepreneurial bricolage framework

Entrepreneurial bricolage framework suggests that entrepreneurs take a different route to identify and exploit opportunities under substantial resource constraints. The notion "bricolage" is defined as "making do by applying combinations of resources at hand to new problems and opportunities" (Baker and Nelson, 2005, p.33). So facing with penurious environment, someone engaged in bricolage refuses to enact resource limitations but make do with what is at hand to solve problems (Baker, 2007; Desa, 2012). Entrepreneurial bricolage captures the process that entrepreneurs, while typically do not possess rich resources (Shepherd et al., 2000), can leverage the physical, customer/markets, skills, labor, and institutional inputs at hand in novel ways to discovery opportunities (Di Domenico et al., 2010; Hoegl et al., 2008; Shepherd and Williams, 2014; Zahra et al., 2009).

Specifically, entrepreneurs may enact bricolage by making do physical materials that are rejected or ignored by other firms with new use-value (Baker, 2007). For instance, a UK-based social enterprise acquired disused fire station building and turned it into a community center; another entrepreneur collected and refurbished the discarded computers from corporations for community use (Di Domenico et al., 2010). Second, by creating products or services that would otherwise be unavailable, entrepreneurs enact bricolage to make do customers/markets resources (Baker and Nelson, 2005). Third, entrepreneurs act as bricoleurs utilize skills inputs that permit and encourage the use of amateur and self-taught skills that would otherwise go unapplied (Fisher, 2012). For example, they can recruit people that are low-skilled or long-term unemployed to provide front-line training to the youth (Di Domenico et al., 2010). Fourth, entrepreneurs can involve stakeholders, such as customers, suppliers, and members of local communities, in decision making and corporate governance, i.e., making do labor resources (Garud and Karnøe, 2003; Shepherd and Williams, 2014). Finally, entrepreneurs may refuse to enact institutional limitations (e.g., rules and regulations) and try to actively engage in the construction of new laws from fragments of existing ones (Di Domenico et al., 2010).

Literature suggests that bricolage activities have both positive and negative impacts. On one hand, entrepreneurial bricolage is effective when other options is to wait for do nothing, i.e., refusal to enact resource constraints and discovery of opportunity in pursuit of market creation (e.g., Baker and Nelson, 2005) and nascent firm growth (e.g., Baker et al., 2003; Senyard et al., 2009). This is particularly successful when entrepreneurs only engage in making do selective types of inputs (Di Domenico et al., 2010). On the contrary, extensive bricolage in multiple types of inputs will result in bricolage "trap" that restricts firm growth (Baker and Nelson, 2005; Fisher, 2012). That is, the solutions built through bricolage are likely to be imperfect (due to the resource constraints) that can hardly meet high quality standards. Hence, entrepreneurs engaged in high level of bricolage may find it difficult to compete with other firms that are less resource constrained and/or satisfy demanding customers (Ciborra, 1996). In sum, bricolage can enable entrepreneurs to overcome resource limitations in the short term, but it can also lock the firm in a reinforcing cycle of providing 'good-enough-only' products/services that harm long-term growth.

2.1.3 Summary: A community-based entrepreneurial action process

Entrepreneurship is the pursuit of opportunity to create value with uncertain outcomes (McMullen and Shepherd, 2006; Shepherd and Patzelt, 2013). The entrepreneurship literature well recognizes the fact that entrepreneurial opportunities are not a product of a solo act, but are rather developed and refined through social interaction and feedback from community members (Autio et al., 2013; Peredo and Chrisman, 2006; Shepherd, 2015). Despite the centrality of community as a perspective and unit of analysis in entrepreneurship, current research tends to treat it as an exogenous environmental factor (e.g., Ardichvili et al., 2003. In this thesis, we explicitly adopt the interaction and community-based perspective to entrepreneurship and theorize entrepreneurs as actors embedded in a network where they recognize, evaluate and exploit potential opportunities within a local economy.

Specifically, an actor interprets the external world and interacts with other actors in the community and, depending on certain prior knowledge and motivation, the actor forms a 'third-person opportunity belief'. That is, the actor perceives that opportunities exist for someone (Patzelt and Shepherd, 2011; Shepherd and DeTienne, 2005; Shepherd et al., 2007). Next, the actor evaluates the feasibility and desirability of a recognized opportunity to form a 'first-person opportunity belief'. In other words, the actor perceives that the opportunity is desirable for him/herself (Autio et al., 2013; Haynie et al., 2009; Shepherd et al., 2007). Finally, the actor engages in a decision making process and decide whether to continue or discontinue the entrepreneurial action by mobilizing resources and people and bear the uncertain outcomes (Choi et al., 2008; Choi and Shepherd, 2004; Lévesque and Maillart, 2008). Although the entrepreneurial action mechanism describes what happens in the market context, it is relevant and applicable to the non-market context such as disasters.

2.2 Pro-social motivation

Once a disaster occurs, pro-social motivation directs an actor's attention to others' suffering and to act entrepreneurially to help and improve others' welfare (Grant, 2007; Grant and Berry, 2011). Prosocial motivation involves the pursuit of multiple goals that include the desire to sustain personal gains (pro-self interest) and to alleviate others' suffering (pro-social interest) (Baron and Ensley, 2006; Penner et al., 2005). For instance, an actor and member of the community may be willing to alleviate the suffering of other less fortunate members because the actor wishes to maintain long-term relationships with them. On the other hand, the actor may do so out of sympathy for others' loss and feel that it is the right thing to do. Therefore, there are two forms of prosocial motivation (Miller et al., 2012): compassion, where pro-social acts are driven by a genuine concern for others; and reciprocal altruism, where pro-social acts are driven by an expectation of future payback by others, and not at the expense of self-interest.

2.2.1 Compassion

Compassion is the disposition to respond empathically to others' pain and stress. In other words, other's suffering can motivate actors to help and benefit others (Dutton et al., 2006; Rynes et al., 2012). When a disaster hits a community, people with the sense of compassion will pay more attention to the needs of suffering others in the local area (e.g., Shepherd and Williams, 2014) by feeling the pains and losses of others and/or coordinate actions to alleviate them. For instance, a non-for-profit organization may distribute the gains from its operation to the victims in the community. Following this logic, compassion often drives action that is costly to oneself but beneficial for others (Batson and Shaw, 1991; Miller et al., 2012).

2.2.2 Reciprocal altruism

Altruism, the desire to help others at one's own costs (Nowak, 2006; Penner et al., 2005), has been acknowledged as a driver to motivate opportunity recognition (e.g., Patzelt and Shepherd, 2011, Zahra et al., 2009) in a system. However, following the reciprocal altruism theory in evolutionary research (e.g., Axelrod and Hamilton, 1981, Nowak, 2006, and Trivers, 1971), altruistic actions occur and evolve only under highly specialized circumstance where the altruists act will eventually returned to him/her and confer (directly or indirectly) its benefit (Nowak et al., 2010; Penner et al., 2005; Trivers, 1971). In other words, reciprocity forms the motive future benefits of an altruistic action will compensate the current sacrifice to help others.

Evolutionary theorists define altruism in terms of consequences, i.e., evolutionary success, instead of motivation (Penner et al., 2005). Evolutionary success is measured as the survival of ones genes in subsequent generations. Five major mechanisms or processes are identified leading to evolutionary success kinship selection, direct reciprocity, indirect reciprocity, group selection and network reciprocity (Nowak, 2006; 2012).

In kinship systems, kin members are genetic related such as parents, siblings, and children, which determine their closeness. There is an evolutionary benefit to those who help close relatives rather than non-relatives (Hamilton, 1964). Direct reciprocity extends the kinships to friendships and long-term cooperative alliances. There is evolutionary advantage to help (genetically) unrelated individuals if the favor is repaid during repeated encounters (Trivers, 1971). Indirect reciprocity, on the other hand, rewards the altruists by establishing a good reputation (Nowak and Sigmund, 2005). Group selection investigates the multilevel (individual and group levels) selection. A group with a larger number of altruists will have an advantage over a group with mostly selfish individuals (Traulsen and Nowak, 2006). Finally, network reciprocity acknowledges that some actors interact more often than others in the real-world social networks; hence it explores the network configuration that allows altruists help each other and form clusters (Lieberman et al., 2005), the focus of this study.

Formally, the altruistic activity occurs when the benefit-to-cost ratio, b/c, exceeds the average number of connected neighbors, w, per actor (i.e., $b/c > w$), where c is the cost to the altruist for helping others, b is the benefit to the recipient in expectation of returning back to the altruist, and w is determined by the network configuration of the community (Lieberman et al., 2005; Nowak, 2006; Ohtsuki et al., 2006). In essence, reciprocal altruism is a social interaction phenomenon where an individual makes sacrifices for another individual in expectation of similar treatment in the future.

In the next section, we elaborate the spatial dimension of entrepreneurship using the graph theoretic methods.

2.3 Graph theoretic method

The graph theoretic method models the possible network configurations of community in which 'prospective' entrepreneurs are embedded to take actions amid disasters. Before introducing the detailed network structures, we first review the terminologies in this field.

2.3.1 Primer on graphs and terminology

A *weighted directed* graph $(\mathbf{\Omega}, \mathcal{N}, \mathbf{\Lambda})$ is a collection of n "nodes" (or vertices) $\mathbf{\Omega} = \{\omega_1, \omega_2, \cdots, \omega_n\}$ with their own rules of behavior, the "arcs" (or edges, links) $\mathcal{N} = \{\mathbb{I}_{ij}(G)\}$ that are directed connections from node i to node j embedded in certain network structure G, and the "arcs weights" $\mathbf{\Lambda} = \{\lambda_{ij}\}$ that are the corresponding degree of connections between the linked nodes, where $i, j \in \{1, 2, \cdots, n\}$. A graph is said to be directed and weighted when the arcs and arcs weights are asymmetric, i.e., $\mathbb{I}_{ij}(G) \neq \mathbb{I}_{ji}(G)$ and $\lambda_{ij} \neq \lambda_{ji}$. (On the contrary, an *undirected* graph is formed with unordered arcs between connected nodes, without regard to whether the link points from i to j or the other way around, and symmetric arc weights: $\mathbb{I}_{ij}(G) = \mathbb{I}_{ji}(G)$ and $\lambda_{ij} = \lambda_{ji}$. Since this study uses the weighted directed graph only, the following sections will use graph/network and weighted directed graph interchangeably.)

For any ordered pair of nodes (i, j), the arc $\mathbb{I}_{ij}(G)$ takes two possible values, 0 or 1, i.e., $\mathbb{I}_{ij}(G) \in \{0, 1\}$. We have $\mathbb{I}_{ij}(G) = 1$ only if a directed link is drawn from node i to node j, denoted as $i \sim j$; in other words, i is j's (first-order) neighbor. Then, $0 \leq \lambda_{ij} \leq 1$ is a measure of their degree of connection, with larger values leading to stronger connection between nodes. Note that in a weighted directed graph, a link from i to j does not imply a link from j to i. The number of nodes that i connects to is defined as its "out-degree" , the number of connections node i have is $\kappa_{(out),i} \equiv \sum \mathbb{I}_{ij}(G)$, and the number of nodes that connect to node i is defined as i's "in-degree" , the number of connections from other nodes to node i is $\kappa_{(in),i} \equiv \sum \mathbb{I}_{ji}(G)$.

A simple weighted directed graph is illustrated in Figure 1, for $n = 6$, and also represented by an incidence matrix in Table 2.3, where a one is recorded in the cell of row i and column j if node i is linked to node j and zero otherwise. Then, the out-degree of each node is the number of 1's in each row, whereas the in-degree is the number of 1's in each column. Note that the incidence matrix of a directed graph may not be symmetric. Yet the total in-degree and out-degree of all nodes are always the same, equal to the total number of connections, denoted M, where $M = 8$ in the example.

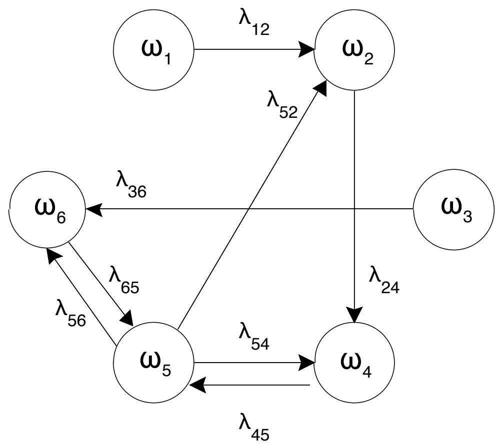


Figure 2.1: A weighted directed graph

Table 2.3: An incident matrix

	1	2	3	4	5	6	$\kappa_{(out),i}$
1	–	1	0	0	0	0	1
2	0	–	0	1	0	0	1
3	0	0	–	0	0	1	1
4	0	0	0	–	1	0	1
5	0	1	0	1	–	1	3
6	0	0	0	0	1	–	1
$\kappa_{(in),i}$	0	2	0	2	2	2	**8**

Based on the incident matrix in Table 2.1, we formalize the graph as $\boldsymbol{\Omega} = \{\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6\}$,

$$\mathcal{N}_{6\times 6} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad \text{and} \quad \boldsymbol{\Lambda}_{6\times 6} = \begin{bmatrix} 0 & \lambda_{12} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \lambda_{24} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda_{36} \\ 0 & 0 & 0 & 0 & \lambda_{45} & 0 \\ 0 & \lambda_{52} & 0 & \lambda_{54} & 0 & \lambda_{56} \\ 0 & 0 & 0 & 0 & \lambda_{65} & 0 \end{bmatrix}.$$

The structure matrix (of arcs) $\mathcal{N}$ and the degree matrix (of arc weights) $\boldsymbol{\Lambda}$ both have n rows and n columns, as well as zero diagonal for irreflexive connections. Matrix $\mathcal{N}$ illustrates the structure of network connection, which characterizes the space dynamical property of a networked system, and matrix $\boldsymbol{\Lambda}$ describes the degree of connection, which regulates the time dynamical property of a networked system. So, these two matrices together depict how nodes interact with each other over time and over space (Albert et al., 2000; Rivkin and Siggelkow, 2007; Szabó and Fáth, 2007).

In general, a structure matrix has $n \times n$ entries, but only $(n^2 - n)$ of its elements can be chosen freely for an asymmetric irreflexive arc. Thus, there can be at most $(n^2 - n)$ arcs, i.e., $0 \leq M \leq (n^2 - n)$. If M take the largest value possible, then every node is connected to every other; if $M = 0$, then the graph only has independent nodes with no arc in between. In these two extreme cases, only one corresponding structure matrix exists. If $M = 1$, there are $(n^2 - n)$ possible structure matrices, depending which arc of the ordered pair of nodes is the one. In other words, there are $\binom{n^2-n}{M}$ or $\frac{(n^2-n)!}{M!(n^2-n-M)!}$ possible structure matrices. For instance, a graph of $n = 6$ and $M = 8$ yields $\binom{30}{8} = 5.85 \times 10^6$ possible structure matrices, suggesting various topological patterns of arcs, i.e., network structures.

2.3.2 Network structures

To investigate and categorize the implied network structures, graph theorists have proposed two measures[1] – degree distribution and average path length (e.g., Barabási and Albert, 1999; Watts and Strogatz, 1998). First, the out-degree and in-degrees distributions, which describe the probability of finding exactly $\kappa_{(out)}$ and $\kappa_{(in)}$ arcs, are the most important topological properties of a weighted directed graph. This measure roughly divide graphs into two groups. Regular graphs have a structure in which all the nodes have the same number of arcs; that is, the out-degrees (in-degrees) of all the nodes are drawn from a delta distribution. The structure matrix $\mathcal{N}$ specifies the out-degree and in-degree of each node by row sum and column sum, respectively. Therefore, the structure matrix of a regular graph has the same number of 1's on each row (column). The other group of complex networks have structures that allow some heterogeneity among the number of arcs. Their out- and in-degree distributions can take the form of Poisson, power-law, exponential, or be arbitrary specified (e.g., Newman et al., 2001). Our example falls into the second group because the six nodes do not have the same out- and in-degrees and node 5 has a relatively larger number of connections.

Second, a path from node i to node j is an adjacent sequence of arcs $\mathbb{I}_{iu_1}(G) = 1, \mathbb{I}_{u_1u_2}(G) = 1, \cdots, \mathbb{I}_{u_kj}(G) = 1$. (Note that in a directed graph, a path from i to j does not imply a path from j to i.) Then the path length is one more than the smallest k for which such a path exists. For an arc $\mathbb{I}_{ij} = 1$, the path length is 1 as $k = 0$. Take the graph in Figure 2.1 as an example. There are two paths from nodes 5 to 4: an arc from 5 to 4 with $k = 0$ and a

[1]Clustering coefficient is another popular measure, the likelihood of two nodes building an arc (i.e., a direct connection) if they have another connection in common. However, it applies only to undirected graphs; so not included in this study.

sequence of two arcs from 5 to 2 to 4 with $k = 1$. So, by taking the smallest $k\,(= 0)$, the path length from node 5 to node 4 is 1. Following this logic, we can calculate the average path length by taking the mean value of path lengths between all pairs of nodes. In general, regular graph structures tend to be associated with longer average path length than complex graph structures (e.g., Albert et al., 2000; Newman and Watts, 1999).

Measuring the specified two properties of a graph, the out- and in-degree distributions and the average path length, is the first step towards understanding its structure. Next, we will discuss the topological features of six well-established graphs, $G = 1, 2, \cdots, 6$, so as to investigate the spatiotemporal dynamics of entrepreneurial action in a networked system. Specifically, they are *square lattices* ($G = 1$), *packs* ($G = 2$), *ring lattices* ($G = 3$), *random* ($G = 4$), *small-world* ($G = 5$), and *scale-free* ($G = 6$). The six network structures in our study can be further divided into two groups. $G = 1, 2, 3$ are regular graphs where each node is connected with the exact number of neighboring nodes. In other words, the out- and in-degree distributions are uniform (Szabó and Fáth, 2007), i.e.,

$$f(\kappa_{(out)}) = \delta(\kappa_{(out)} - \kappa_{(out),0}), \quad f(\kappa_{(in)}) = \delta(\kappa_{(in)} - \kappa_{(in),0}).$$

Numerically, all nodes have the same out-degree (in-degree) – each row (column) of the connection matrix has the same number of 1's. Considering a graph of n interacting nodes, in our study, $\forall\, \omega_i \in \mathbf{\Omega}$, $\kappa_{(out),i} = 4$ and $\kappa_{(in),i} = 4$ if the graph has $\mathcal{N} = \{\mathbb{I}_{ij}(G)\}$, $G = 1, 2, 3$.

The other three types allow for more heterogeneity among the connections. For instance, the graph in Figure 1 is embedded in a random topology ($G = 4$) where the arcs are placed between pairs of nodes chosen uniformly at random. The resulting in-degree distribution and out-degree distributions are binomial, or Poisson in the limit of large graph size ($n \to \infty$):

$$f(\kappa_{(out)}) = \frac{z_1^{\kappa_{(out)}} \mathrm{e}^{-z_1}}{\kappa_{(out)}\,!}, \quad f(\kappa_{(in)}) = \frac{z_2^{\kappa_{(in)}} \mathrm{e}^{-z_2}}{\kappa_{(in)}\,!},$$

where z_1 and z_2 are the values of the mean out-degree and mean in-degree of the graph. Scale-free networks ($G = 6$), instead of taking a poisson form, have a power-law tail (Barabási and Albert, 1999),

$$f(\kappa_{(out)}) \propto \kappa_{(out)}^{-\gamma_{out}}, \quad f(\kappa_{(in)}) \propto \kappa_{(in)}^{-\gamma_{in}},$$

where typically $2 < \gamma_{out}, \gamma_{in} < 3$, for instance, $\gamma_{out} \simeq 2.45$ and $\gamma_{in} \simeq 2.1$ for the world-wide web (Albert et al., 1999). This distribution allows for a few actors of very large in- and out-degree to exist. In general, for some ω_i, $\omega_j \in \mathbf{\Omega}$ and $i \neq j$, $\kappa_{(out),i} \neq \kappa_{(out),j}$ and/or $\kappa_{(in),i} \neq \kappa_{(in),j}$ if the graph has $\mathcal{N} = \{\mathbb{I}_{ij}(G)\}$, $G \in \{4, 5, 6\}$. Accordingly, we are able to explore whether entrepreneurship can thrive in certain directed graphs.

Square lattice ($G = 1$) networks. On a square lattice network we consider the standard *von Neumann* neighborhood including four neighbors to the east, south, west, and north, $\kappa_{(in),i} = \kappa_{(out),i} = \kappa_i = 4$ (e.g., Hauert and Szebó, 2003; Ohtsuki et al., 2006). The lattice then characterizes a system where the behavior of each node depends much more upon the behavior of its nearest connections than that of distant connections. When making an decision on entrepreneurial tasks, for instance, one individual is more likely to be influenced by his/her spouse than distant relatives. Square lattices is an initial network structure for the creation of more realistic graphs, introduced later.

This network topology has been widely studied in evolutionary game theory literature. Scholars place individual players in a two-dimensional spatial array and investigate their interaction to examine the emergence of cooperative behaviors (Hauert and Szebó, 2003; Lieberman et al., 2005; Nowak and May, 1993). They find that the connection structures have pronounced effects on the fate of cooperators, who pay a cost for another individual to receive a benefit: A single cooperator could be wiped out immediately by several neighboring defectors, who pay no cost and do not distribute benefits; a cluster of cooperative neighbors, on the contrary, can help each other such that cooperation thrives in the network (Hauert and Szebó, 2003; Lieberman et al., 2005; Nowak, 2006; Ohtsuki et al., 2006).

In our study, we arrange n nodes into a square lattice network that has c columns and r rows. So, a actor i will be located at row $\{\lfloor i/c \rfloor\}$ and column $\{i - (\lfloor i/c \rfloor) \times c\}$, where $\lfloor x \rfloor$ is the largest integer not greater than x. No statistical rule is needed to define the lattice's degree distribution because the number of degrees (4) is the same for each node. The topological rule is that each actor is connected to all of its four nearest neighbors:

Algorithm 1 (Square lattice networks)**.** *Choose* $i = 0, 1, \cdots, n-1$*,*

Connect actors to north neighbors;

  if $\lfloor i/c \rfloor < r$

    set $\mathbb{I}_{i,i+c}(1) = 1$*;*

  else

    set $\mathbb{I}_{i,i+c-n}(1) = 1$*;*

Connect actors to east neighbors;

  if $i - (\lfloor i/c \rfloor) \times c < c$

    set $\mathbb{I}_{i,i+1}(1) = 1$*;*

  else

    set $\mathbb{I}_{i,i+1-c}(1) = 1$*;*

Connect actors to south neighbors;

  if $\lfloor i/c \rfloor = 0$

    set $\mathbb{I}_{i,i+(r-1)\times c}(1) = 1$*;*

  else

    set $\mathbb{I}_{i,i-c}(1) = 1$*;*

Connect actors to east neighbors;

  if $i - (\lfloor i/c \rfloor) \times c = 0$

    set $\mathbb{I}_{i,i+c-1}(1) = 1$*;*

  else

    set $\mathbb{I}_{i,i-1}(1) = 1$*.*

Pack ($G = 2$ ***) networks.*** The topology of pack networks has the key property of nearly decomposability (Simon, 1962) and is related to the notion of modularity (Baldwin and Clark, 2000). Specifically, nodes form cliques for decision-making such that nodes within each clique all connect with each other but are relatively weakly connected to nodes in other cliques. In other words, the cliques are discernable, at the same time are dependent through cross-clique connections. In the short run, the dynamics of one clique is approximately independent of another clique, whereas the long-run dynamics of any clique depends on all other cliques in an aggregate way (Simon, 1962).

A number of physical and social networks in product and organization design demonstrate this topological characteristic in pursuit of desirable outcomes (Ethiraj and Levinthal, 2004). For instance, an organizational structure combined with formal and informal communication networks is nearly decomposable for knowledge searching and sharing so that the organization's innovation quality can be enhanced (Yayavaram and Ahuja, 2008). Following Rivkin and Siggelkow (2007), we will compare pack networks to other graphs to examine the entrepreneurial action dynamics.

In our study, we arrange n nodes into $n/4$ packs (i.e., cliques) so that each pack has four nodes. Specifically, node i will be located at pack J_q if $4(q-1) \leq i < 4q$, where $q = 1, \cdots, n/4$. The nodes in the same pack are densely connected among themselves, while packs are loosely coupled. We create the pack network in two steps:

Algorithm 2 (Pack networks)**.**

Connect actors within the packs;

Choose $i = 0$*,*

repeat

$\mathbb{I}_{4i,4i+1}(2) = \mathbb{I}_{4i,4i+2}(2) = \mathbb{I}_{4i,4i+3}(2) = 1,$

$\mathbb{I}_{4i+1,4i}(2) = \mathbb{I}_{4i+1,4i+2}(2) = \mathbb{I}_{4i+1,4i+3}(2) = 1,$

$\mathbb{I}_{4i+2,4i}(2) = \mathbb{I}_{4i+2,4i+1}(2) = \mathbb{I}_{4i+2,4i+3}(2) = 1,$

$i = i + 1;$

until $i = n/4 - 1.$

Connect actors across the packs;

Choose $i = 0, 1, \cdots, n-1,$

if $i < n - 4$

$\mathbb{I}_{i,i+4}(2) = 1;$

else

$\mathbb{I}_{i,i+4-n}(2) = 1.$

Ring lattice ***(****$G = 3$****) networks.*** In a ring lattice network, each node is assumed to be connected by its adjacent neighbors on either side of it. This topolog describe a sequentially interdependent system: nodes are in series where the behavioral output of one node becomes the input to another one (Thompson, 1967). In production systems, loop-based plant layout is one common design of facility planning and material handling (Asef-Vaziri and Laporte, 2005). Interfirm examples include the various buyer-supplier relationship along a value chain or a logistic chain (Kumar and van Dissel, 1996).

Pulling one node out of a loop is like breaking the chain; the subsequent set of nodes will be negatively affected (Kumar and van Dissel, 1996). In extreme cases, the whole system may cease to function. For instance, the literature on supply chain disruption has investigated this distinctive phenomenon. One entity that hit by unanticipated and unplanned events cannot support the normal flow of goods and materials within a supply chain. Consequently, all supply chain entities are exposed to operational and financial risks (Craighead et al., 2007; Kleindorfer and Saad, 2005). Therefore, the behavior of any node is likely to affect at least the adjacent and possibly all nodes in the system. According to Ohtsuki et al. (2006), cooperative actions will be refrained if one cooperator is surrounded by defective neighbors. Following this logic, we will investigate the impact of ring lattices on the fate of entrepreneurs.

In our study, we spread out n nodes on a ring. Each node is connected to four adjacent neighbors, for instance, node 5 is affected by nodes 3 and 4 on its left side, as well as by nodes 6 and 7 on its right side. Specifically,

Algorithm 3 (Ring lattice networks)**.** *Choose* $i = 0, 1, \cdots, n-1$,

Connect actors to nearest right neighbors;

    if $i < n-1$

        set $\mathbb{I}_{i,i+1}(3) = 1$;

    else

        set $\mathbb{I}_{i,i+1-n}(3) = 1$;

Connect actors to next-nearest right neighbors;

    if $i < n-2$

        set $\mathbb{I}_{i,i+2}(3) = 1$;

else

set $\mathbb{I}_{i,i+2-n}(3) = 1$*;*

Connect actors to nearest left neighbors;

if $i > 0$

set $\mathbb{I}_{i,i-1}(3) = 1$*;*

else

set $\mathbb{I}_{i,i+n-1}(3) = 1$.

Connect actors to nest-nearest left neighbors;

if $i > 1$

set $\mathbb{I}_{i,i-2}(3) = 1$*;*

else

set $\mathbb{I}_{i,i+n-2}(3) = 1$.

Random (*$G = 4$****) graphs.*** A random graph $G_{n,M}$ consists of n nodes and M acrs (Erdős and Rényi, 1960), where the connections between nodes are drawn randomly. Consequently, every node does not necessarily have the same number of out- and in-degrees as nodes embedded in regular graphs.

Traditionally, networks of complex topology have been described as random graphs. Epidemiology (Kretzschmar and Morris, 1996), ecological food web (Williams and Martinez, 2000), and many other fields have employed random graphs as models of real-world networks. For instance, the susceptible–infectious–recovered epidemiological models frequently make an assumption of fully mixed approximation. That is, the contact (i.e., arcs) between nodes, either infected with the disease or susceptible to it, are random (Kretzschmar and Morris, 1996). However, studies show that random graphs cannot fully capture the real-world phenomena (Williams and Martinez, 2000), whereas small-world and scale-free networks provide a better understanding on the topological properties of large networks (Newman et al., 2001), introduced next.

To generate a random graph in our study, we simply throw down M arcs between node paris chosen at random from n initially unconnected nodes, with the constraint that any pair of nodes cannot have more than two connections from the same direction. In other words, the elements in the structure matrix, $\mathcal{N}$, can only take values of 0 and 1.

Algorithm 4 (Random graphs)**.**

Choose $k = 1$*,*

repeat

Take a random pair of nodes (i, j)*,* $i, j = 0, 1, \cdots, n-1, i \neq j$*, and* $i \nsim j$*,*

$\mathbb{I}_{ij}(4) = \mathbb{I}_{ji}(4) = 1$,

$k = k + 1$*;*

until $k = 2n$.

Small-world (**$G = 5$**) networks. Following Watts and Strogatz (1998), a small-world network is created from a ring lattice network by randomly rewiring a fraction α of connections in a way that conserve the out- and in-degree for each node. In the limit $\alpha \to 0$ the depicted topology is equivalent to a ring lattice network. If all connections are randomly rewired ($p = 1$), we derive a random graph. That is, the small-world network interpolates between ring lattice network and random graph. After all, most of real-world networks are neither entirely regular nor entirely random. Graphically, most nodes embedded in the small-world network are connected to the adjacent neighbors, yet a few have distant connections.

In the language of graph theory, the core features of small-world networks are both high clustering, like ring lattice networks, and short path length, like random graphs (Newman, 2001; Watts and Strogatz, 1998). First, clustering measures the likelihood of two nodes building a direct connection if they have another neighbor in common. Watts and Strogatz (1998) define a network having high clustering if it is much greater than a random graph of the same population size and average out- and in-degrees. As to the path length, regular graphs, such as square lattice and ring lattice networks, that do not offer short path length for remote node pairs because a long and circuitous route is required to connect them. Examples include two nodes located on posit sides of the loop. In this sense, the distant connections in the small-world topology create "shortcuts" within the network (Milgram, 1967; Newman and Watts, 1999). They significantly reduce the path length between randomly chosen pair of nodes. Accordingly, the average path length of the small-world network is relatively short.

The small-world topology has been documented in many real-world networks, including alliance network of U.S. firms (Schilling and Phelps, 2007), business networks of board interlocks of the Fortune 1000 companies (Newman et al., 2001), neural network of the nematode worm *C. elegant* (Watts and Strogatz, 1998), collaboration networks of scientists (Newman, 2001) and power grid of the western U.S. (Watts and Strogatz, 1998). Generally, entities embedded in small-world networks can efficiently access a wide range of connections due to short path length and are likely to cooperate due to high clustering. Thus, this network topology has been recognized as an important structure to foster innovation (Schilling and Phelps, 2007; Uzzi and Spiro, 2005).

In our study, following the algorithm by Watts and Strogatz (1998), we allocate n nodes on a ring lattice network, then randomly rewire each arc of the network with probability α. Note that we allow varying α such that the transition between regular ($\alpha = 0$) and random ($\alpha = 1$) can be closely monitored.

Algorithm 5 (Small-world networks)**.** *Set a rewiring probability* $\alpha \in [0, 1]$.

Choose $i = 0$,

repeat

Take a random number $r_1 \in (0, 1)$,

if $r_1 < \alpha$

choose a random actor $j \neq i$ *and* $j \nsim i$,

$\mathbb{I}_{ij}(5) = \mathbb{I}_{ji}(5) = 1$,

else

if $i < n - 1$

$\mathbb{I}_{i,i+1}(5) = \mathbb{I}_{i+1,i}(5) = 1$,

else

$\mathbb{I}_{i,i+1-n}(5) = \mathbb{I}_{i+1-n,i}(5) = 1$;

Take a random number $r_2 \in (0, 1)$,

if $r_2 < \alpha$

choose a random actor $j \neq i$ *and* $j \nsim i$*,*

$\mathbb{I}_{ij}(5) = \mathbb{I}_{ji}(5) = 1,$

else

if $i < n - 2$

$\mathbb{I}_{i,i+2}(5) = \mathbb{I}_{i+2,i}(5) = 1,$

else

$\mathbb{I}_{i,i+2-n}(5) = \mathbb{I}_{i+2-n,i}(5) = 1;$

$i = i + 1;$

until $i = n - 1.$

Scale-free (**$G = 6$**) networks. In a scale-free network, the out- and in-degree distributions have power-law tails, indicating that some nodes have significantly larger connections than others (Albert et al., 1999; Barabási and Albert, 1999). As such, those highly connected nodes affect a great number of others' decisions. This distinctive phenomenon is practically absent in random graphs and Watts-Strogatz small-world networks, where the probability of finding a node with large degree decreases exponentially with the κ value (Albert et al., 2000). Comparing to the other five graphs, we have a large chance to find highly connected nodes in a scale-free network.

To explain the origin of power-law tails, Barabási and Albert (1999) proposed a model based on preferential attachment. In their model, starting with a small number of nodes, network expands by the continuous addition of new nodes to the system. The new node connects to the existing nodes, not randomly, but based on their degrees. Specifically, the probability that the new one links to a highly connected node is much greater than that the new one links to other nodes with small connections. In other words, the existing nodes gain new connections in proportion to the number they already have (Albert and Barabási, 2002); thus, an initial heterogeneity in out- and in-degrees will further increase as the network expands. This is also called the "rich–become–richer" phenomenon. The absence of preferential attachment eliminates the scale-free feature of the degree distribution.

A number of networks have been shown to be scale-free such as the world-wide web

(Albert et al., 1999), the physical Internet (Faloutsos et al., 1999), transportation network (Banavar et al., 1999), and citation network (Redner, 1998). In this sense, we may consider prospective techonogy-based entrepreneurs, who identify opportunities arising from social media and other web tools, as nodes embedded in scale-free networks. Then the highly connected nodes are responsible for the reduction of average path length of the network, which facilitates better coordination and flow of information and higher degree of robustness against random failures (Albert et al., 2000). For instance, our ability to locate information on the web is not affected by the temporary unavailability of some web pages. It is worth noting that the robustness property is not shared by random graphs and small-world networks, as it is much easier to remove a few actors to tear the network apart. Consequently, we expect that the dynamics of entrepreneurship actions in a scale-free network is not likely to be disrupted by disastrous events.

We propose a model in which the network expands by the addition of one new node at one time, with two in-degrees and two out-degrees linking to the nodes already in the network. New nodes will preferentially connect to two existing nodes with large degrees. As such, the total number of connections (M) is comparable to that of the other five networks of the same size.

Algorithm 6 (Scale-free networks)**.**

Choose $i = 0, 1, 2, 3, 4$,

set $\mathbb{I}_{i,i+1}(6) = 1$ *for* $i = 0, 1, 2, 3$ *and* $\mathbb{I}_{i,i-4}(6) = 1$ *for* $i = 4$.

Growing and preferentially connecting,

Choose $i = 5$,

repeat

choose node j *with a probability of* $\kappa_j / \sum_j \kappa_j$, $j = 0, 1, \cdots, i-1$,

$\mathbb{I}_{ij}(6) = \mathbb{I}_{ji}(6) = 1$,

choose node $h \neq j$ *with a probability of* $\kappa_h / \sum_h \kappa_h$, $h = 0, 1, \cdots, i-1$,

$\mathbb{I}_{ih}(6) = \mathbb{I}_{hi}(6) = 1$,

$i = i + 1$;

until $i = n - 1$.

To capture the entrepreneurial process in space-time, a dynamic behavioral model is required. We next introduce computational social science as a new field that facilitates process-oriented research.

2.4 Computational social science

Computational social science (CSS) is a field that "leverages the capacity to collect and analyze data at a scale that may reveal patterns of individual and group behaviours" (Lazer et al., 2009, p.721). The foundations of CSS is complex adaptive system – a system of interdependent elements change their states in response to changing conditions (Miller and Page, 2007). The operations of complex adaptive system are through phase transitions in order to maintain collective performance under dynamic environmental conditions (Gilbert and Troitzsch, 2005). A community is an example of a complex adaptive system based on business and social connections in a geographic area, such as the well-known von Neumann neighborhood where an actor interacts with four neighboring actors to the east and west and to the south and north, that relies on a small set of initial conditions and intuitive rules (e.g., Gilbert and Troitzsch, 2005; Miller and Page, 2007). Once a disaster occurs, community members take actions to adapt the resulting dramatic changes and create collective values for community to endure. Hence, CSS offers enormous but untapped opportunities to explore social complexity and study patterns of group (macro) behavior from assumptions at the individual (micro) level using the computational approach.

Computation is a language to formalize theory and empirical findings to by studying 'what ifs' and experimentation (e.g., Cioffi-Revilla, 2014). CSS includes two types of computational techniques: equation-based paradigm including queuing models and system dynamics (SD) models, and object-based simulation models such as cellular automata (CA) and agent-based models (ABM) Cioffi-Revilla, 2014. Each technique in CSS takes a feedback view to simulate the actions and interactions of actors in the business and social environment

(Gilbert and Troitzsch, 2005).

For instance, queuing models, based on queuing theory in operations research literature, are applied for social systems and processes where queues of entities (e.g., customers, patients,) are serviced by various kinds of stations or processing units. Likewise, SD models depict nonlinear feedback systems in which variables are in circular causal relationships and influence each other (Kunc and Morecroft, 2009; Sterman, 2000). This computational technique has been greatly used in organization and strategy studies. For example, Sastry (1997) study discontinuous or punctuated organizational change by modeling it as a function of organization–environment fit and of trial periods following reorientation during which the change process is suspended. Repenning (2002), Repenning and Sterman (2002), and Rahmandad et al. (2009) examine the dynamic process that influences the members' adoption of new innovation in an organization. In this sense, SD models are useful to produce dynamic management theory and help practitioners understand and predict various potential consequences of their proposed policies and strategies.

CA and ABM relax the homogeneity and perfect mixing assumptions of SD models; they can capture heterogeneity across actors and spatial interactions among them, hence show how aggregate behavior emerges from the interactions (Rahmandad and Sterman, 2008). Both types of models can show how aggregate behavior emerges from the interactions among In particular, CA models study emergent patterns based on localized interaction between neighboring cells (e.g., actors) on a given landscape. One well-known example is Shelling's Segregation model on racial segregation in a community (Miller and Page, 2007), showing how segregation emerges when actors are tolerant of different race. On the other hand, ABMs have become increasingly significant to explore systems consisting of heterogeneous actors and networks of relationships among them that evolve over time (Bonabeau, 2002; Rahmandad and Sterman, 2008). This computational technique has been widely applied to study complex crisis and emergencies (Cioffi-Revilla, 2014).

In entrepreneurship literature, there is a growing trend among scholars to study emergence of entrepreneurial actions using object-based simulation models (e.g., Keyhani et al., 2015; McMullen and Dimov, 2013; Yang and Chandra, 2013). Emergence is a phenomenon when system-level behavior arises out of the micro, localized interactions among individual actors and where the interactions are nonlinear, characterized by action threshold, and if-then rules (Lichtenstein et al., 2007; Miller and Page, 2007), which is unable to be explored using traditional static methods. Therefore, computational social science approach is an excellent way of exploring the proposed spatiotemporal process in our study. We embrace the CSS approach and employ computational techniques to study entrepreneurial emergence in the context of disaster using an interaction- and community-based perspective. Stylized simulation models are built to examine the entrepreneurial action dynamics in space-time through systematic experimentation on key model parameters.

Chapter 3

Robust supply chain strategies for recovering from unanticipated disasters

3.1 Introduction

Today's global business landscape is characterized by increasing uncertainty and vulnerabilities. Recent years have brought unforeseeable disasters – man-made and natural – including terrorist attacks, computer viruses and 'hackings', financial crises, earthquakes, tsunamis, the SARS and Ebola epidemics, and nuclear reactor accidents, etc. Anecdotal evidence about the global production plummet due to Japan's March 2011 earthquake and nuclear reactor semi-meltdown shows that most serious, unpredictable disasters can disrupt the normal flow of goods and materials within and across supply chains. Such unpredictable disasters expose firms enormous operational and financial risks (Kleindorfer and Saad, 2005; Papadakis, 2006; Xiao and Yu, 2006; Bueno-Solano and Cedillo-Campos, 2014). Motivated by these real-world observations this paper examines the effectiveness of popular recovery strategies when a supply chain faces unpredictable, hazardous events, and then provides managerial insights for supply chain managers.

Historical data indicate that the total number of natural and man-made disasters has soared dramatically over the last two decades (see e.g., www.cred.be; www.munichre.com). For instance, the March 2000 lightning bolt that struck a Philips semiconductor plant in Albuquerque, New Mexico, created a 10-minute blaze that contaminated millions of IC chips and subsequently delayed deliveries to its two major clients, nokia and Ericsson (Latour, 2001). Thailand's 2011 massive flooding affected the supply chains of computer manufacturers dependent on hard disk drives and of Japanese auto companies including Honda, Toyota, and Nissan with factories in Thailand (BBC, 13/10/2011), among others. Empirical observations indicate that most supply chains tend to break down during major disruptions and many cannot recover afterwards (e.g., Eskew 2004; Tang 2006). The detrimental effects of various catastrophic disasters (Hendricks and Singhal, 2005; Green et al., 2011) motivate us to identify robust supply chain strategies to promptly and effectively address unanticipated disasters; that is, strategies enable supply chains to maintain their operations during and closely after disaster-caused disruptions.

To pursue the research motive, we construct a behavioral supply chain model using the cellular automata (CA). CA, a simulation method used in management research, enables an exploratory examination of supply chain dynamics by considering strategic interactions among neighboring firms (Davis et al., 2007; Harrison et al., 2007; Nair et al., 2009; Yang and Chandra, 2013). Using the aforementioned lightning-sparked fire in New Mexico and floods in Thailand as examples, we employ CA to model how an unanticipated disaster in a supply chain firm places the entire supply chain's operational and financial performance at risk, following the forest fire model in physical science (see Robertson and Caldart, 2008). Therefore, our model mirrors many real-world supply chain disruption cases.

Research that explores ways to minimize the adverse impact of supply chain disruptions has generally followed one of two streams: disruptions caused by anticipated and unanticipated disasters. In practice, a supply chain frequently faces disruptions with anticipated probability of occurrence and magnitude of impact, due to forecast errors caused by demand fluctuations, machine breakdown, and poor supplier performance (e.g., Hilletofth and Hilmola, 2008; Lättilä and Saranen, 2011). The first stream, anticipated disaster-caused disruptions, suggests that the disruption's adverse impact can be mitigated by taking steps to diminish the *likelihood* of a disruption (e.g., Chang et al., 2007); on this, Altay and Green (2006) offer a comprehensive literature survey. However, a question arises: How can a firm reduce the chance of a disruption if the probability distribution of the hazards is *unknowable*, such as those caused by unpredictable, sudden-onset natural and man-made disasters? The first stream of research cannot address this thorny problem, which is important in global supply chain management of product production ranging from airplanes to consumer goods to chemicals (Sheffi, 2007; Simchi-Levi et al., 2014). But the second stream of research, unanticipated disaster-caused disruptions, attempts to address this problem of unforeseeable incidents.

In the past decade, managers of supply chains and operations have become much more concerned about the potential consequences of unanticipated disasters at their facilities and those of their supply chain partners (Sheu, 2007; Kunz and Reiner, 2012). The increased concern is partly the result of greater inter- and intra-organizational complexity and increased exposure to unpredictable natural and man-made disasters. These events will inevitably disrupt supply chains because shipping, air freight, trains, and other transportation modes along with fuel shortages, communication and electricity outages and electricity supply disruptions, will be greatly affected by increasingly extreme weather events. As noted earlier, Ericsson lost 400 million euros after its supplier's semiconductor lab in New Mexico caught fire in 2000; Ford closed five vehicle manufacturing factories for several days when all air traffic was suspended after September 11, 2001 terrorist attack, and Japan's 2011 earthquake and tsunami halted Toyota's production at three plants for several days and damaged American dealerships (see Chopra and Sodhi (2004; 2014) for more details and examples).

To address the practitioners' and researchers' increased concern about unanticipated disasters, a second stream of research has recently emerged that explores the role of supply chain disruptions caused by unpredictable natural and man-made disasters (Sheu, 2007). For instance, Bueno-Solano and Cedillo-Campos (2014) develop a system dynamics model to analyze the devastating effects of terrorist acts on global supply chain performance. Qi et al. (2004) examine a one-supplier-one-retailer supply chain experiencing demand disruptions and the resultant impacts on supply chain's coordination mechanisms in pursuit of maximum supply chain performance. Xiao and Qi (2008) extend Qi et al.'s (2004) analysis of a one-manufacturer-two-competing-retailers supply chain under disruption. However, most studies in this stream explore the effects of supply chain disruptions but fail to consider recovery strategies – the major focus of this work (see, Altay and Green, 2006; Sheu, 2010). We extend this research stream by developing a formal model of supply chain dynamics under unanticipated disasters and their effects on member firms over time. Also, we summarize several observations by carefully analyzing extensive simulation outcomes.

Our key qualitative findings are as follows. An incremental recovery strategy mitigates disruptions from unanticipated disasters by incrementally improving the supply chain's recovery performance; this strategy performs well when bringing the entire supply chain operations from a poor to good state consumes considerable resources. However, with the incremental recovery strategy, the supply chain may not perform as well as expected if the above condition – high resource consumption requirement – does not hold. As Lee (2004) highlights, a good supply chain strategy for recovery must perform at "triple-A" job by employing agility, adaptability, and alignment. Our computational analysis demonstrates that a radical (the most rapid) recovery strategy – one that contains the impact of a disaster within the effected firms and strives to immediately fix the disruption – is most robust. That is, in most disruptive cases, the radical recovery strategy consistently performs reliably. In contrast, strategies using the state-of-immediate-neighbors as a reference point are not as effective as the radical strategy to inhibit the contagion effect of disasters across the supply chain, leading to relatively low recovery performance. Their lack of efficiency is more significant when the supply chain is relatively large (e.g., the supply chain has ten echelons). These findings and insights under the supply chain structure generally hold in a stochastic setting in which a firm's recovery strategy is altered over time. We describe those conditions and strategies in detail, and justify these insights and other results in subsequent sections.

3.2 Model

While our model encompasses a wide range of technical systems (e.g., information systems, manufacturing processes), we focus on supply chains. A long tradition in the model-based literature on operations, supply chain, and organization (see, Cachon and Netessine, 2004;

Davis et al., 2007; Harrison et al., 2007) leads us to conceptualize the supply chain as the interaction of all member firms each of which makes a number of interdependent decisions. Specifically, each firm follows its strategy to interact with its adjacent upstream and downstream neighbor firms; together their unique interactions influence the supply chain's overall performance.

In the context of modeling the supply chain's evolution, the cellular automata (CA) framework assumes that each firm interacts within a supply chain following fixed, homogeneous rules. Since a supply chain consists of autonomous or semiautonomous business entities (i.e., firms) engaged in various independent and interdependent activities, CA is an ideal research methodology to explore supply-chain issues (Nair et al., 2009). The firms in our model populate a one-dimensional array; consider a supply chain in which every firm interacts with its adjacent upstream and downstream neighbors. We refer to N as the *size* of the supply chain; thus N firms populate the supply chain. Without loss of generality, we number these firms consecutively $1, 2, \cdots, N$ so that firm 1 is the most upstream (the first or start) firm and thus firm N is the most downstream (the last or end) firm. As a result, firm 1 has only one (downstream) neighbor, firm 2, and firm N has also only one (upstream) neighbor, firm $N - 1$.

3.2.1 Firm performance

In our stylized supply chain model, each firm can operate in one of three states based on supply chain events or circumstances: *bad*, *normal*, and *good*, designated by $0, 1$ and 2, respectively. We denote the state of firm i at period t by $s_i(t) \in \{0, 1, 2\}$, where $i = 1, 2, \cdots, N$ and $t = 1, 2, \cdots, T$. Parameter T indicates the simulation periods of each run. The supply chain's performance at period t is

$$S(t) = \sum_{i=1}^{N} s_i(t).$$

Accordingly, our model is a discrete dynamic system with discrete and integral space, time, and states (see Robertson and Caldart, 2009).

A firm's state can change due to an unanticipated disaster. Suppose that a disaster occurs. A bad state (0) represents major damage to terminal facilities and/or halted production. At the other extreme, a good state (2) indicates restored operations from disruptions, which represents the firm functioning well. The normal state (1) represents the intermediate status whereby day-to-day operations are not fully recovered yet still functional, for instance, the firm utilizes supply chain collaboration, inventory, and/or transportation rerouting to remain operational (Rogers, 2012).

For the sake of simplicity, each firm in the supply chain at each period has a probability f of being derailed when encountering an operations shutdown from "severe" disasters and a probability g of being affected by "mild" disasters. Note that our study focuses on sudden-onset disasters that arrive rapidly with little or no forewarning, such as tsunamis, earthquakes, acts of war, and terrorist attacks; slow-onset disasters such as famines and droughts are not sudden onset and thus are not considered in this study (van Wassenhove, 2006). Specifically, upon encountering a mild disaster at period t, firm i's operational performance is

$$\xi_i(t) = \max\{s_i(t-1) - 1, 0\};$$

during disruption from a severe disaster at period t, firm i's operational performance post disaster at that time is

$$\xi_i(t) = 0,$$

irrespective of its state prior to encountering the disaster, $s_i(t-1)$.

3.2.2 Recovery strategy

Following CA modeling convention, we assume that each firm's behavior is controlled by an identical decision rule, and that this rule uses the firm's post-disaster state (bad – 0, normal – 1, or good – 2) and the post-disaster states of its two adjacent neighbors (upstream and downstream) to determine the recovery state. Theoretically, a decision rule is a mapping of each possible input state (i.e., post-disaster performance, $\xi_j(t)$, $j \in \{i-1, i, i+1\}$) to an output state (i.e, recovery performance, $s_i(t)$) for every firm in the supply chain. A decision rule thus specifies a supply chain 'strategy' to restore every member firm's performance to its pre-disruption state following a disaster .

Given that each firm has three possible states, a fully specified rule will map the 27 (= 3^3) possible combinations of actions that the firm and its two neighbors can take to achieve the firm's new state. Because the rule must designate one of three possible states for each of the 27 situations, 3^{27} possible rules could direct a firm's behavior. Therefore, searching for optimal strategies is unrealistic and impractical in most CA models (Miller and Page, 2007). Following the modeling practice for complex adaptive systems (Gintis, 2009; Miller and Page, 2007), we choose ten possible rules (or strategies) based on their similarity to real-world decision making for supply chain recovery activities. Table 3.1 illustrates the ten decision rules selected, which determine the state of firm i at period t given $\xi_i(t)\ \forall i$.

To sum up, a recovery strategy represents a firm's option to change its state (i.e., operational performance). The action set, however, is limited and localized to the firm itself and two of its adjacent upstream and downstream neighbors. In this sense, our model can be viewed as a modeling framework of behavioral game theory similar to nonlinear dynamic systems, following the principle of cognitive limits in human and organizational decision-making and judgement (see Gintis, 2009; Robertson and Caldart, 2009).

Table 3.1: Recovery strategies considered

	Mathematical representation	**Remark**
DR1	$s_i(t) = 2$. Firm i will return to the good state (2) no matter what states its upstream and downstream neighbors held post disaster.	This rule can be considered a *radical* recovery strategy to reach the best state recovered from a disaster-caused disruption. A real-world example is Japan's semiconductor supply chain responding to the 2011 earthquake/tsunami, where each supply chain firm worked to successfully repair damaged facilities and fix the electrical power supply interruptions that had hindered chemical plants and fabs (SEMI, 2011).
DR2	$s_i(t) = 2$ if $\max\{\xi_{i-1}(t), \xi_i(t), \xi_{i+1}(t)\} = 2$; otherwise $s_i(t) = 1$. Firm i will return to the good state (2) if there is one good-state firm among the neighbors and itself post disaster; otherwise, the recovery will be to the normal state (1).	This rule can be considered a *benchmarking* recovery strategy since it returns a firm to the best state of itself and of the neighboring firms. A real-world example this is following the 2011 earthquake/tsunami when Toyota paid its workers to help its hard-hit suppliers in Japan return to functional production, leading to a quick supply chain disruption recovery (Guardian, 11/03/2012).
DR3	$s_i(t) = 2$ if there are any two $j \in J = \{i-1, i, i+1\}$ such that $\xi_j(t) = 2$: at least two firms have a good state (the value of 2) in the set J; otherwise $s_i(t) = 1$. Firm i will return to the good state (2) if there are two good-state firms among the neighbors and itself post disaster; otherwise, the firm will recover to the normal state (1).	This rule is less likely to return a firm to a good state (2) than DR2. A real-world example is Entergy New Orleans's slow restoration following hurricanes Katrina and Rita in 2005, when flooding destroyed gas facilities and equipment of its domiciled response contractors, and brought massive damage to its supply chain's logistics and communications; that is, both Entergy New Orleans and its upstream contractors were not in the good post-disaster state. It took Entergy New Orleans two years of bankruptcy protection and numerous efforts to recover fully.

	Mathematical representation	**Remark**
DR4	$s_i(t) = 2$ if $\xi_{i-1}(t) + \xi_i(t) + \xi_{i+1}(t) = 6$; otherwise $s_i(t) = 1$. Firm i will return to the good state (2) if it and both of its adjacent neighbors (up- and down-stream) had been in a good state (2) post disaster; otherwise, the firm will recovery to the normal state (1).	This rule is the least likely to return the firm to a good state (2) compared to DR2 and DR3. A real-world example: Malaysian Airline had difficulties in coping with the catastrophic losses of Flight 370 that went missing over the Indian Ocean in May 2014 and Flight 17 shot down over Ukraine in July, 2014.
DR5	$s_i(t) = 1$ if $\xi_{i-1}(t) + \xi_i(t) + \xi_{i+1}(t) = 6$; otherwise $s_i(t) = 2$. DR5 is similar to DR1 except for one situation in which firm i's state will change from good (2) to normal (1).	A member firm in a supply chain adopting this rule does not just reinstate what the disaster had destroyed, but improves the supply chain over its post-disaster state.
DR6	$s_i(t) = \max\{\xi_{i-1}(t), \xi_i(t), \xi_{i+1}(t)\}$. Firm i will recover to the best post-disaster state of its adjacent neighbors and of itself.	This rule can be considered a *matching* recovery strategy because it matches the state of its up- and down-stream neighbors. A real-world example is the Unitited States Enrichment Corporation (USEC), one of the biggest suppliers of uranium to Tokyo Electric Power (TEPCO), who maintains the Fukushima reactor before the meltdown caused by Japan's 2011 earthquake/tsunami. Its recovery activities were largely constrained by the lack of demand from the downstream firm in the supply chain, TEPCO, and the low market prices.
DR7	$s_i(t) = \min\{\xi_i(t) + 1, 2\}$. Firm i will recover its post-disaster state incrementally, going from bad (0) to normal (1), normal (1) to good (2), or maintain the good state (2).	This rule can be considered an *incremental* recovery strategy. Real-world examples are small- and medium-size-firms' recovery activities that are hindered by no or little access to capital, resulting in a slower recovery than expected.

	Mathematical representation	**Remark**
DR8	$s_i(t) = \xi_{i-1}(t)$ if $\xi_i(t) \neq \xi_{i-1}(t)$; otherwise $s_i(t) = \min\{\xi_i(t) + 1, 2\}$. Firm i will adjust its recovery state to its adjacent upstream neighbor's post-disaster state when its state differs from that of its upstream neighbor post disaster; otherwise, the firm will recover its state by one additional unit.	A member firm in a supply chain adopting this rule follows the post-disaster state of its upstream neighbor. This strategy, similar to the *reverse bullwhip effect*, implies that upstream firms are more powerful to initiate recovery activities after disasters and this action will correctly align the rest of the chain.
DR9	$s_i(t) = \xi_{i+1}(t)$ if $\xi_i(t) \neq \xi_{i+1}(t)$; otherwise $s_i(t) = \min\{\xi_i(t) + 1, 2\}$. Firm i will adjust its recovery state to its immediate downstream neighbor's post-disaster state when a difference exists between its state and that of its downstream neighbor post disaster; otherwise, the firm will improve its state by one unit.	A member firm in a supply chain adopting this rule follows the state of its downstream neighbor. This strategy, similar to the *bullwhip effect*, assumes that downstream firms have more power to initiate recovery activities after disasters.
DR10	$s_i(t) = \max\{\xi_{i-1}(t), \xi_{i+1}(t)\}$ if $\xi_i(t) \neq \max\{\xi_{i-1}(t), \xi_{i+1}(t)\}$; otherwise $s_i(t) = \min\{\xi_i(t) + 1, 2\}$. Firm i will adjust its recovery state to match the highest post-disaster state of its adjacent downstream and upstream neighbors; otherwise, the firm will improve its state by one unit.	A member firm in a supply chain adopting this rule follows the post-disaster state of its neighbor immediately before and after it. This strategy assumes that firms in the literal centre of the chain have more power to initiate recovery activities after disasters.

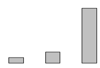
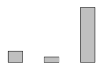
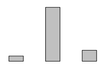
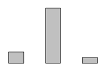
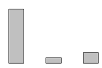
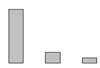
3.2.3 Resource consumption

Undoubtly, a firm needs to consume a degree of resources to increase its post-disaster operational performance. We thus assume that the firm does not need to consume any resources for decreases in its performance. The resource consumption function for firm i with post-disaster state $\xi_i(t)$ to reach recovery state $s_i(t)$ is given by:

$$C(\xi_i(t), s_i(t)) = \begin{cases} c_1 & \text{for } \xi_i(t) = 0 \text{ and } s_i(t) = 1, \\ c_2 & \text{for } \xi_i(t) = 1 \text{ and } s_i(t) = 2, \\ c_3 & \text{for } \xi_i(t) = 0 \text{ and } s_i(t) = 2, \end{cases}$$

where c_3 is the resource amount spent to recover from a severe disaster at one time unit, c_2 is the resource amount spent to recover from a mild disaster, and c_1 is the resource amount needed to find alternatives, such as another supplier and a substitute route, in order to maintain day-to-day operations following a severe disaster. We consider six scenarios of resource consumption, listed in Table 3.2, where $c_1, c_2, c_3 \in \{1, 2, 10\}$ and $c_1 \neq c_2 \neq c_3$. (Our results are insensitive to the choice of C in the experiments, see the supplementary notes in Section 3.7.)

Table 3.2: Six resource consumption scenarios

	Recovery Degree			
Scenario	0→1 (c_1)	1→2 (c_2)	0→2 (c_3)	Graph
RC1	1	2	10	
RC2	2	1	10	
RC3	1	10	2	
RC4	2	10	1	
RC5	10	1	2	
RC6	10	2	1	

Firm i's resource amount at period t is $R_i(t)$; there is an increase Δ in resources per period. Parameter Δ can be thought of as a firm's investment in risk mitigation in each period. So firm i's resource level at period t is

$$R_i(t) = \begin{cases} R_i(t-1) + \Delta - C(\xi_i(t), s_i(t)) & \text{if } \xi_i(t) < s_i(t), \\ R_i(t-1) + \Delta & \text{otherwise.} \end{cases}$$

3.2.4 Simulating the model

The simulation procedure for the proposed model is as follows. At period 0, we assign the recovery strategy, the resource consumption scenario, the probabilities of disasters (f and g), and the initial state for each firm. Since firm 1 has no upstream neighbor and firm N has no downstream neighbor, we assume that either firm 1's upstream neighbor or firm N's downstream neighbor is in a good state, or has the value of 2. (This assumption does not impact our outcomes since these two firms are outside the boundaries of our framework.) The simulation is executed until time T is reached. Next, we calculate the supply chain's performance by adding up the state of each member firm to evaluate the robustness of the ten recovery strategies employed by the N supply chain firms.

Figure 3.1 illustrates a recovery procedure at time period t: this simple example of five firms shows how recovery dynamics operate in our supply chain model. The numbers in the five large squares in the bottom row stand for state or operational performance, the numbers in the five small top-row squares present the level of the remaining resources, and the two firms denoted by circles present firm 1's upstream supplier and firm 5's downstream customer. DR2 and RC1 are applied to the recovery strategy and resource consumption scenario; and, each firm obtains one unit of resource at the start of each time period. Note that recovery actions following a strategy require adequate resources for implementation; that is, if the resource level is too low to execute the recovery strategy, the firm will remain in its original state (see Firm 1 as an example).

The objectives of this chapter are to consider the model in which the recovery actions reflect popular strategies in practice and capture the interactions among supply chain members, to assess how such actions can result in a firm's counterintuitive behaviors in supply chain dynamics, and ultimately to gain insights into supply chain risk management strategies. The simulation of the CA model was carried out in a Java program, and is similar to the forest fir models introduced by Miller and Page (2007). As Robertson and Caldart (2009) note, CA is a dynamic network found in nature. We simulated our CA model in a

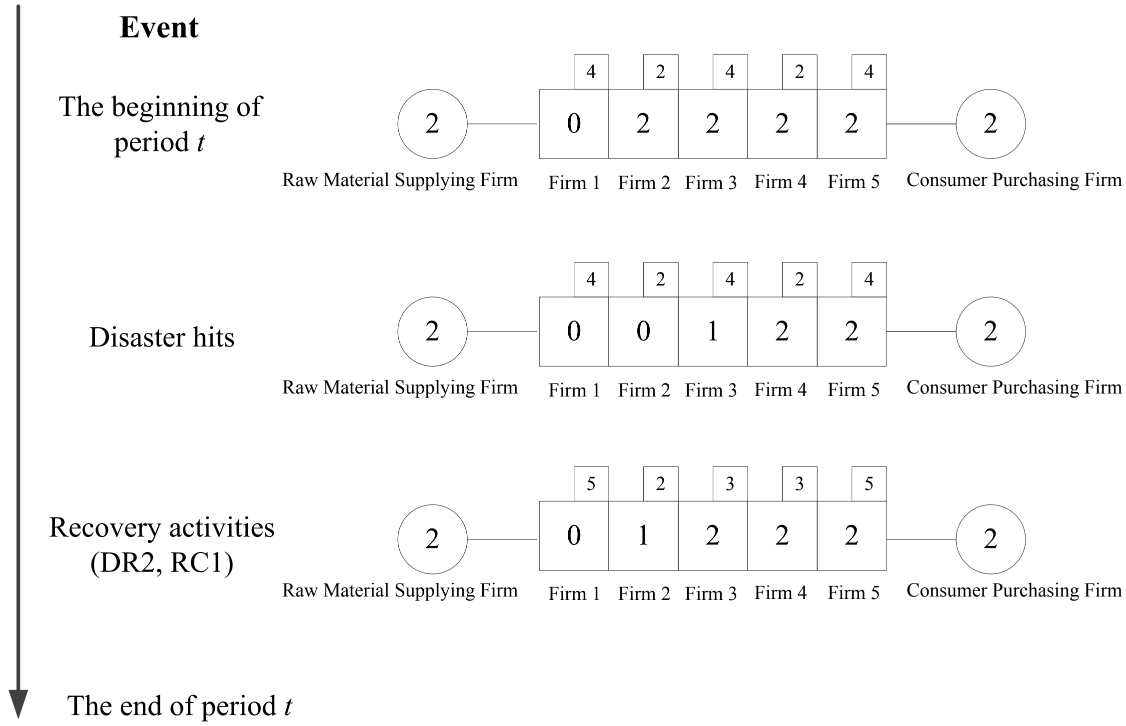


Figure 3.1: An illustration of a recovery procedure

MATLAB program.

In the next section, we unpack the robustness of recovery strategies for supply chains facing disruptions caused by unanticipated natural and man-made disasters using a careful computational analysis.

3.3 Analysis

3.3.1 Base case

Prior to running an extensive experimental analysis, and based on simulation research practice, we perform a base case in a pilot study: $N = 5$, $T = 365$, $R_i(0) = 3$, and $\Delta = 1$. We set $g = 134/365$ and $f = 17/365$ for the probabilities of mild and severe disasters occurring during a year based on Sheffi's (2007) empirical analysis, thus, these values are also fixed in our experimental study. Each firm's operational performance at period 0 is either a good state ("good" setting) or randomly assigned (bad – 0, normal – 1, or good – 2) state ("random" setting) for the outcome reliability. Every parameter instance is repeated 200 times for outcome reliability; we observe that the firm's initial state does not significantly impact the robustness of recovery strategies. Specifically, panels 1 to 3 in Table 3 show the average of supply chain performance S per period, the average of $(S/S_{\max}) \times 100\%$ per period, and the standard deviation of S per period. $S_{\max}$ is the upper bound of supply chain performance, which is 10 $(= N \times 2)$ in the base case.

In the supply chain risk management arena, we are primarily concerned about worst-case-scenarios rather than average and optimistic scenarios of unanticipated disasters (Tang, 2006). Thus, Table 3.4 cannot identify which recovery strategy best addresses routine disruptions and major disruptions caused by unanticipated disasters (e.g., a 7.5 Richter scale earthquake at a major production plant) because the measure is the average number of all simulated events across a supply chain. Following risk analysis and management best practices (e.g., Myerson, 2004), we address this concern by reporting the 25th percentile, 5th percentile, and 1st percentile of supply chain performance S among the 200 simulations (see Table 3.4). These three performance measures result in very similar ranking outcomes across all the ten strategies considered. Hence, we use the 1st percentile as the only performance measure to rank recovery strategies since it provides a strict standard by which to evaluate the performance of strategies used to recover disruptions caused by unanticipated disasters.

Tables 3.3 and 3.4

show that in the base case, only the radical recovery strategy, DR1, and the incremental recovery strategy, DR7, achieve first place among the ten strategies considered. That is, they are the most orbust recovery strategies. Notice that the increment strategy, DR7, is ranked first only under either RC1 or RC3. The common characteristics of these two resource consumption scenarios is $\max[c_1, c_2, c_3] = c_3$; that is, to restore the firm's state from bad to good in the next period requires the firm to spend a great deal of resources. if this condition of resource consumption does not hold, the performance of incremental strategies is not as good as most other recovery strategies. Based on our results, the radical recovery strategy, DR1, can achieve success under various resource consumption scenarios; that is,

Table 3.3: Base case results for the supply chain performance

	RC1		RC2		RC3		RC4		RC5		RC6	
	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random
Panel 1. Average of supply chain performance (*S*) per period												
DR1	7.606	7.531	9.740	9.651	8.025	8.026	8.175	8.171	10.000	10.000	9.995	9.995
DR2	7.788	7.747	9.198	9.182	7.387	7.387	7.429	7.422	9.670	9.654	9.646	9.653
DR3	5.025	5.010	5.014	5.002	5.016	5.011	5.010	5.004	1.277	1.246	1.274	1.255
DR4	5.003	5.002	4.996	4.992	5.005	7.649	4.998	4.991	1.223	1.217	1.233	1.216
DR5	5.613	5.595	7.024	6.975	7.645	7.649	7.768	7.780	9.072	9.071	9.049	9.060
DR6	7.594	7.591	9.228	9.125	7.362	7.391	7.431	7.431	9.656	9.657	9.652	9.642
DR7	9.619	9.604	9.629	9.623	5.789	5.787	5.169	5.146	8.073	7.957	4.494	4.437
DR8	5.709	5.726	6.272	6.235	5.338	5.332	5.109	5.095	6.443	6.399	6.242	6.207
DR9	5.710	5.694	6.243	6.194	5.340	5.335	5.103	5.106	6.436	6.431	6.235	6.240
DR10	7.136	7.045	8.661	8.632	6.823	6.835	6.863	6.866	9.560	9.555	9.480	9.486
Panel 2. Average of (S/S_{max}) × 100% per period												
DR1	76.060	75.305	97.400	96.507	80.250	80.255	81.750	81.707	100.00	100.00	99.950	99.951
DR2	77.884	77.473	91.978	91.820	73.870	73.867	74.285	74.224	96.70	96.54	96.459	96.530
DR3	50.251	50.095	50.143	50.015	50.159	50.105	50.099	50.044	12.77	12.46	12.737	12.549
DR4	50.034	50.016	49.961	49.916	50.047	76.486	49.975	49.912	12.23	12.17	12.326	12.163
DR5	56.132	55.947	70.241	69.746	76.449	76.486	77.675	77.796	90.72	90.71	90.494	90.598
DR6	75.943	75.909	92.276	91.252	73.618	73.908	74.305	74.306	96.56	96.57	96.518	96.419
DR7	96.188	96.036	96.287	96.234	57.889	57.871	51.687	51.461	80.73	79.57	44.940	44.367
DR8	57.085	57.255	62.723	62.347	53.382	53.322	51.085	50.954	64.43	63.99	62.418	62.068
DR9	57.101	56.941	62.431	61.936	53.400	53.352	51.032	51.058	64.36	64.31	62.350	62.395
DR10	71.364	70.446	86.606	86.315	68.226	68.349	68.632	68.664	95.60	95.55	94.800	94.859
Panel 3. Standard deviation												
DR1	0.429	0.527	0.076	0.075	0.156	0.167	0.069	0.071	0.000	0.000	0.006	0.006
DR2	0.374	0.385	0.124	0.119	0.257	0.250	0.138	0.147	0.057	0.059	0.069	0.063
DR3	0.020	0.013	0.012	0.011	0.022	0.018	0.014	0.018	0.081	0.075	0.084	0.091
DR4	0.005	0.004	0.006	0.002	0.012	0.012	0.011	0.012	0.067	0.071	0.074	0.065
DR5	0.218	0.218	0.051	0.050	0.227	0.192	0.048	0.049	0.047	0.048	0.043	0.048
DR6	0.453	0.407	0.122	0.122	0.245	0.245	0.129	0.153	0.059	0.060	0.064	0.068
DR7	0.045	0.052	0.067	0.063	0.049	0.047	0.067	0.062	0.493	0.524	0.611	0.673
DR8	0.365	0.355	0.091	0.091	0.276	0.281	0.111	0.107	0.201	0.189	0.188	0.202
DR9	0.335	0.365	0.088	0.080	0.276	0.274	0.120	0.110	0.189	0.197	0.207	0.212
DR10	0.387	0.362	0.110	0.111	0.282	0.308	0.114	0.122	0.047	0.043	0.073	0.071

Note. "Good" is the good setting where each supply chain firm operations in a good state (2) at period 0. "Random" is the random setting where each firm's state is randomly assigned. Each result is an average of 200 runs of 365 period experiments.

Table 3.4: Base case results for the performance ranking of the recovery strategies

	RC1		RC2		RC3		RC4		RC5		RC6	
	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random	Good	Random
Panel 1. The 25th percentile												
DR1	7.307	7.169	9.655	9.534	7.977	7.977	8.123	8.121	10.000	10.000	9.992	9.992
DR2	7.566	7.490	9.019	9.012	7.296	7.308	7.332	7.326	9.634	9.618	9.606	9.608
DR3	5.011	5.000	5.003	4.992	5.008	5.003	5.003	4.992	1.218	1.197	1.216	1.192
DR4	5.000	5.000	4.992	4.986	5.000	5.000	4.993	4.984	1.175	1.169	1.186	1.167
DR5	5.492	5.462	6.874	6.826	7.612	7.614	7.736	7.744	9.041	9.034	9.021	9.029
DR6	7.296	7.295	9.060	8.980	7.285	7.306	7.330	7.326	9.615	9.616	9.611	9.599
DR7	9.592	9.570	9.596	9.592	5.743	5.741	5.121	5.099	7.784	7.611	4.078	3.969
DR8	5.462	5.493	6.112	6.049	5.280	5.269	5.033	5.030	6.300	6.271	6.134	6.078
DR9	5.477	5.389	6.056	6.036	5.277	5.282	5.021	5.040	6.312	6.289	6.097	6.110
DR10	6.870	6.781	8.473	8.395	6.748	6.751	6.780	6.789	9.526	9.527	9.441	9.440
Panel 2. The 5th percentile												
DR1	7.003	6.684	9.408	9.353	7.901	7.904	8.067	8.058	10.000	10.000	9.981	9.984
DR2	7.155	7.114	8.738	8.762	7.175	7.203	7.193	7.166	9.575	9.555	9.532	9.540
DR3	5.003	4.997	4.980	4.973	5.000	5.000	4.988	4.980	1.143	1.135	1.153	1.115
DR4	5.000	5.000	4.973	4.969	5.000	5.000	4.978	4.970	1.110	1.101	1.121	1.118
DR5	5.256	5.214	6.648	6.685	7.570	7.563	7.685	7.703	8.995	8.997	8.980	8.982
DR6	6.880	6.945	8.753	8.699	7.155	7.173	7.243	7.174	9.552	9.552	9.536	9.533
DR7	9.544	9.507	9.559	9.543	5.688	5.699	5.056	5.047	7.184	7.040	3.564	3.416
DR8	5.110	5.067	5.789	5.775	5.180	5.189	4.941	4.918	6.125	6.099	5.944	5.859
DR9	5.149	5.164	5.747	5.681	5.208	5.190	4.908	4.927	6.147	6.141	5.907	5.864
DR10	6.529	6.455	8.162	8.092	6.647	6.666	6.675	6.675	9.477	9.480	9.345	9.358
Panel 3. The 1st percentile												
DR1	6.425	6.167	9.280	9.214	7.834	7.837	8.021	8.030	10.000	10.000	9.974	9.975
DR2	6.918	6.871	8.552	8.527	7.095	7.059	7.099	7.086	9.529	9.492	9.433	9.510
DR3	5.000	4.997	4.958	4.948	5.000	5.000	4.978	4.958	1.111	1.101	1.114	1.066
DR4	5.000	5.000	4.963	4.951	5.000	5.000	4.966	4.953	1.069	1.075	1.067	1.088
DR5	5.036	5.041	6.522	6.558	7.512	7.530	7.664	7.675	8.975	8.960	8.927	8.936
DR6	6.488	6.833	8.611	8.440	7.058	7.092	7.156	7.122	9.523	9.500	9.500	9.471
DR7	9.503	9.475	9.523	9.500	5.627	5.638	5.021	5.003	6.843	6.651	2.988	3.032
DR8	4.907	4.943	5.573	5.488	5.141	5.123	4.870	4.833	5.956	6.037	5.766	5.689
DR9	4.993	5.012	5.471	5.466	5.174	5.151	4.821	4.818	6.008	5.997	5.733	5.711
DR10	6.051	6.264	7.907	7.912	6.549	6.585	6.606	6.611	9.451	9.462	9.277	9.307
Panel 4. Ranking of recovery strategy												
DR1	4	5	2	2	1	1	1	1	1	1	1	1
DR2	2	2	4	3	3	4	4	4	2	3	3	2
DR3	7	9	10	10	9	9	7	7	9	9	9	10
DR4	7	8	9	9	9	9	8	8	10	10	10	9
DR5	6	6	6	6	2	2	2	2	5	5	5	5
DR6	3	3	3	4	4	3	3	3	3	2	2	3
DR7	1	1	1	1	6	6	6	6	6	6	8	8
DR8	10	10	7	7	8	8	9	9	8	7	6	7
DR9	9	7	8	8	7	7	10	10	7	8	7	6
DR10	5	4	5	5	5	5	5	5	4	4	4	4

Note. Each result is based on 200 runs of 365 period experiments.

it is the most robust strategy because its worst performance still achieves the second place among nine others. Following this logic, we examine the mean rankings of each recovery strategy across all six resource consumption scenarios for the robustness analysis. We find that a highly ranked strategy can effectively restore the supply chain performance following unanticipated disasters.

3.3.2 Experimental design

To characterize the range of recovery performance after unpredictable disasters and to assess the impact of each parameter, we analyze the proposed model under a variety of parameter instances (Montgomery, 2004). Hence, a full factorial design is employed to explore the proposed model and to check whether the insights derived from the base case are applicable in other circumstances as well. We examine 12 ($= 2 \times 3 \times 2$) parameter instances consisting of every combination in Table 3.5. These parameter instances are selected to provide a wide range of possible scenarios (i.e., a low-to-high resource increase per period, Δ, a small, medium, or large supply chain size, N, and short-to-long simulated periods, T). We run each parameter instance 200 times to achieve statistical reliability. This computational analysis enables us to identify the underlying conditions for one recovery strategy to dominate another.

Table 3.5: Parameter instances used in our simulation experiments

Parameter	**Values**
Δ for resource	1, 10
N for size	3, 5, 10
T for period	365 days (1 year), 3650 days (10 years)

Table 3.6 shows the impact of each experiment factor (parameter Δ, N, or T) on recovery dynamics among the ten recovery strategies. We highlight the parameters that lead to significant differences in the performance ranking of recovery strategies at $p < 0.05$. We find that chain size (N) has the greatest impact on the ranking of recovery strategies (seven p-values are less than 0.05; three are not: DR1, DR3, and DR4) over the other two factors,

Table 3.6: Impact of experimental parameters on the ranking of recovery strategies

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
Δ	{1}	**1.500**	2.778	8.625	8.736	**4.514**	3.444	**5.069**	7.472	7.694	4.708
		(0.993)	(0.716)	(0.985)	(1.492)	**(2.169)**	(1.362)	**(2.661)**	(1.233)	(1.328)	(0.458)
	{10}	**1.000**	2.708	9.000	9.139	**5.986**	3.139	**3.556**	7.403	7.583	4.528
		(0.000)	(0.680)	(0.000)	(0.348)	**(0.118)**	(0.997)	**(1.288)**	(0.494)	(0.496)	(0.581)
N	{3}	1.188	**2.500**	8.938	8.729	**5.625**	**3.021**	**5.521**	**6.958**	**7.146**	**4.312**
		(0.571)	**(0.505)**	(0.522)	(1.498)	**(1.721)**	**(1.695)**	**(2.052)**	**(0.771)**	**(0.743)**	**(0.468)**
	{5}	1.271	2.625	8.979	9.146	5.271	3.042	**4.208**	**7.333**	**7.646**	**4.812**
		(0.792)	(0.761)	(0.526)	(0.545)	(1.594)	(0.713)	**(1.978)**	**(0.630)**	**(0.978)**	**(0.394)**
	{10}	1.292	**3.104**	8.521	8.938	**4.854**	**3.812**	**3.208**	**8.021**	**8.125**	4.729
		(0.849)	**(0.660)**	(0.945)	(1.019)	**(1.726)**	**(0.762)**	**(2.021)**	**(1.041)**	**(1.024)**	(0.574)
T	{365}	1.292	2.833	8.681	9.014	5.278	3.278	4.181	7.542	7.736	4.542
		(0.759)	(0.822)	(0.728)	(0.911)	(1.762)	(0.953)	(2.381)	(1.006)	(1.061)	(0.580)
	{3650}	1.208	2.653	8.944	8.861	5.222	3.306	4.444	7.333	7.542	4.694
		(0.730)	(0.535)	(0.690)	(1.259)	(1.646)	(1.411)	(2.048)	(0.856)	(0.934)	(0.464)

Note. The ranking of recovery strategies is based on the 1st percentile of supply chain performance per period on an average of the six resource consumption scenarios of the good and random initial state settings; each is based on 200 runs of 12 experiments. Standard deviations are in parentheses. Recovery strategies with smaller numbers rank higher in supply chain recovery performance, where 1 is the best possible ranking.

resource increment (Δ) and time (T). Chain size has both positive and negative effects on supply chain performance and the resulting ranking of recovery strategies; for instance, chain size has the strongest positive effect in DR7 and DR5 as it increases their ranking by 1.313 (= 5.521 − 3.208) and 0.771 (= 5.625 − 4.854), respectively. Chain size has the strongest negative effect in DR8, DR9, and DR6, as it decreases their ranking by 1.063 (= 8.021 − 6.958), 0.979 (= 8.125 − 7.146), and 0.791 (= 3.812 − 3.021), respectively. This suggests that when the chain size grows larger, DR7 and DR5 will generate better supply chain performance. In contrast, strategies that depend on the good state of immediate neighbors (up- and down-stream) as a reference, such as DR6, DR8 and DR9, will lead to inferior supply chain performance.

Table 3.6 also shows that resource increment (Δ) is the second most influential moderating factor, where the effects are significant for DR1, DR5 and DR7 with $p < 0.05$. The resource increment appears to have a strong positive effect on DR7 with a 1.513 increase in ranking and on DR1 with a 0.5 increase. On the other hand, resource increment has a strong negative moderating effect on DR5 with a 1.472 decrease in ranking. Finally, the time period (T) has an insignificant impact ($p > 0.05$) on the ten recovery strategies' performance ranking. As a result, we omit parameter T in our discussion.

To illustrate the ranking of the ten recovery strategies, we provide a boxplot in Figure 3.2, where the robustness of each strategy is clearly expressed by its mean and variation in their performance ranking. For example, DR1 is the most robust recovery strategy for unanticipated disasters because it has the lowest mean values and a very small variation in ranking, followed by DR2 and DR6. In contrast, DR3 and DR4 have poor supply chain performance. DR10, DR5 and DR7 have relatively moderate rankings (despite DR7's very large variations). Table 3.6 and Figure 3.2 illustrate some interesting findings at a more granular level, summarized as follows.

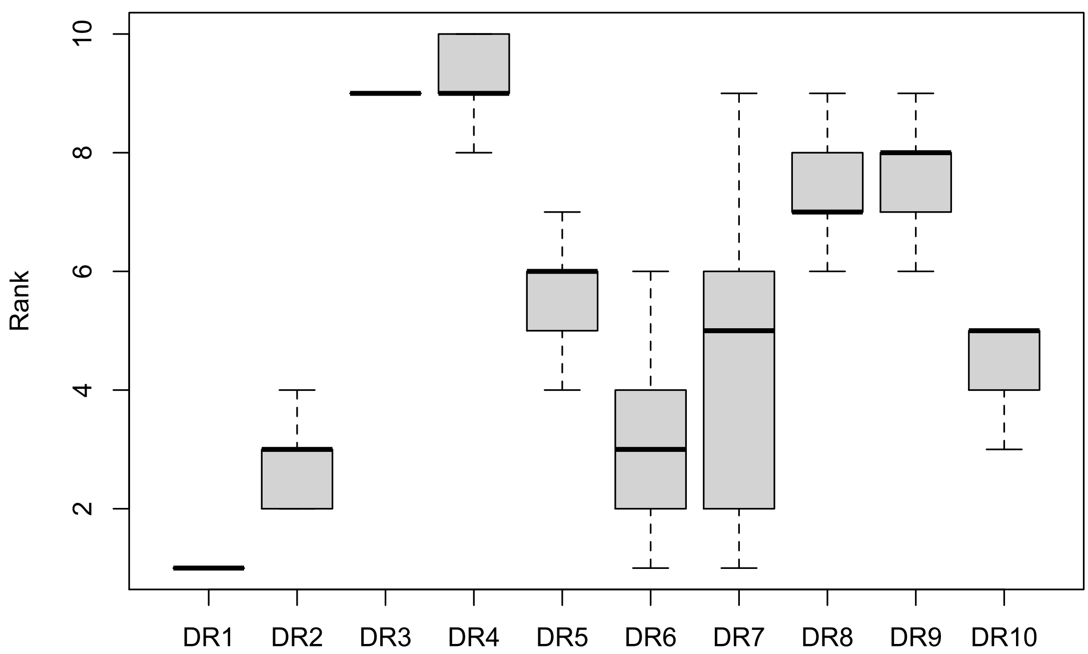


Figure 3.2: Boxplot of the 1st percentile performance ranking of recovery strategies.

The firms using DR1 return to best supply chain performance following unanticipated disasters when they have greater resource increments per period. This is in line with the base-case result in that DR1 must consume a large amount of resources, and therefore ranks lower under RC1 and RC2 than under the other four resource consumption scenarios. Yet a small variance implies it has a consistently high recovery performance under the six RC scenarios. In contrast, the amount of resources does not play a significant role in DR2 and DR6. These two strategies are more effective in restoring supply chain performance following unanticipated disasters as the number of firms in a supply chain decreases from ten to five (or three).

The robustness of DR5 and DR7 is dependent on both the amount of resource increments and the supply chain size. In DR5, the supply chain's recovery performance increases as the chain size increases, yet decreases as the amount of resource increments increases. In contrast, a large supply chain using DR7 is likely to have better recovery performance when firms receive greater resource increments per period. While the resource impact of DR7 is similar to DR1, the supply chain's recovery performance is more sensitive to chain size when the supply chain's firms incrementally returns to a good state than rapidly and radically returning to a good state following a disaster.

DR8, DR9, and DR10 show consistent ranking patterns suggesting that the chain size is a significant factor of influencing supply chain recovery performance, which negatively affects the performance following unanticipated disasters. This pattern for these three strategies reinforces our findings observed in strategies DR2 and DR6 that when a supply chain grows larger, if firms use the state of their adjacent upstream and downstream neighbors as a benchmark, the overall recovery performance decreases.

Finally, DR3 and DR4 are not responsive to the resource increment and chain size parameters, and they are less robust than the other eight recovery strategies that rank 9 and 10 in average.

3.4 Robustness of the model and insights

Thus far, we have examined supply chain performance in which all member firms implement an identical rule over time based on CA convention. In this section, we extend our model settings to incorporate plausible real-world situations to investigate the robustness of the findings in Section 3.3. That is, we relax the identical rule assumption and allow member firms to make stochastic decision rules during the simulation period. This model further validates our understanding of the robustness of each proposed recovery strategy against disruptions caused by unanticipated disasters, obtained in Section 3.3.

This model extension specifies that member firms in a supply chain implement heterogeneous recovery strategies over time, which impacts the chain's overall performance. Specifically, we introduce a new decision rule, DR11, which is a function of the discrete probability distribution of the ten recovery strategies (Table 3.1). Supply chain firms that adopt DR11 can change a selected recovery strategy at each time period based on its recovery performance in the preceding period. The rationale for DR11 is that firms are inclined to choose a recovery strategy that has been proven effective to restore supply chain performance following a disaster.

DR11 begins with period 0, where member firms select one of the ten strategies, DR1 to DR10, each strategy with an equal probability 0.1 of being selected. If the chosen strategy improves supply chain performance from the previous period, then, at period 1 its probability increases to 0.109, taking 0.001 from each of the other nine (not chosen) strategies. That is, the probabilities are no longer equally distributed among the ten strategies: one has a probability of 0.109 and nine have the probability of 0.009. As a result, the proven robust recovery strategy (the one with probability 0.109) has a larger chance of being chosen again in the subsequent period. For instance, DR1 is robust in most scenarios (see Figure 3.2); therefore, DR1 is likely to become the dominant strategy once it is selected. In contrast, consider a scenario where a strategy is constantly passed by member firms or fails to generate positive supply chain performance. Its probability diminishes as time proceeds and will

Table 3.7: Impact of experimental parameters on the ranking of the stochastic decision rule

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10	DR11
Δ	{1}	**1.528**	2.944	9.611	10.014	**5.347**	3.375	**5.708**	8.472	8.694	5.097	4.972
		(1.061)	(0.837)	(0.972)	(1.081)	**(2.579)**	(0.926)	**(3.208)**	(1.233)	(1.328)	(0.754)	(1.363)
	{10}	**1.000**	2.875	10.000	10.139	**6.806**	3.306	**3.889**	8.403	8.583	4.694	5.347
		(0.000)	(0.711)	(0.000)	(0.348)	**(0.432)**	(0.973)	**(1.588)**	(0.494)	(0.496)	(0.799)	(1.620)
N	{3}	1.479	2.750	9.521	9.917	**5.562**	3.104	**5.438**	**8.604**	**8.812**	4.771	5.542
		(1.010)	(0.786)	(0.850)	(1.069)	**(2.475)**	(0.857)	**(2.946)**	**(1.180)**	**(1.249)**	(0.831)	(0.743)
	{5}	1.188	2.979	10.104	10.292	**6.312**	3.521	**4.417**	**8.083**	**8.250**	4.875	**5.417**
		(0.673)	(0.887)	(0.371)	(0.544)	**(1.776)**	(1.031)	**(2.916)**	**(0.647)**	**(0.729)**	(0.761)	**(1.674)**
	{10}	1.125	3.000	9.792	10.021	6.354	3.396	4.542	**8.625**	**8.854**	5.042	**4.521**
		(0.606)	(0.619)	(0.713)	(0.668)	(1.509)	(0.917)	(2.021)	**(0.815)**	**(0.850)**	(0.798)	**(1.701)**
T	{365}	1.319	2.833	9.681	10.014	5.861	3.306	4.514	8.542	8.736	4.708	**5.861**
		(0.853)	(0.822)	(0.728)	(0.911)	(2.085)	(0.988)	(2.778)	(1.006)	(1.061)	(0.795)	**(0.810)**
	{3650}	1.208	2.986	9.931	10.139	6.292	3.375	5.083	8.333	8.542	5.083	**4.458**
		(0.730)	(0.722)	(0.678)	(0.678)	(1.865)	(0.911)	(2.572)	(0.856)	(0.934)	(0.765)	**(1.703)**

Note. The experimental settings are identical to those in Table 3.6.

eventually become extinct.

We examine 12 (= 2×3×2) parameter instances consisting of every combination (see Table 3.5) and analyze the impact of parameters Δ, N and T on the eleven recovery strategies, as illustrated in Table 3.7. The patterns in DR1 to DR10 are predominantly consistent with those in Table 3.6, showing the reliability of our chief findings in Section 3. However, different from the results of those ten strategies, time is a significant factor of DR11. Specifically, member firms adopting DR11 return to a better recovery performance when the simulated period is 10 years. Specifically, we observe a large increase in DR11's performance ranking 1.403 (= 5.861 − 4.458) because it takes the robust strategies such as DR1 and DR2 some time to dominate the others (e.g., DR3 and DR4) and achieve a high supply chain recovery performance. As illustrated in Figure 3.3, DR1 ranks higher than DR11, yet DR11 can perform slightly better than DR5 and DR7. These observations support our main result (in Section 3.3) – that the radical recovery strategy (DR1) is most robust in resolving supply chain functioning following unanticipated disasters.

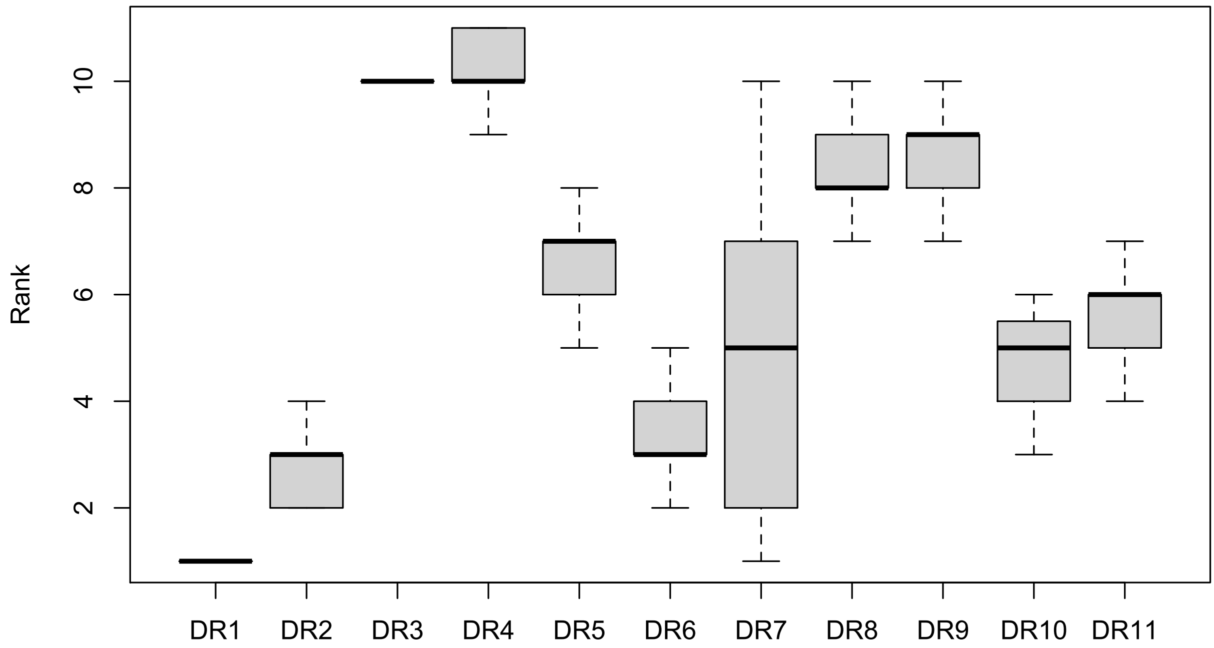


Figure 3.3: Boxplot of the 1st percentile performance ranking of the stochastic decision rule.

In summary, the chief insights we derived from Section 3.3 are generally consistent with the extension of the stochastic decision rule.

3.5 Case study and model validation

In this section, we use the case of Taiwan's 2011 food contamination scandal to validate our findings on the robustness of supply chain recovery strategies in a real-world setting. This food safety scandal arose when Taiwan's health department discovered that upstream firms had used an industrial plasticizer, DEHP, rather than the customary palm oil in food and drinks as a clouding agent and to reduce costs (Economist, 11/06/2011). Evidence shows that repeated exposure to DEHP among children could lead to cancer and developmental problems as it affects hormones. The customers, both locally and globally, stopped buying those contaminated products and were in shock and panic about the fact that these two firms' immoral conduct had gone unnoticed for two decades. The discovery and ensuing embargo on the contaminated foods severely damaged major food and drink supply chains in Taiwan; the food contaminated an estimated 780 products including beverages, soda fruit juices, sports drinks, tea, jam, syrups, health supplements, pastries, and yoghurt powder (TaipeiTimes, 05/06/2011).

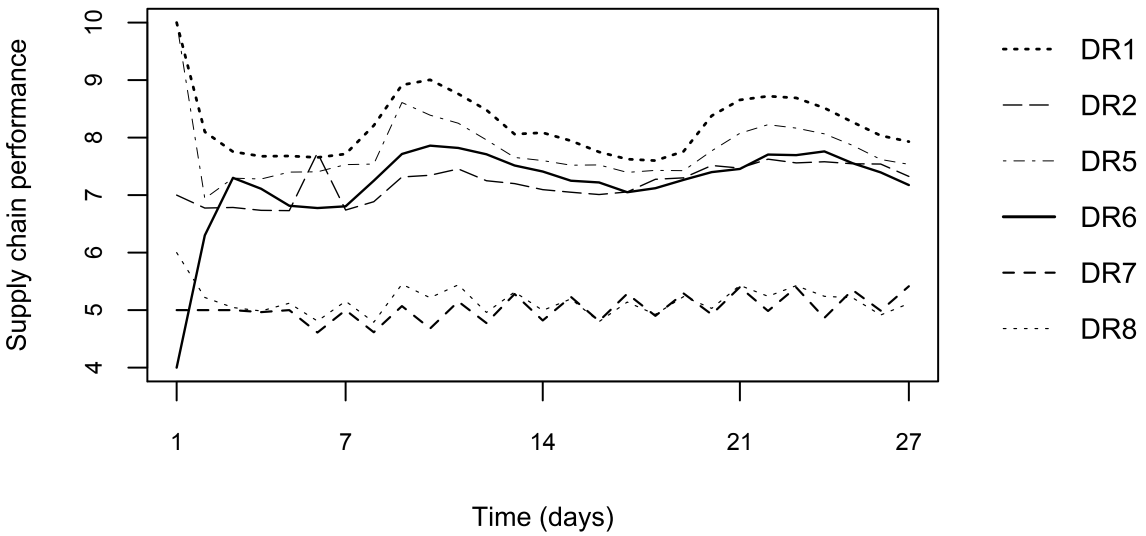
3.5.1 Background and parameter settings

The food scandal was exposed on May 23, 2011, affecting five echelons of member firms, the DEHP supplier, emulsifier supplier who substituted palm oil with the toxic plasticizer (Yu Shen Chemical Co.), food ingredient supplier (Seicheng Biotechnology Group), manufacturer (Triko Foods Co.), and retailer (7-Eleven), i.e., $N = 5$. As the downstream firms claimed innocence, their investment in mitigating food safety risk was small or $\Delta = 1$. Taiwan's health department had carried out a large-scale domestic food inspection for approximately one month from May 23 until June 18, 2011 ($T = 27$), up to 465,638 bottles of DEHP-tained beverages had been taken off from shelves, after which the department declared that food products should be relatively safe.

In order to amid the food safety scares, the supply chain firms took a radical strategy (i.e., DR1) to restore customer confidence. Specifically, the manufacturer immediately stopped production and sales of all of its manufacturing processes, recalled the tailed products and voluntarily submitted their products to government inspectors for DEHP test; the retailer pulled the tailed products from its shelves without sending the foods through DEHP tests. The manufacturer and retailer's rapid, radical, yet costly recovery actions of pulling off the food enabled them to maintain day-to-day operations. However, this hazardous event had dented Taiwan's once good reputation as a reliable and safe exporter of food. Several countries banned Taiwanese food imports, such as Malaysia (which lifted its import restriction in March 2012) and Singapore (which dropped its restrictions in March 2012). So, reinstating the supply chain's reputations worldwide cost even more than the actions of pulling off the food, i.e., $c_1 < c_2$. A fundamental and cheap solution was available when the government enforced new food safety regulations – The manufacturer and retailer knocked out the unscrupulous emulsifier supplier and replaced it with other reliable firms. This case study's resource consumption scenario is similar to RC4 so we adopt it in the section. Based on the above information, we use this case to verify our findings, obtained by our formal modeling, on the robustness of recovery strategies for restoring supply chain performance following this specific disaster.

3.5.2 Model validation

Figure 3.4 illustrates the supply chain recovery performance based on the parameter settings considered in the Taiwan food disaster case study. In addition to the adopted radical recovery strategy (DR1), we also include the recovery performance resulting from the five next best strategies, including DR2, DR5, DR6, DR7, and DR8.



Note. The parameters used in the Taiwan food disaster case study are $N = 5$, $\Delta = 1$, $T = 27$, $f = 17/365$. A small Δ can also mean that when food supply chains encounter a safety disaster, they rarely receive government or humanitarian support for recovery. $s_i(0) = 0$ and RC4 is applied.

Figure 3.4: Simulating 1st percentile supply chain performance for the case study of Taiwan's 2011 food scandal.

It is clear that DR1 is more effective and robust than the other five strategies in the Taiwan food disaster case in terms of restoring supply chain's performance following the disaster. In other words, supply chains are more likely to return to their pre-disrupted condition when using DR1. This result is in line with the findings in Figure 3.2: the radical recovery strategy, in general, dominates other strategies (e.g., DR2, DR5, and DR6) in which firms use their neighbors' state as a reference. In fact, the Taiwan's food supply chain recovered well from this disaster by containing the devastated impact to the emulsifier supplier by quickly excluding them from the supply chain. We can predict that an incremental strategy, DR7, which carries out recovery activities in a gradual manner, does not reinstate consumers' confidence as well as other strategies, as evidenced by the low ranking in Figure 6. Likewise, strategies such as DR8, in which firms adjust only to the state of one upstream firm (in the Taiwan case, that would be the dishonest supplier), would halt the entire supply chain. In summary, as the main insight generated in our formal analysis, the radical recovery strategy, DR1, is most effective in preventing a crisis from escalating and in recovering the supply chain to a good state.

3.6 Discussion and managerial implications

In this section, we discuss the findings and their empirical and management implications.

The simulation outcomes, illustrated in Figures 3.2 and 3.3, suggest that DR1 is the most effective strategy for recovering from unanticipated disasters (since we consider only the 1st percentile results as our performance measure). Results also suggest a rather small variation in DR1's performance ranking in comparison to the other nine strategies. Consistent with Chopra and Sodhi's (2014) strategy on regionalizing the supply chain, the radical recovery strategy DR1 will mitigate the negative impact of disruptions caused by unanticipated disasters within the affected region because one bad-stated firm will not drag the entire supply chain down. In other words, the supply chain becomes less fragile as the devastating impact of a disruption will be halted quickly, and will not spread to all member firms. Table 3.6 shows that the robustness of DR1 increases in resource increments per period (parameter Δ). Table 3.4 reports no clear relationship between the initial states of firms (i.e., either good or randomly assigned) and supply chain performance following the simulations. From this, we can infer that recovery strategies have a greater impact on supply chain performance than do resource consumption scenarios and the firms' initial states. Drawing on these findings, we propose the following observations:

Observation 1a. *A supply chain is robust against disruptions from unanticipated disasters if each supply chain member employs a radical recovery strategy aimed to return to a good state following a disruption.*
Observation 1b. *The robustness of the radical recovery strategy increases with resource increment.*

Our analysis statistically demonstrates that the radical strategy (DR1) is the most effective among the nine others for supply chains striving to recover from an unanticipated disaster, no matter how serious the disaster is. However, using the radical strategy may be unrealistic in practice due to the high level of resource consumption (high costs) that a firm must invest in order to return to a good state after a disruption (i.e., in RC1 and RC2). Therefore, we search for alternative recovery strategies under scenarios RC1 and RC2. We first consider DR2 and find that it generates the best recovery performance among the ten strategies (see panel 4 of Table 3.4). As reported in Table 3.6, benchmarking recovery strategy leads to better performance following unanticipated disasters when the chain size is small. This leads to the next observation,

Observation 2a. *A supply chain is robust against disruptions caused by unanticipated disasters if firms employ a recovery strategy using the strategy of at most one neighboring firm with good performance as a benchmark to improve their operational performance following a disruption.*
Observation 2b. *The robustness of the benchmarking recovery strategy in a supply chain decreases as the chain size increases.*

We now consider DR7 that firms take recovery activities incrementally. Similar to DR2, we find that DR7 can perform well under RC1 or RC2 (for details, see panels 3 and 4 of Table 3.4 and Figure 3.2). In other words, DR7 is quite effective in recovering from extreme disasters when the recovery process that involves changing a firm's state from bad (0) to good (2) requires plenty of resources. If this resource consumption condition does not hold, the performance of the incremental recovery strategy is not as good as most other recovery strategies. Also, we find that the robustness of DR7 increases as the chain size (N) increases, as shown in Table 3.6. Formally,

Observation 3a. *Supply chain performance following unanticipated disasters is sensitive to resource consumption requirements for recovery when an incremental recovery strategy is employed by each supply chain member.*

Observation 3b. *The robustness of an incremental recovery strategy increases as the size of the supply chain increases.*

The insights from the analysis and discussion are distilled into a conceptual framework in Figure 3.5, which provides managerial insights in the demarcating regions of robustness of a supply chain's various recovery strategy options. Specifically, the radical strategy is the best recovery option for scenarios in which the resource consumption requirements are relatively low for recovery activities from a bad state (0) to a good state (2). A benchmarking strategy is a good option for a small supply chain with high recovery resource needs. When the supply chain size is large and the recovery resource consumption requirements are high, the use of incremental recovery strategy among member firms in a supply chain is expected to outperform all the nine other strategies.

This chapter contributes to the literature by examining the robustness of practical supply chain strategies for recovering from unanticipated disasters in a dynamic setting. We develop a supply chain model of unanticipated disasters using cellular automata (CA), a complex adaptive system found in nature (Miller and Page, 2007). The proposed CA model incorporates the spirit of behavioral game theory as do past studies (e.g., Xiao and Yu, 2006; Gintis, 2009) and the key features extracted from real-world supply chain recovery activities (e.g., Kunz and Reiner, 2012; Rogers, 2012). Our stylized, behavioral model depicts the dynamic evolution of supply chain performance under the disruptive threat of unpredictable

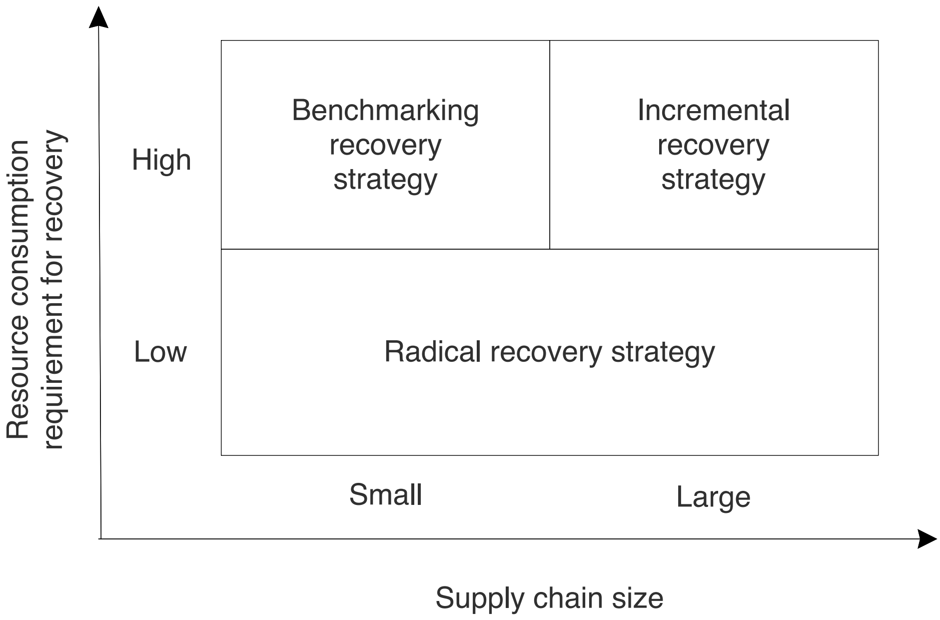


Figure 3.5: Robust supply chain recovery strategies.

disasters. Through carefully chosen computational analysis, we uncover the weaknesses of popular incremental strategies for supply chain recovery when the chain size is relatively small. We further find that supply chain member firms using a radical recovery strategy can help maintain a positive supply chain performance over time. Counterintuitively, playing strategically for recovery by looking at what one's neighbors do in a large supply chain may hurt the entire supply chain's performance in the long run.

3.7 Supplementary Notes

This section reports the experimental results under two resource consumption functions, $\mathbb{C}$, where $c_1, c_2, c_3 \in \{1, 5, 10\}$, and $\mathfrak{C}$, where $c_1, c_2, c_3 \in \{1, 8, 10\}$. Together with the function employed in the main analysis, C, where $c_1, c_2, c_3 \in \{1, 2, 10\}$, our study considers a wide range of possible resource consumption scenarios. Following the experimental design in Section 3.3.2, we apply $\mathbb{C}$ and $\mathfrak{C}$, respectively, to verify the robustness of recovery strategies to restore supply chain performance following unanticipated disasters. The results are consistent with the findings in Section 3.3.

Table 3.8: Experimental results under $\mathbb{C}$ ($c_1, c_2, c_3 \in \{1, 5, 10\}$)

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
Δ	$\{1\}$	**2.417**	3.125	**7.958**	**7.986**	**4.889**	3.361	**5.014**	7.417	7.444	**5.347**
		(3.015)	(1.034)	**(2.185)**	**(2.635)**	**(2.678)**	(1.011)	**(2.976)**	(1.123)	(1.277)	**(1.090)**
	$\{10\}$	**1.000**	2.875	**9.000**	**9.181**	**5.944**	3.083	**3.583**	7.403	7.583	**4.500**
		(0.000)	(0.786)	**(0.000)**	**(0.387)**	**(0.285)**	(1.045)	**(1.275)**	(0.494)	(0.496)	**(0.605)**
N	$\{3\}$	1.771	**2.688**	8.500	8.521	**5.938**	**2.833**	**5.104**	7.250	7.354	**4.500**
		(2.299)	**(0.776)**	(1.726)	(2.114)	**(1.405)**	**(1.018)**	**(2.205)**	(0.758)	(1.041)	**(1.130)**
	$\{5\}$	1.688	2.917	8.604	8.458	5.479	2.938	**4.333**	7.417	7.583	**5.104**
		(2.233)	(0.895)	(1.634)	(1.967)	(2.000)	(0.836)	**(2.157)**	(0.942)	(0.794)	**(0.515)**
	$\{10\}$	1.667	**3.396**	8.333	8.771	**4.833**	**3.896**	**3.458**	7.562	7.604	5.167
		(2.234)	**(0.962)**	(1.534)	(1.848)	**(2.282)**	**(0.905)**	**(2.551)**	(0.873)	(1.047)	(1.038)
T	$\{365\}$	1.736	3.167	8.361	8.597	5.333	3.333	4.208	7.458	7.514	4.875
		(2.270)	(0.993)	(1.698)	(2.080)	(2.014)	(1.187)	(2.367)	(0.887)	(1.075)	(1.100)
	$\{3650\}$	1.681	2.833	8.597	8.569	5.500	3.111	4.389	7.361	7.514	4.972
		(2.226)	(0.822)	(1.553)	(1.868)	(1.936)	(0.848)	(2.430)	(0.844)	(0.856)	(0.839)

Note. The experimental settings are identical to those in Table 3.6.

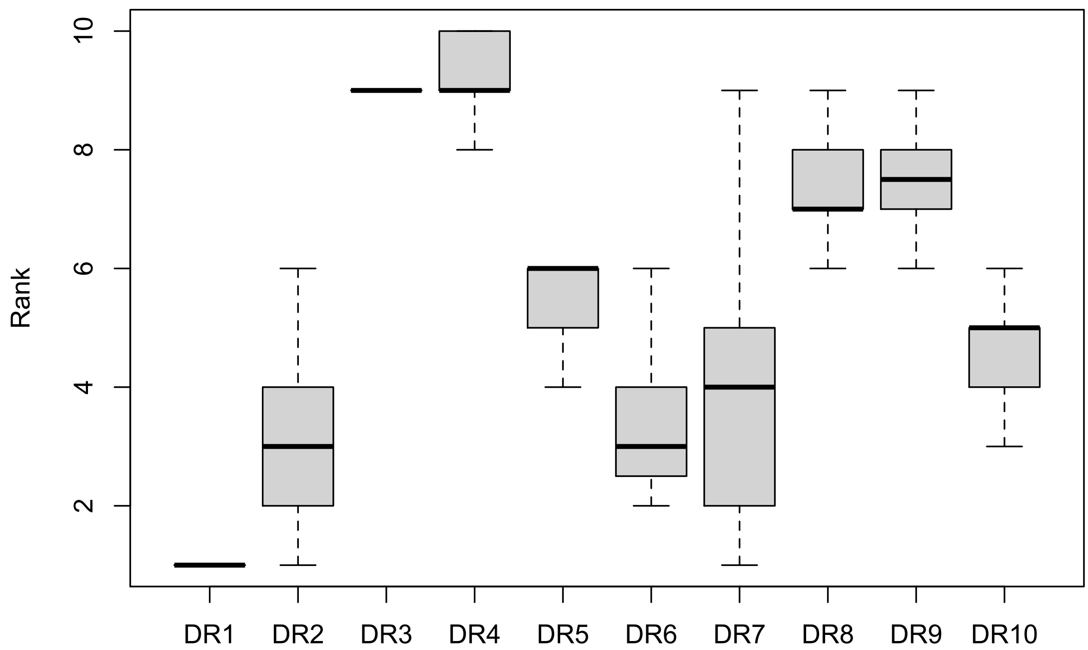


Figure 3.6: Boxplot of the ranking of recovery strategies under $\mathbb{C}$.

First, $\mathbb{C}$ is applied so that the overall resource consumption requirement for recovery increases in comparison to C. As illustrated in Table 3.8, resource increment (parameter Δ) and chain size (parameter N) both have significant impacts on the performance ranking of the recovery strategies, where time period (parameter T) does not impose a significant impact. Figure 3.6 further shows that the radical recovery stately (DR1) and the benchmarking recovery strategy (DR2) are the most robust to restore supply chain performance following unanticipated disasters. Further, DR1's ranking outcome increases as the resource increment increases; DR2's ranking outcome increases as the chain size decreases. On the other hand, the performance ranking of the incremental recovery strategy (DR7) increases in chain size, yet is sensitive to the resource consumption scenarios (as evidenced by the large variability of its boxplot). These findings are consistent with the results in Section 3.3 and the derived observations in Section 3.6.

Table 3.9: Experimental results under $\mathfrak{C}$ ($c_1, c_2, c_3 \in \{1, 8, 10\}$)

Par	value	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
Δ	{1}	**3.306**	3.500	**7.125**	**7.194**	**5.542**	3.736	**4.403**	7.181	7.375	**5.514**
		(3.347)	(0.993)	**(2.818)**	**(3.450)**	**(3.314)**	(1.267)	**(3.300)**	(0.998)	(0.926)	**(0.904)**
	{10}	**1.000**	2.681	**9.000**	**9.167**	**5.944**	3.250	**3.569**	7.556	7.431	**4.514**
		(0.000)	(0.747)	**(0.000)**	**(0.375)**	**(0.231)**	(1.031)	**(1.287)**	(0.500)	(0.499)	**(0.556)**
N	{3}	2.125	**2.750**	8.042	7.979	**6.167**	**3.083**	**5.021**	7.208	7.375	**4.688**
		(2.598)	**(0.786)**	(2.315)	(2.740)	**(2.046)**	**(1.334)**	**(2.329)**	(0.824)	(0.815)	**(1.206)**
	{5}	2.167	3.042	8.021	8.125	5.771	3.229	**3.979**	7.438	7.396	**5.250**
		(2.668)	(0.922)	(2.178)	(2.695)	(2.425)	(1.016)	**(2.320)**	(0.712)	(0.707)	**(0.438)**
	{10}	2.167	**3.479**	8.125	8.438	**5.292**	**4.167**	**2.958**	7.458	7.438	5.104
		(2.668)	**(1.052)**	(2.140)	(2.509)	**(2.518)**	**(0.834)**	**(2.551)**	(0.874)	(0.712)	(0.805)
T	{365}	2.139	3.208	7.986	8.208	5.625	3.639	4.000	7.389	7.319	4.944
		(2.613)	(1.020)	(2.211)	(2.690)	(2.486)	(1.325)	(2.573)	(0.848)	(0.688)	(0.963)
	{3650}	2.167	2.972	8.139	8.153	5.861	3.347	3.972	7.347	7.486	5.083
		(2.659)	(0.903)	(2.197)	(2.604)	(2.216)	(0.995)	(2.506)	(0.772)	(0.787)	(0.835)

Note. The experimental settings are identical to those in Table 3.6.

Next, in Table 3.9 we report the experimental results under $\mathfrak{C}$, where $c_1, c_2, c_3 \in \{1, 8, 10\}$, an even higher resource consumption requirement than $\mathbb{C}$ and C. In this case, recovery activities mostly cost the firm a huge amount of resource units. In Table 3.9 we observe that firms' adopting a radical recovery strategy achieve the best recovery performance when the resource increment is high. Additionally, the performance ranking of the benchmarking recovery strategy, DR2, decreases in chain size; the incremental recovery strategy, DR7 increases in chain size. In spite of DR7's large variability, these three strategies are generally robust and have high ranking outcomes, as illustrated in Figure 3.7.

In sum, the observations we derived from Section 3.3 are preserved under various resource consumption requirements.

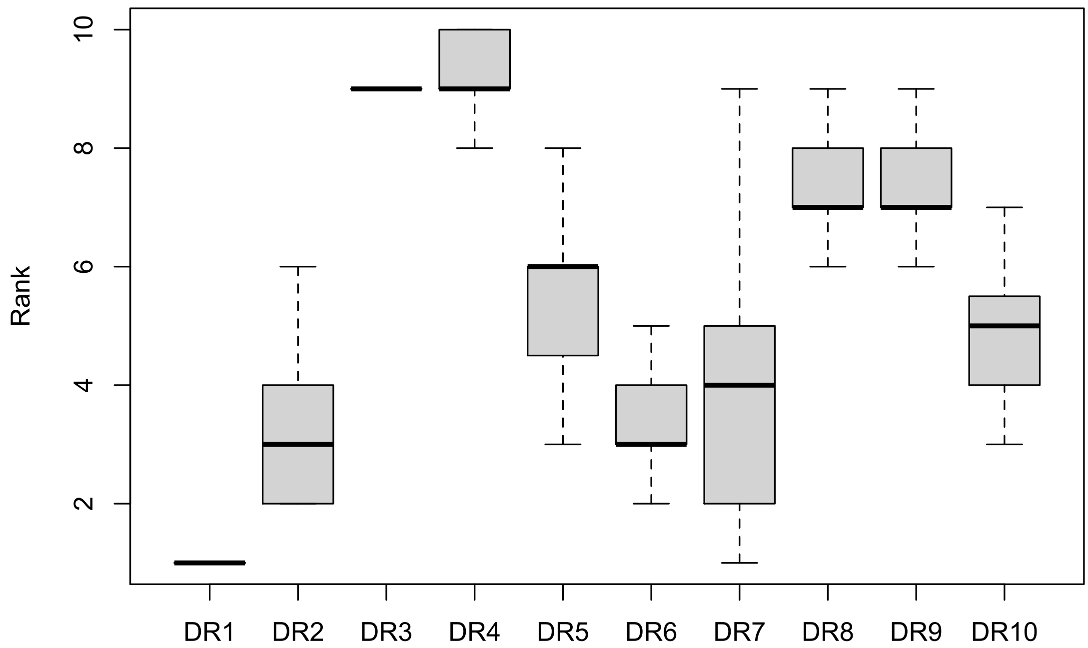


Figure 3.7: Boxplot of the ranking of recovery strategies under $\mathfrak{C}$.

Chapter 4

Resolving the altruist's dilemma: Towards a theory of altruistic entrepreneurship in times of disaster

4.1 Introduction

We, humans, live in a world that is fraught with dangers and disasters. Throughout the history, nature-made and man-made disasters have repeatedly destroyed cities and lives, and even wiped many civilizations. Despite its centrality to societies and organizations, the behavioral aspect amid disasters is under-researched and has, to-date, remained a mystery. The quest for knowledge about this disaster-prone world calls for more studies beyond Gaussian averages (i.e., "at the tail of the bell curve").

This study of disasters is intertwined with two research streams: entrepreneurship and altruism. Disasters create recovery "opportunities" for potential economic, social and environmental value creation (Shane and Venkataraman, 2000). In pursuit of such opportunities, actors (e.g., people, teams, firms) need to bear uncertainty, create value, and importantly, motivate to improve the welfare of other actors or known as altruism (Nowak, 2006; Penner et al., 2005). Christopher Girdwood and his Recovery Pledge is a notable example of pursuing altruistic opportunities to address disastrous events. Recovery Pledge is founded to help small businesses recover from disasters by connecting them with customers to stabilize their sales. Specifically, a customer can purchase recovery pledges once a disaster occurs, which are the vouchers for the goods and services that are produced by small businesses in need (recoverypledge.com). His/her consumption behavior not only satisfies personal needs, but also offers cash to small businesses that is essential to their recovery from a disaster. In other words, recovery pledges build a reciprocal relationship between customers and small businesses in times of disasters. In this sense, Recovery Pledge identified and exploited this opportunity to launch a crowd-funding campaign in pursuit of both customer satisfaction and small business survival.

The role of altruism has been recently recognized in the study of entrepreneurship (Shepherd and Patzelt, 2011). In times of disaster, altruistic behavior is essentially entrepreneurial as it involves bearing uncertainty through expending resources and efforts to save/help others instead of accumulating them for self benefits; absorbing sunk costs of (possibly) not receiving any reciprocal help from others in future disasters; and, creating entrepreneurial spill over as it can stimulate others to behave in a similar manner. Given the interface between entrepreneurship and altruism in the context of disasters, we introduce altruism-related variables such as benefit-cost ratio, the average number of neighbors in the networked system, and different beliefs of discovering and exploiting recovery opportunities, to extend the theory of entrepreneurial action into the context of disasters.

We conduct this study using a two-dimensional cellular automata (CA) model, which is a special type of agent-based computational model and mimics the real-world supply network disruptions. Our CA model is structured as a network of interconnected actors, each with east, west, south, and north neighbors that are hit by disasters with minor and major probabilities. Actors are given opportunity beliefs with different levels of altruistic reciprocity and each entrepreneurial act is influenced by different opportunity evaluation rules and cost scenarios for recovery. In this chapter, we are interested in how altruistic reciprocity can provide a deeper understanding of the entrepreneurial action process.

Our results provide a clear view of what might be called the strong altruistic entrepreneurship hypothesis. Our simulation analysis demonstrates how altruistic opportunity beliefs generate better recovery performance than the non-altruistic opportunity beliefs under many cost scenarios. Through this study, we discover that the processes leading to entrepreneurial recovery action and ultimately the collective value creation is strongly moderated by the joint altruistic reciprocity, cost scenarios for recovery, and network size (i.e., the number of actors in the network). These results resolves the "altruists dilemma" by highlighting the boundary conditions of altruistic entrepreneurship in times of disaster. Our findings advance entrepreneurship research by linking the theories of entrepreneurial action and altruistic reciprocity for better explaining entrepreneurial processes and outcomes in the context of disasters.

4.2 Altruistic Entrepreneurship

Altruism, the desire to help others at one's own costs (Nowak, 2006; Penner et al., 2005), has been acknowledged as a driver to motivate opportunity recognition (Patzelt and Shepherd, 2011; Zahra et al., 2009). The reciprocal altruism theory in evolutionary research (Axelrod and Hamilton, 1981; Nowak, 2006; Trivers, 1971) posit that altruistic actions occur and evolve only under highly specialized circumstance where the altruists act will eventually returned to him/her and confer (directly or indirectly) its benefit (Nowak et al., 2010; Penner et al., 2005; Trivers, 1971). In other words, reciprocity forms the motive future benefits of an altruistic action will compensate the current sacrifice to help others. Following McMullen and Shepherd (2006) and Haynie et al. (2009), altruistic reciprocity essentially constructs the entrepreneurial action decision as future-oriented judgment on "feasibility" (costs to help others are affordable given the existing resource endowments) and "desirability" (can fulfill the underlying reciprocal motive). We therefore consider altruistic reciprocity an mechanism for explain why some actors act entrepreneurially whereas others are not in times of disasters.

We define *altruistic entrepreneurial action* as behavior in response to a judgmental decision under uncertainty about a possible opportunity for reciprocal benefits. According to the reciprocal altruism theory, an altruistic entrepreneurial action occurs when the benefit-to-cost ratio, b/c, exceeds the average number of neighbors, w, in the network (i.e., $b/c > w$), where c is the cost to the altruist for helping others, and b is the benefit to the recipient in expectation of returning back to the altruist (Axelrod and Hamilton, 1981; Nowak, 2006;

Ohtsuki et al., 2006). Follow this logic, altruistic entrepreneurial action is inherently long-term self-serving since it is motivated by potential future benefits derived from reciprocity (Kenrick et al., 2009; Trivers, 1971).

The notion of reciprocity distinguishes altruistic entrepreneurial action from action taken by social entrepreneurs. Although both types of action take others' benefit into account, social entrepreneurship literature always emphasizes compassion – unselfish sacrifice of self benefits to create social values (Penner et al., 2005; Shepherd and Patzelt, 2011), which does not impose strong assumption on reciprocal return. It expects capable social entrepreneurs to scarify self to develop benefits to weak others for the sake of social wealth creation. Herein, the underlying motivation is to develop benefit for 'others' to address social problems and achieve fairness (Austin et al., 2006). In contrast, altruistic entrepreneurial action focuses on the long-term personal benefit. It can emerge as a direct consequence of the "selfish"motive of a rational player (Axelrod and Hamilton, 1981; Nowak, 2006). Either economic wealth, or social wealth, or both can drive the altruistic act, as long as altruistic entrepreneurs perceive satisfactory benefits feedback from such actions. Put it simple, do onto others as s/he would have others do unto s/he.

Additionally, altruistic entrepreneurial action differentiates itself from commercial actions in terms of the altruistic motive. According to Austin et al. (2006), commercial entrepreneurs pursue personal economic gains. Altruistic acts incurring sacrifice are detrimental to this goal, hence barely taken by commercial entrepreneurs. Yet the altruistic entrepreneur's desire to help others will motive such actions (Penner et al., 2005). And the reciprocal feedback further allows him/her to tolerant short-term sacrifice and create mutual benefits in the long run (Kenrick et al., 2009; Ohtsuki et al., 2006). As a result, we expect altruistic entrepreneurs to recognize more opportunities since they pay attention to changes in not only his/her but also others business environment. This is consistent with anecdotal evidence in the entrepreneurship literature that emphasizes altruism as motivating opportunity recognition (Austin et al., 2006; Patzelt and Shepherd, 2011; Zahra et al., 2009).

Above we have illustrated the altruistic reciprocity mechanism to stimulate entrepreneurial actions, and how such actions are different from social and commercial actions. Building on the reciprocal altruism theory and entrepreneurship literatures, we define *altruistic entrepreneurship* as the study of recognition and evaluation of altruistic opportunity, and the mobilization of resources and efforts in pursuit of reciprocal benefits for self and others. The process involves identifying altruistic opportunity for someone (third-person altruistic opportunity), evaluating whether the opportunity is reciprocal to him/her self (first-person altruistic opportunity), engaging or disengaging from altruistic action by mobilizing resources and efforts with uncertain outcomes and payoffs (altruistic entrepreneurial action).

Specifically, actors need to escape ignorance in order to detect a third-person altruistic opportunity (McMullen and Shepherd, 2006; Shepherd et al., 2007). On one hand, agents who attend to the reputation of potential partners and their encounter history are more likely to figure out an opportunity to reciprocate (Axelrod and Hamilton, 1981; Ohtsuki et al., 2006). Reciprocity is indeed an obligation derived from a history of exchanges and favors (Trivers, 1971). Actors who have sufficient memory and knowledge on what others have done to them are more likely to detect an altruistic opportunity. On the other hand, the motive of helping others and receiving equivalent repayment will direct focused attention. Following Nowak and May (1993) and Nowak (2006), a robust strategy for altruistic entrepreneurs is as follow: if the reciprocal motive is fulfilled, the actor will continue the altruistic actions; if the partner cheats, the agent will stop his/her altruistic move until the partner starts to repay the benefit.

Given the recognition of third-person altruistic opportunity, actors next need to overcome doubt in order to form a first-person altruistic opportunity (Shepherd et al., 2007). The doubt is derived from the time lag one helps the other and must wait a period of time before s/he is helped in turn (Axelrod and Hamilton, 1981; Trivers, 1971). Therefore, agents enhance the feasibility of the altruistic opportunity with the knowledge, skills, and abilities to shorten the time lag, so that the resources are adequate to support his/her own value creation during this waiting period. Meanwhile, agents assess the desirability of acting on a third-person opportunity, i.e. action threshold (McMullen and Shepherd, 2006). In the long run, an agent surrounded by other altruists is more likely to detect altruistic opportunity since the reciprocal return can be secured (Ohtsuki et al., 2006). And reciprocal altruistic actions are most desirable within a long-lived community where agents have an opportunity to interact not once but frequently (Nowak et al., 2010).

We next formalize the altruistic entrepreneurial action process in times of disasters. In particular, seven beliefs on the existence of entrepreneurial opportunity are introduced that vary in the level of altruistic reciprocity, such that we can explore the robustness of altruistic entrepreneurship in the following sections.

4.3 Model

Following Robertson and Caldart (2009) and Yang and Chandra (2013), we consider entrepreneurial dynamics of networked actors that evolve over discrete time steps. The actors populate a two-dimensional network in our model, which includes K rows and N columns, thus a *size* of $K \times N$. The network is unwrapped so that there are "walls" around the edge of the network. This could represent the bounded organizational and market landscape in which the interdependent decision-making on entrepreneurial recovery actions takes place after disasters (Parker, 2008). Without the loss of generality, we model the standard *von Neumann* neighborhood where an actor interacts with his/her two row neighbors to the east and west, as well as two column neighbors to the south and north, see Figure 4.1a for an example of an actor at column $n \in \{1, \cdots, N\}$ and row $k \in \{1, \cdots, K\}$. (Note that actors at the edge will have less neighbors.) Together their unique interactions influence the network's overall entrepreneurial value creation.

In our stylized model, the actors can have *poor*, *fair*, or *good* entrepreneurial states by taking recovery actions, designated by $0, 1$ and 2. A good state (2) indicates entrepreneurial growth or value creation. At the other extreme, a poor state (0) stands for entrepreneurial failure or severe damage to the actor's value. Then a fair state (1) represents the intermediate status that the actor survives without much market success (Bosma et al., 2004). We denote

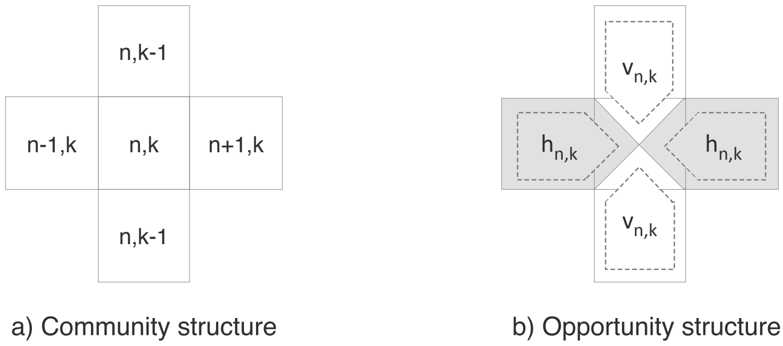


Figure 4.1: The standard *von Neumann* neighborhood.

an actor's post-recovery state at time $t-1$ by $\psi_{n,k}(t-1) \in \{0,1,2\}$, where $t \in \{1, \cdots, T\}$ indicates the simulation period.

Disasters may sway the network and damage the actor's entrepreneurial state from the preceding period. We denote this prior-recovery state (post disaster) at period t by $\phi_{n,k}(t) \in \{0,1,2\}$. To make it simple, each networked actor has a probability θ_0 of being hit by 'major' disasters and a probability θ_1 of being affected by 'minor' disasters at each period. The two types of disasters vary in the levels of severity. Specifically, encountering a major disaster at period t, an actor's prior-recovery state is

$$\phi_{n,k}(t) = 0,$$

regardless of recovery efforts in the preceding period, $\psi_{n,k}(t-1)$; whereas suffering a minor disaster at period t, an actor's prior-recovery state is

$$\phi_{n,k}(t) = [\psi_{n,k}(t-1) - 1] \vee 0,$$

where $a \vee b := \max\{a, b\}$ for $a, b \in \mathbf{R}$.

Entrepreneurial actions are taken to improve the prior-recovery states. So an entrepreneurial *opportunity* is the attainment of the good state post recovery. In this chapter, we consider altruistic reciprocity a mechanism that facilitates the actors' recognition of entrepreneurial opportunities in the network. An altruistic actor shares his/her information and experiences with each neighbor at a cost of c and help them explore the benefit (b) of achieving the good-recovery state. In other words, the altruist's cost and the recipient's benefits are measured in terms of entrepreneurial opportunities. We say the benefits can be reciprocated if $b/c > w$, as with Lieberman et al. (2005), Nowak (2006), and Ohtsuki et al. (2006), where w is the number of neighbors. We define the overall entrepreneurial states of networked actors post recovery (or the overall entrepreneurial value creation) at period t as

$$\Psi(t) = \sum_{k=1}^{K} \sum_{n=1}^{N} \psi_{n,k}(t).$$

4.3.1 Recognizing third-person opportunities

Entrepreneurial opportunities arise from disaster-caused state changes. Someone who receives possible help from neighbors is more likely to acknowledge an opportunity. In the network setting, we separate the benefits acquired from the row neighbors and those from the column neighbors such that each actor can be exposed to a large pool of third-person opportunities. As illustrated in Figure 4.1b, we denote the possible opportunity identified in the row and column by $h_{n,k}(t)$ and $v_{n,k}(t)$, individually. Following CA modeling convention, we assume that each actor's entrepreneurial action is controlled by a fixed, homogeneous rule, and that this rule uses the pre-recovery state of the actor and the pre-recovery states of its two adjacent row- (or column-) neighbors to determine the new state. In this sense, our model can be viewed as a modeling framework of behavioral game theory similar to nonlinear dynamic systems, following the principle of cognitive limits in human and organizational decision-making and judgement (see Gintis, 2009; Robertson and Caldart, 2009).

Theoretically, a decision rule is a mapping of each possible input state, $\phi_{j,k}(t), j \in \{n-1, n, n+1\}$ ($\phi_{n,l}(t), l \in \{k-1, k, k+1\}$), to an output state, $h_{n,k}(t)$ ($v_{n,k}(t)$), for every actor in the network. A decision rule thus specifies a *belief* on the existence of a third-person entrepreneurial opportunity following a disaster. Following the modeling practice for complex adaptive systems (Miller and Page, 2007; Gintis, 2009), we choose seven possible rules (or opportunity beliefs) in this chapter based on their similarity to real-world decision making in times of disasters. In particular, to examine the effectiveness of altruistic entrepreneurial actions, we deliberately consider both opportunity beliefs that satisfy altruistic reciprocity (i.e., $b/c > w$), namely *altruistic opportunity beliefs*, and opportunity beliefs that go against altruistic reciprocity (i.e., $b/c \leq w$), namely *non-altruistic opportunity beliefs*. Table 4.1 illustrates the seven beliefs selected, which determine each actor's identification of entrepreneurial opportunities at period t (i.e., $h_{n,k}(t) = 2$, $v_{n,k}(t) = 2$).

4.3.2 Evaluating and exploiting first-person opportunities

After identifying possible opportunities based on $h_{n,k}(t)$ and $v_{n,k}(t)$, an actor next must choose one among the possible courses of actions (Haynie et al., 2009; Shepherd et al., 2007). Specifically, we consider the actor's commitment to either pursue the best possible state post recovery regardless of the possible time lag of receiving reciprocal return (i.e., the max-rule)

$$\Phi_{n,k}(t) = \max\{h_{n,k}(t), v_{n,k}(t)\},$$

or act conservatively subject to the concerns on time lag (i.e., the min-rule)

$$\Theta_{n,k}(t) = \min\{h_{n,k}(t), v_{n,k}(t)\},$$

such that $\psi_{n,k}(t) \in \{\Phi_{n,k}(t), \Theta_{n,k}(t)\}$. Table 4.1 illustrates these two rules on evaluating first person opportunities. In general, $\psi_{n,k}(t)$ is easily determined if $h_{n,k}(t)$ and $v_{n,k}(t)$ return the same entrepreneurial state. Otherwise, the actor needs to chose between these two possible future states.

Additionally, it is essential for the actors to examine their possessed value since they can only act upon feasible opportunities. An actor's value at period t is

$$U_{n,k}(t) = U_{n,k}(t-1) + \Delta - C(\phi_{n,k}(t), \psi_{n,k}(t)),$$

where parameter Δ is the increase in value per period, and parameter C is the cost function for an actor with prior-recovery state $\phi_{n,k}(t)$ to reach post-recovery state $\psi_{n,k}(t)$. This cost

Table 4.1: Entrepreneurial opportunities motived by altruistic reciprocity in times of disaster

	Third-person opportunities	**Altruistic reciprocity**	**First-person opportunities**
O1	Let $H = \{\phi_{n-1,k}, \phi_{n,k}, \phi_{n+1,k}\}$, $h_{n,k} = \begin{cases} 2 & \text{if } \wedge_{\phi_j \in H}\, \phi_j = 2, \\ 1 & \text{otherwise.} \end{cases}$ Let $V = \{\phi_{n,k-1}, \phi_{n,k}, \phi_{n,k+1}\}$, $v_{n,k} = \begin{cases} 2 & \text{if } \wedge_{\phi_j \in V}\, \phi_j = 2, \\ 1 & \text{otherwise.} \end{cases}$	The recipients will *not* reciprocate the benefits as $\frac{b}{c} = \frac{0/36}{16/18} < 2.$	$\Phi_{n,k} = \begin{cases} 2 & \text{if } \phi_{n,k} \wedge [(\phi_{n-1,k} \wedge \phi_{n+1,k}) \vee (\phi_{n,k-1} \wedge \phi_{n,k+1})] = 2, \\ 1 & \text{otherwise.} \end{cases}$ $\Theta_{n,k} = \begin{cases} 2 & \text{if } \wedge_{\phi_j \in (H \cup V)}\, \phi_j = 2, \\ 1 & \text{otherwise.} \end{cases}$
	Remark: This opportunity belief reflects an interaction history among neighboring actors that an altruist cannot receive reciprocal payback, i.e., $b/c < 2$. Hence, an actor is not motivated to act selflessly to help his/her neighbors. The recognition of a recovery opportunity is dependent upon three good-state actors post disaster.		
O2	Let $q_1 = \phi_{n-1,k} \vee \phi_{n,k}$, $q_2 = \phi_{n,k} \vee \phi_{n+1,k}$, $q_3 = \phi_{n-1,k} \vee \phi_{n+1,k}$, and $Q_h = \{q_1, q_2, q_3\}$, $h_{n,k} = \begin{cases} 2 & \text{if } \wedge_{q_j \in Q_h}\, q_j = 2, \\ 1 & \text{otherwise.} \end{cases}$ Let $q_4 = \phi_{n,k-1} \vee \phi_{n,k}$, $q_5 = \phi_{n,k} \vee \phi_{n,k+1}$, $q_6 = \phi_{n,k-1} \vee \phi_{n,k+1}$, and $Q_v = \{q_4, q_5, q_6\}$, $v_{n,k} = \begin{cases} 2 & \text{if } \wedge_{q_j \in Q_v}\, q_j = 2, \\ 1 & \text{otherwise.} \end{cases}$	The recipients will *not* reciprocate the benefits as $\frac{b}{c} = \frac{4/36}{8/18} < 2.$	$\Phi_{n,k} = \begin{cases} 2 & \text{if } [\wedge_{q_j \in Q_h} q_j] \vee [\wedge_{q_l \in Q_v} q_l] = 2, \\ 1 & \text{otherwise.} \end{cases}$ $\Theta_{n,k} = \begin{cases} 2 & \text{if } \wedge_{q_j \in (Q_h \cup Q_v)}\, q_j = 2, \\ 1 & \text{otherwise.} \end{cases}$
	Remark: While the benefit-cost-ratio (b/c) is higher than that of O1, an actor does not believe the cost of helping neighbors can be returned. The recognition of a recovery opportunity is dependent upon at least two good-state actors post disaster.		

<table>
<tr><th></th><th>Third-person opportunities</th><th>Altruistic reciprocity</th><th>First-person opportunities</th></tr>
<tr><td>O3</td><td>Let $A_1 = \{\phi_{n-1,k} = 2\}$,
$A_2 = \{\phi_{n-1,k} = 1, \phi_{n,k} = 1\}$,
$A_3 = \{\phi_{n-1,k} = 0\}$ and $A_4 = \{\phi_{n,k} > 0\}$,
$h_{n,k} = \begin{cases} 2 & \text{if } A_1 \cup A_2, \\ 0 & \text{if } A_3 \cap A_4, \\ 1 & \text{otherwise.} \end{cases}$
Let $B_1 = \{\phi_{n,k-1} = 2\}$,
$B_2 = \{\phi_{n,k-1} = 1, \phi_{n,k} = 1\}$, and
$B_3 = \{\phi_{n,k-1} = 0\}$,
$v_{n,k} = \begin{cases} 2 & \text{if } B_1 \cup B_2, \\ 0 & \text{if } B_3 \cap A_4, \\ 1 & \text{otherwise.} \end{cases}$</td><td>The recipients will not reciprocate the benefits as
$\frac{b}{c} = \frac{18/36}{12/18} < 2.$</td><td>$\Phi_{n,k} = \begin{cases} 2 & \text{if } (A_1 \cup A_2) \cup (B_1 \cup B_2), \\ 0 & \text{if } A_4 \cap (A_3 \cap B_3), \\ 1 & \text{otherwise.} \end{cases}$
$\Theta_{n,k} = \begin{cases} 2 & \text{if } (A_1 \cup A_2) \cap (B_1 \cup B_2), \\ 0 & \text{if } A_4 \cap (A_3 \cup B_3), \\ 1 & \text{otherwise.} \end{cases}$</td></tr>
<tr><td></td><td colspan="3">Remark: An actor holding opportunity belief O3 is not motivated to help neighbors altruistically since the returned benefit cannot compensate the cost, i.e., $b/c < 2$. The recognition of a recovery opportunity is dependent upon either 1) an actor having a good-state upstream neighbor post disaster, or 2) an actor and his/her upstream neighbor both having a normal post-disaster state.</td></tr>
<tr><td>O4</td><td>$h_{n,k} = \begin{cases} 1 & \text{if } \wedge_{\phi_j \in H} \phi_j = 2, \\ 2 & \text{otherwise.} \end{cases}$
$v_{n,k} = \begin{cases} 1 & \text{if } \wedge_{\phi_j \in V} \phi_j = 2, \\ 2 & \text{otherwise.} \end{cases}$</td><td>The recipients will reciprocate the benefits as
$\frac{b}{c} = \frac{36/36}{2/18} > 2.$</td><td>$\Phi_{n,k} = \begin{cases} 1 & \text{if } \wedge_{\phi_j \in (H \cup V)} \phi_j = 2, \\ 2 & \text{otherwise.} \end{cases}$
$\Theta_{n,k} = \begin{cases} 1 & \text{if } \phi_{n,k} \wedge [(\phi_{n-1,k} \wedge \phi_{n+1,k}) \vee (\phi_{n,k-1} \wedge \phi_{n,k+1})] = 2, \\ 2 & \text{otherwise.} \end{cases}$</td></tr>
<tr><td></td><td colspan="3">Remark: This opportunity belief reflects an interaction history among neighboring actors that an actor's altruistic act will be returned, i.e., $b/c > 2$. Hence, he/she is motivated to act selflessly to help his/her neighbors in times of disaster. The recognition of a recovery opportunity is dependent upon no one or two good-state actors post disaster.</td></tr>
</table>

	Third-person opportunities	Altruistic reciprocity	First-person opportunities
O5	$h_{n,k} = \vee_{\phi_j \in H} \phi_j$. $v_{n,k} = \vee_{\phi_j \in V} \phi_j$.	The recipients will reciprocate the benefits as $b/c \to \infty$.	$\Phi_{n,k} = \vee_{\phi_j \in (H \cup V)} \phi_j$. $\Theta_{n,k} = \phi_{n,k} \vee [(\phi_{n-1,k} \vee \phi_{n+1,k}) \wedge (\phi_{n,k-1} \vee \phi_{n,k+1})]$.
	Remark: An actor holding the opportunity belief O5 is willing to help his/her neighbors at a very low cost, which can be easily reciprocated. The recognition of a recovery opportunity is dependent upon at least one good-state actors post disaster.		
O6	$h_{n,k} = \begin{cases} 2 & \text{if } \vee_{\phi_j \in H} \phi_j = 2, \\ 1 & \text{otherwise.} \end{cases}$ $v_{n,k} = \begin{cases} 2 & \text{if } \vee_{\phi_j \in V} \phi_j = 2, \\ 1 & \text{otherwise.} \end{cases}$	The recipients will reciprocate the benefits as $b/c \to \infty$.	$\Phi_{n,k} = \begin{cases} 2 & \text{if } \vee_{\phi_j \in (H \cup V)} \phi_j = 2, \\ 1 & \text{otherwise.} \end{cases}$ $\Theta_{n,k} = \begin{cases} 2 & \text{if } \phi_{n,k} \vee [(\phi_{n-1,k} \vee \phi_{n+1,k}) \wedge (\phi_{n,k-1} \vee \phi_{n,k+1})] = 2, \\ 1 & \text{otherwise.} \end{cases}$
	Remark: This opportunity belief reflects that there is very low cost associated with acting selflessly. Hence, an actor is motivated to help his/her neighbors. The recognition of a recovery opportunity is dependent upon no less than one good-state actor post disaster.		
O7	$h_{n,k} = 2$. $v_{n,k} = 2$.	The recipients will reciprocate the benefits as $b/c \to \infty$.	$\Phi_{n,k} = 2$. $\Theta_{n,k} = 2$.
	Remark: This opportunity belief reflects an interaction history that all actors will strive to recover self and help others. That is, an altruist will always receive reciprocal payback from the recipients.		

Note. Following the standard convention, $a \vee b := \max\{a, b\}$ and $a \wedge b := \min\{a, b\}$ for $a, b \in \mathbf{R}$. The details for calculating the benefit-to-cost ratios under each opportunity belief are included in Supplementary note.

function is given by

$$C(\phi_{n,k}(t), \psi_{n,k}(t)) = \begin{cases} 0 & \text{for } \{\phi_{n,k}(t) = \psi_{n,k}(t)\}, \\ y_1 & \text{for } \{\phi_{n,k}(t) = 0\} \cap \{\psi_{n,k}(t) = 2\}, \\ y_2 & \text{for } \{\phi_{n,k}(t) = 0\} \cap \{\psi_{n,k}(t) = 1\}, \\ y_3 & \text{for } \{\phi_{n,k}(t) = 1\} \cap \{\psi_{n,k}(t) = 2\}, \end{cases}$$

where the actor does not need to pay for a decreased state, y_1 is the cost spent to pursue an opportunity under major disasters, y_2 is the cost spend to act upon an opportunity under minor disasters, and y_3 is the cost required to maintain survival. Table 4.2 lists the full combinations of $y_1, y_2, y_3 \in \{1, 5, 10\}$ and $y_1 \neq y_2 \neq y_3$, where $a \wedge b := \min\{a, b\}$ for $a, b \in \mathbf{R}$. These six cost scenarios are further divided into three categories, each describing an innovative way of pursuing an opportunity (with the minimum cost).

Table 4.2: Recovery cost scenarios

Scenarios	y_1 $(0 \to 2)$	y_2 $(0 \to 1)$	y_3 $(1 \to 2)$	Remark
Y1	1	5	10	$y_1 = \wedge_{i \in \{1,2,3\}} y_i$
Y2	1	10	5	
Y3	10	1	5	$y_2 = \wedge_{i \in \{1,2,3\}} y_i$
Y4	5	1	10	
Y5	10	5	1	$y_3 = \wedge_{i \in \{1,2,3\}} y_i$
Y6	5	10	1	

Specifically, cost scenarios 1 (Y1) and 2 (Y2) illustrate the cases that an actor can effectively commit to the pursuit of an opportunity arising from major disasters such that $y_1 < y_2$ and $y_1 < y_3$. Likewise, cost scenarios 5 (Y5) and 6 (Y6) suggest the innovative use of possessed values to pursue an opportunity arising from minor disasters, i.e., $y_2 = \wedge_i y_i, i \in \{1, 2, 3\}$. For instance, in our opening example, Findus's audition on its suppliers is a cost-efficient way to pursue a sustainable opportunity and restore customers' confidence after the "horse-meat" scandal. Finally, Y3 and Y4 are costly for the actor to exploit an opportunity of $\psi_{n,k} = 2$, or $y_1, y_3 > y_2$. In other words, the actor experiences cost barriers to pursue the good state post recovery under these two scenarios. In this chapter, we consider all the six cost scenarios to evaluate the robustness of altruistic entrepreneurship.

4.3.3 Simulating the model

The simulation procedure for the proposed model as follows. At period 0, we assign the entrepreneurial opportunity belief (O_i), the cost scenario (Y_i), the probabilities of disasters (f and g), and the initial state ($\psi_{n,k}(0)$) for each networked actor. We assume the neighbors outside the edge of the network have the good state. (This assumption does not impact our outcomes.) The simulation is executed until time T is reached. Next, we calculate the entrepreneurial value creation of the network by adding up the state of each actor to evaluate the robustness of the seven opportunity beliefs.

Figure 4.2 illustrates the entrepreneurial action process at period t. After a disaster occurs, the networked actors share information with each other for discovering opportunities, which may arise from an altruist's exploitation of a specific opportunity. Next an actor will act upon an identified opportunity that is feasible and desirable to his/her recovery from a disastrous event. In sum, the network portrays a feedback system where the actors act in cooperation to pursue entrepreneurial opportunities in times of disasters.

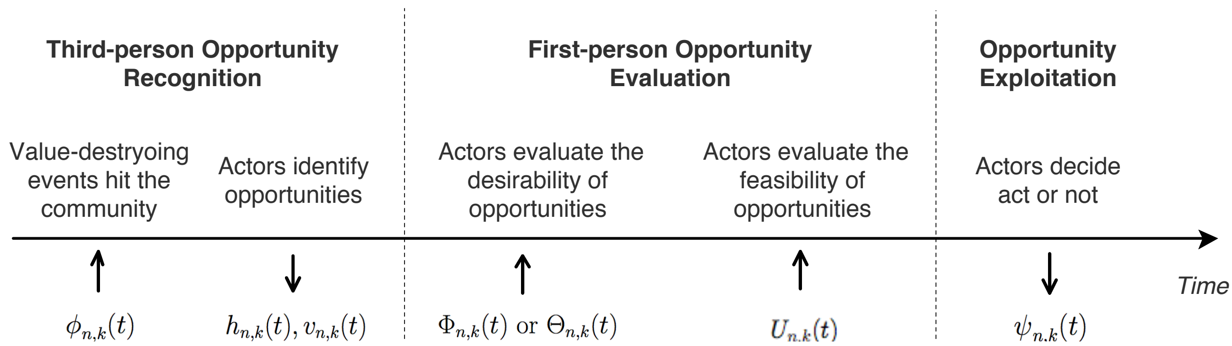


Figure 4.2: Timeline of entrepreneurial action process.

Our objective is to explore the mechanism of altruistic reciprocity that explains why some systems facilitate a large number of entrepreneurial opportunity recognition whereas others do not, to examine how this mechanism influence an actor's seemingly counterintuitive behaviors in the network, and particularly in times of disasters. We simulated our CA model in a MATLAB program.

4.4 Results

In this section, we unpack the robustness of opportunity recognition beliefs in the presence of altruistic reciprocity for networked actors facing disasters using a careful computational analysis. Following the simulation research practice, we first perform a base case in a pilot study, and then run an extensive experimental analysis. The results are summarized below.

4.4.1 Base case analysis

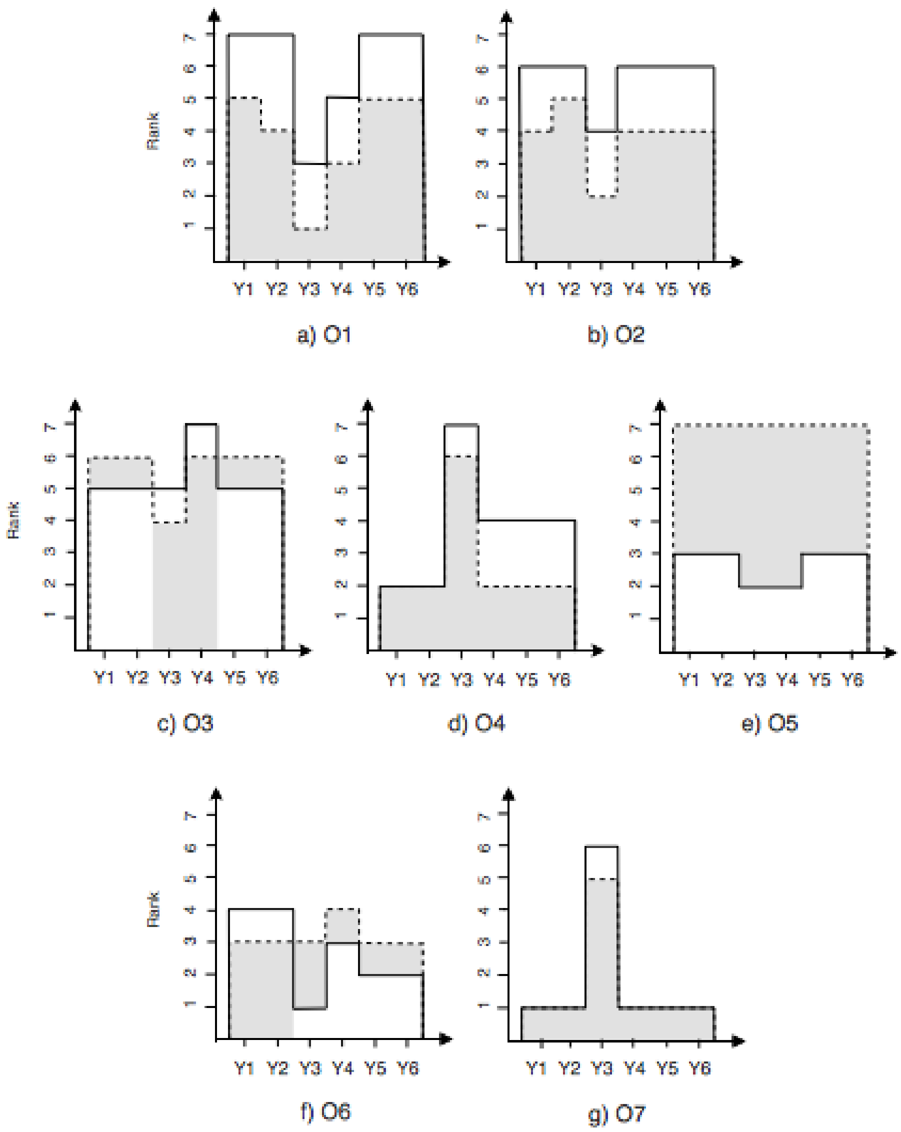
We set $N = 5$, $K = 3$, $T = 365$, $U_{n,k}(0) = 3$, $\Delta = 1$ in the base case. Based on Sheffi's (2007) empirical study, $g = 134/365$ and $f = 17/365$ are chosen for the probabilities of minor and major disasters occurring during a year, and these values are also fixed in our experimental analysis. Each actor's state at period 0 is randomly assigned, poor (0), fair (1), or good (2). Every parameter instance is repeated 200 times for outcome reliability. Table 4.3 shows the average, the 5th percentile, and the 1st percentile of entrepreneurial value creation Ψ per period. These three measures results in very similar ranking outcomes across the seven opportunity beliefs. In line with the emergency management and risk analysis literatures (e.g., Myerson, 2004; Tang, 2006), we primary concerne about the worst-case-scenario rather than average outcomes of disasters since it provides a strict standard by which to assess the effectiveness of entrepreneurial opportunity beliefs in times of disasters.

To visualize the entrepreneurial value creation in Panel 3 of Table 4.3, we plot the rankings of the seven opportunity beliefs in Figure 4.3. Notice that each opportunity belief's performance is dependent on the opportunity-evaluation rules and the cost scenarios. Specifically, under the max-rule (see the solid line), we observe that altruistic opportunity beliefs, O4 to O7, generally result in a better value-creation than the non-altruistic opportunity beliefs, O1 to O3, expect for the relatively low ranking of O4 and O7 under the cost scenario Y3. Under the min-rule (see the dashed line), on the other hand, some non-altruistic oppor-

Table 4.3: Base case result on entrepreneurial value creation

	O1		**O2**		**O3**		**O4**		**O5**		**O6**		**O7**	
	max	min	max	min	max	min	max	min	max	min	max	min	max	min
Panel 1: Average of value per period														
Y1	14.646	14.608	14.764	14.597	19.142	7.151	48.683	46.168	45.439	0.658	45.289	14.932	49.057	49.031
Y2	7.261	7.308	7.557	7.327	30.107	3.524	51.800	48.221	51.560	0.611	51.516	7.716	52.524	52.510
Y3	30.012	30.001	30.046	30.017	27.617	21.747	22.008	19.337	31.853	0.806	32.144	30.065	22.247	22.182
Y4	30.012	30.001	30.060	30.0108	29.614	21.107	37.898	33.667	38.030	0.860	38.162	30.084	38.509	38.550
Y5	14.630	14.547	14.786	14.657	19.293	6.159	53.328	39.818	56.833	0.610	56.781	14.893	57.986	57.979
Y6	7.303	7.627	7.517	7.336	40.790	3.126	57.873	50.429	59.455	0.792	59.492	7.888	59.838	59.848
Panel 2: The 5th percentile of value per period														
Y1	13.981	14.010	14.178	13.919	18.049	6.736	48.173	45.810	43.899	0.345	43.899	14.252	48.580	48.497
Y2	6.793	6.842	7.031	6.810	27.822	3.353	51.341	47.942	50.831	0.230	50.831	7.147	51.990	52.060
Y3	30.000	30.000	28.984	30.000	27.144	21.493	20.782	18.353	30.859	0.382	31.253	29.992	20.926	20.881
Y4	30.000	30.000	30.004	30.000	29.067	20.889	36.851	32.700	37.147	0.501	37.220	30.008	37.504	37.471
Y5	13.890	13.817	14.125	13.952	17.149	6.082	51.473	37.899	55.048	0.288	54.711	14.158	56.869	56.704
Y6	6.834	6.801	6.999	6.859	35.901	3.045	57.559	49.331	59.211	0.230	59.252	7.167	59.655	59.704
Panel 3: The 1st percentile of value per period														
Y1	13.726	13.755	13.915	13.825	17.733	6.501	47.963	45.686	43.599	0.177	42.867	14.129	48.312	48.325
Y2	6.625	6.690	6.867	6.534	26.897	3.292	51.090	47.782	50.663	0.078	50.453	6.933	51.851	51.842
Y3	30.000	30.000	29.971	29.992	26.975	21.374	20.228	17.823	30.539	0.247	31.052	29.963	20.408	20.478
Y4	30.000	30.000	29.992	29.992	28.956	20.725	36.571	32.384	36.884	0.374	36.814	29.992	37.085	37.192
Y5	13.541	13.488	13.718	13.722	16.669	6.066	50.458	37.130	53.342	0.144	53.971	13.911	56.384	55.973
Y6	6.629	6.666	6.756	6.695	33.448	3.025	57.428	48.908	59.051	0.082	59.071	6.834	59.499	59.622

Note. The upper bound of entrepreneurial value creation is 30 ($= N \times K \times 2$) that every networked actor has a good state. Each result is an average of 200 runs of 365 period experiments.



Note. The plots are based on the 1st percentile of value ranking of the opportunity recognition beliefs in Panel 3 of Table 4.3. The solid line represents the max-rule; the dashed line depicts the min-rule. Opportunity beliefs with smaller numbers rank higher in entrepreneurial value creation, where 1 is the best possible ranking.

Figure 4.3: Base case plot on the ranking of entrepreneurial opportunity beliefs.

tunity beliefs, O1 and O2, facilitate actions in pursuit of high value creation under the cost scenarios Y3 and Y4, whereas an altruistic one, O5, consistently has the worst ranking on value creation among the seven opportunity beliefs. In sum, the ranking variations mostly occur under the cost scenarios Y3 and Y4 so that we examine the average ranking of each opportunity belief in the three categories of cost scenarios – Y1-Y2, Y3-Y4, and Y5-Y6 (see Table 4.2) – for robustness analysis. We find that when all actors act aggressively (i.e., following the max-rule), the altruistic opportunity beliefs result in better positivest-disaster states following disasters.

4.4.2 Experimental design

To assess the impact of each parameter and characterize the range of entrepreneurial value creation in times of disasters, we analyze the proposed model under a variety of parameter instances (Montgomery, 2004). Hence, a full factorial design is employed to explore the proposed model and to check whether the insights derived from the base case are applicable in other circumstances as well. We examine 72 ($= 3 \times 3 \times 2 \times 2 \times 2$) parameter instances consisting of every combination in Table 4.4. These parameter instances are selected to provide a wide range of possible scenarios (i.e., one of the three categories of cost scenarios Y, a small, medium, or large number of network columns, N, a small-to-large number of network rows, K, a low-to-high value increase per period, Δ, and short-to-long simulated periods, T). We run each parameter instance 200 times to achieve statistical reliability. This computational analysis enables us to identify the underlying conditions for one opportunity belief to dominate another.

Table 4.4: Parameter values in experiments

Parameter	Values	Meaning
Y	{Y1-Y2, Y3-Y4, Y5-Y6}	The cost scenarios
N	{3, **5**,10}	The number of columns in the network
K	{**3**,5}	The number of rows in the network
Δ	{**1**,10}	Value creation at each time period
T	{**365**, 3650}	Simulation period of each run

4.4.3 Max-rule analysis

Table 4.5 shows the main effects of experimental factors under the max-rule. We highlight the parameters that lead to significant differences in the value ranking of opportunity beliefs at $p < 0.05$. Consistent with the base case results (see Figure 4.3), the recovery cost scenario has the largest impact on all opportunity beliefs, followed by the value increment (parameter Δ), the network size (parameters N and K). Note that time (parameter T) does not have significant impacts; so we omit it in the following analysis. Specifically, under the cost scenarios Y3 and Y4, two altruistic opportunity beliefs, O4 and O7, decrease their ranking by up to 1.458 ($= 4.750 - 3.292$) and 1.250 ($= 2.250 - 1.000$), respectively. In contrast, the rankings of the three non-altruistic opportunity beliefs, O1 to O3, increases under Y3 and Y4 by up to 1.208 ($= 6.625 - 5.417$), 0.833 ($= 6.125 - 5.292$), and 0.333 ($= 5.250 - 4.917$), respectively. Besides, O5 and O6 performs better under the cost scenarios Y5 and Y6 whose ranking increase by up to 0.292 ($= 2.542 - 2.250$) and 0.666 ($= 3.083 - 2.417$), respectively. This suggests that the altruistic opportunity beliefs lead to better post-recovery states when the actors can use the possesses values innovatively to act upon entrepreneurial opportunities arising from either major (i.e., Y1 and Y2) or minor (i.e., Y5 and Y6) disasters.

As illustrated in Table 4.5, we observe that value increment (Δ) is the second most influential factor, where the effects are significant for O1, O2, O5 and O7 with $p < 0.05$. The parameter Δ negatively impacts the ranking of O1 and O2 by 0.709 ($= 6.528 - 5.819$) and 0.375 ($= 6.000 - 5.625$), respectively. On the contrary, it has a positive effect on O5 with a 0.389 ($= 2.639 - 2.250$) increase in ranking and on O7 with a 1.069 ($= 2.069 - 1.000$) increase. Finally, the number of network columns (N) and rows (K) significantly influence the rankings of O1, O5 and O6. For instance, O1 will lead to worse entrepreneurial value creation as the network grows larger in either rows or columns. On the other hand, the number of network rows (K) has a positive impact on the ranking of O5 yet a negative impact on that of O6.

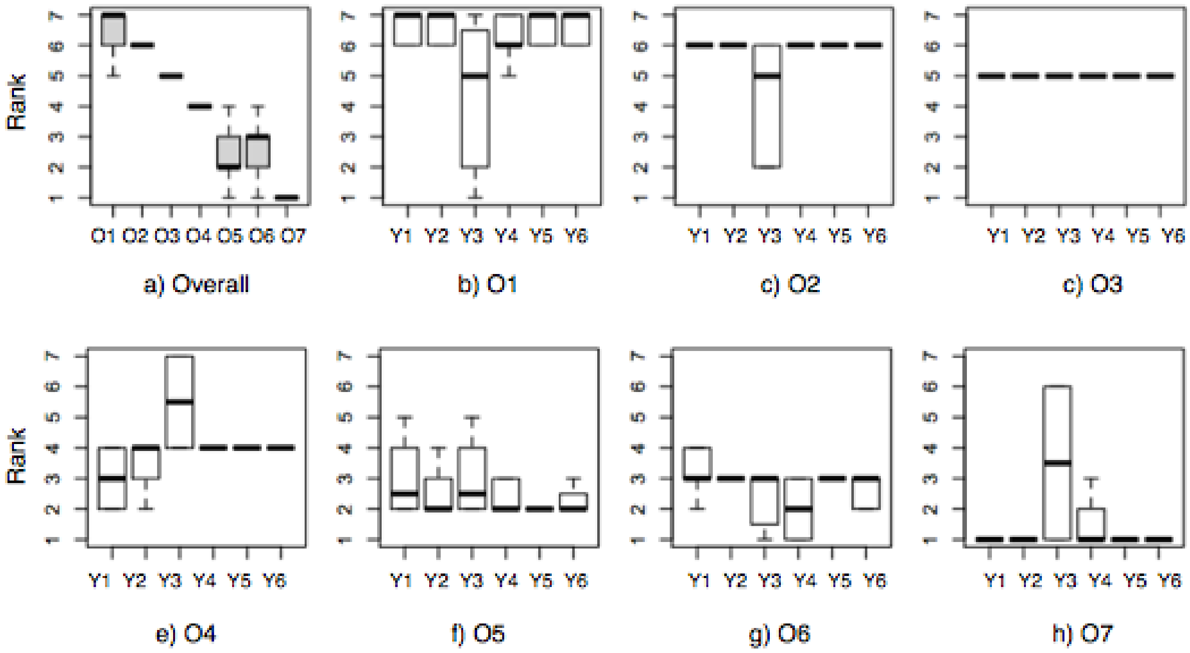
Figure 4.4 shows the boxplots of the opportunity beliefs' ranking under the six recovery

Table 4.5: Experimental results under the max-rule

Parameter	**value**	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**	**O7**
Y	{Y1-Y2}	**6.625**	**6.125**	5.000	**3.292**	**2.542**	**3.083**	**1.000**
		(0.495)	**(0.338)**	(0.000)	**(0.955)**	**(0.658)**	**(0.717)**	**(0.000)**
	{Y3-Y4}	**5.417**	**5.292**	**4.917**	**4.750**	2.542	**2.625**	**2.250**
		(2.062)	**(1.732)**	**(0.282)**	**(1.327)**	(0.977)	**(0.711)**	**(2.212)**
	{Y5-Y6}	6.458	6.042	**5.250**	**4.000**	**2.250**	2.417	1.292
		(0.658)	(0.359)	**(0.676)**	**(0.000)**	**(0.442)**	(0.830)	(0.624)
N	{3}	5.958	5.792	4.958	4.083	2.354	2.812	1.604
		(1.515)	(1.202)	(0.202)	(1.048)	(0.812)	(0.704)	(1.440)
	{5}	**6.021**	5.833	5.042	4.021	2.458	2.688	1.542
		(1.422)	(1.226)	(0.289)	(1.082)	(0.651)	(0.879)	(1.429)
	{10}	**6.542**	5.812	5.167	3.917	2.521	2.583	1.458
		(1.051)	(0.673)	(0.559)	(1.200)	(0.618)	(0.846)	(1.398)
K	{3}	**5.986**	5.861	5.069	4.014	**2.583**	**2.556**	1.528
		(1.449)	(1.066)	(0.422)	(1.107)	**(0.687)**	**(0.803)**	(1.424)
	{5}	**6.361**	5.764	5.042	4.000	**2.306**	**2.833**	1.542
		(1.248)	(1.055)	(0.354)	(1.113)	**(0.685)**	**(0.805)**	(1.414)
Δ	{1}	**5.819**	**5.625**	5.111	4.014	**2.639**	2.694	**2.069**
		(1.795)	**(1.477)**	(0.545)	(1.570)	**(0.844)**	(1.057)	**(1.856)**
	{10}	**6.528**	**6.000**	5.000	4.000	**2.250**	2.694	**1.000**
		(0.503)	**(0.000)**	(0.000)	(0.000)	**(0.436)**	(0.464)	**(0.000)**
T	{365}	6.292	5.750	5.056	4.000	2.472	2.694	1.542
		(1.399)	(1.045)	(0.441)	(1.113)	(0.769)	(0.816)	(1.414)
	{3650}	6.056	5.875	5.056	4.014	2.417	2.694	1.528
		(1.320)	(1.074)	(0.331)	(1.107)	(0.622)	(0.816)	(1.424)

Note. The ranking of (third-person) opportunity beliefs is based on the 1st percentile of entrepreneurial value creation per period; each is based on 200 runs of 24 experiments. Standard deviations are in parentheses. Third-person opportunity beliefs with smaller numbers have higher rankings, where 1 is the best possible ranking.

cost scenarios, where the robustness of each belief is clearly expressed by its mean and variation in value ranking. We observe a large variation under Y3 and Y4 across all the seven opportunity beliefs in Figure 4.4b-h. Yet as illustrated in Figure 4.4a, the four altruistic opportunity beliefs (O4–O7) on average rank higher than the non-altruistic ones (O1–O3), in line with our findings in Table 4.5.



Note. Figure a) illustrates the overall ranking of the seven opportunity beliefs under the max-rule. Figures b)–h) depict the ranking of each opportunity belief under the six cost scenarios.

Figure 4.4: Ranking of opportunity beliefs under the max-rule.

4.4.4 Min-rule analysis

Under the min-rule, results in Table 4.6 shows that the value ranking of opportunity beliefs are consistently influenced by the cost scenarios (Y), the value increment (Δ), and network size (N and K). Moreover, the impacts of these parameters differ between the altruistic and non-altruistic opportunity beliefs. For instance, O1 to O3 (the non-altruistic beliefs) increases their rankings by 1 unit when the cost scenarios Y3 and Y4 are applied, such as 1.542 ($= 4.292 - 2.750$) for O1, 1.167 ($= 4.167 - 3.000$) for O2, and 0.917 ($-6.000 - 5.083$)

Table 4.6: Experimental results under the min-rule

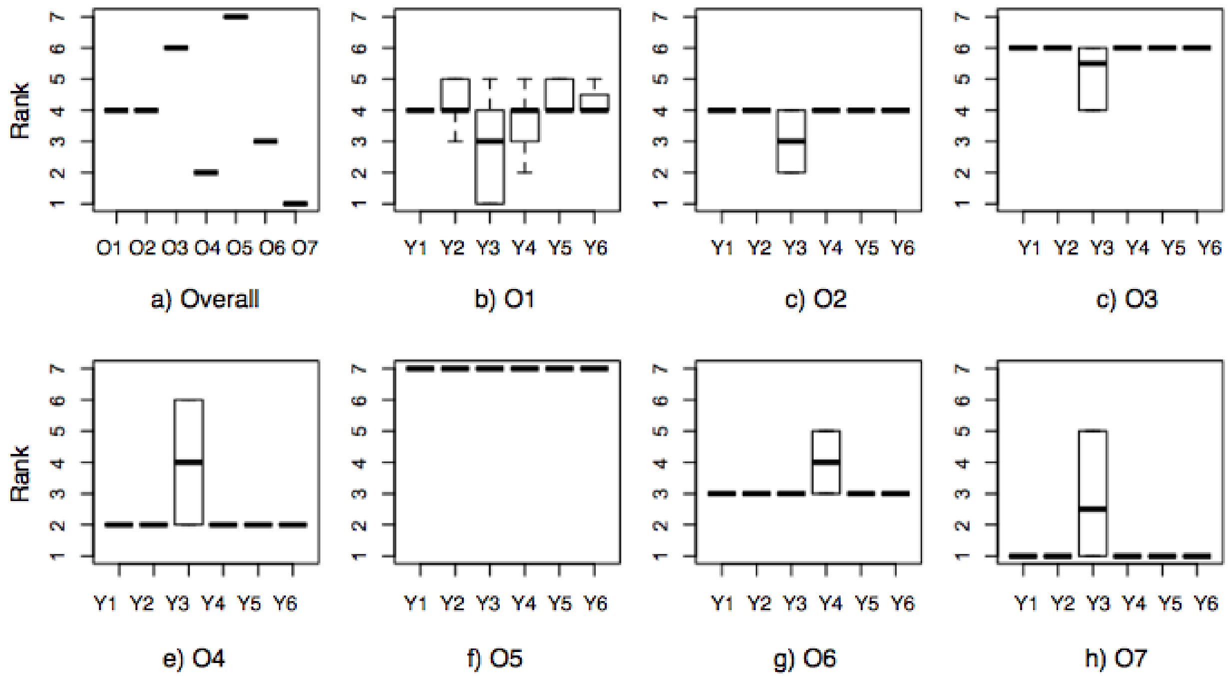
Parameter	**value**	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**	**O7**
Y	{Y1-Y2}	**4.292**	**4.167**	**6.000**	**2.000**	7.000	**3.167**	**1.000**
		(0.550)	**(0.381)**	**(0.000)**	**(0.000)**	(0.000)	**(0.381)**	**(0.000)**
	{Y3-Y4}	**2.750**	**3.000**	**5.083**	**4.000**	7.000	3.125	**2.917**
		(1.422)	**(1.022)**	**(0.974)**	**(2.043)**	(0.000)	(0.338)	**(1.976)**
	{Y5-Y6}	3.938	4.083	6.000	2.062	7.000	**3.583**	1.000
		(0.633)	(0.347)	(0.000)	(0.433)	(0.000)	**(0.794)**	(0.000)
N	{3}	3.854	3.938	5.833	2.396	7.000	**3.458**	1.333
		(0.922)	(0.697)	(0.559)	(1.180)	(0.000)	**(0.651)**	(1.117)
	{5}	3.875	3.938	5.833	2.333	7.000	**3.250**	1.333
		(0.937)	(0.697)	(0.559)	(1.117)	(0.000)	**(0.565)**	(1.117)
	{10}	4.021	3.938	5.875	2.333	7.000	**3.208**	1.292
		(0.956)	(0.697)	(0.444)	(1.117)	(0.000)	**(0.582)**	(0.988)
K	{3}	**3.722**	3.958	5.833	2.375	7.000	**3.444**	1.333
		(0.982)	(0.740)	(0.557)	(1.156)	(0.000)	**(0.625)**	(1.113)
	{5}	**4.111**	3.917	5.861	2.333	7.000	**3.167**	1.306
		(0.848)	(0.645)	(0.484)	(1.113)	(0.000)	**(0.557)**	(1.030)
Δ	{1}	**3.764**	3.875	**5.694**	**2.708**	7.000	**3.403**	**1.639**
		(1.284)	(0.978)	**(0.705)**	**(1.524)**	(0.000)	**(0.744)**	**(1.447)**
	{10}	**4.069**	4.000	**6.000**	**2.000**	7.000	**3.208**	**1.000**
		(0.256)	(0.000)	**(0.000)**	**(0.000)**	(0.000)	**(0.409)**	**(0.000)**
T	{365}	3.986	3.917	5.847	2.375	7.000	3.264	1.319
		(1.000)	(0.666)	(0.522)	(1.156)	(0.000)	(0.556)	(1.072)
	{3650}	3.847	3.958	5.847	2.333	7.000	3.347	1.319
		(0.867)	(0.721)	(0.522)	(1.113)	(0.000)	(0.653)	(1.072)

Note. The experiment settings are identical to those in Table 4.5.

for O3. Yet the performance of the two altruistic ones, O4 and O7, significantly decrease by $2(= 4.000 - 2.000)$ and $1.917(= 2.917 - 1.000)$, respectively. Likewise, the value increment and network size both generate positive effects on the altruistic opportunity beliefs such as O6, yet negative impacts on non-altruistic beliefs like O1. Therefore, the altruistic opportunity beliefs seem being associated with greater value creation when the actors are in a large network, have higher value increment per period, and Y3 and Y4 are not applied. The impact of time (T) is again insignificant ($p > 0.05$), so omitted in our analysis.

To illustrate the rankings of the seven opportunity beliefs, we provide the boxplots under various cost scenarios in Figure 4.5. This time, the performance of the beliefs are fairly insensitive to the cost scenarios expect for Y3. As a result, we almost observe no variations in value ranking (see Figure 4.5a). O7 is consistently the best opportunity belief to attain good recovery state following disasters. O4 and O6 are the next best opportunity beliefs that outperform the three non-altruistic beliefs (O1, O2 and O3). However, compared to the results under the max rule in Table 4.5, a notable difference is the dramatic decrease of O5's ranking from 2.5 (see Figure 4.4) to 7. This surprising finding suggests that under the min-rule, while altruistic opportunity beliefs can be a necessary condition for value creation in times of disasters (see O4, O6 and O7), they are not sufficient conditions to facilitate entrepreneurial action (e.g., O5). The rule on evaluating first-person opportunities also matters in the entrepreneurial action decision process: When actors doubt about the attractiveness of the identified opportunities (i.e., low desirability), eventually they are less likely to take actions to recover from the disasters. The interaction between the altruistic beliefs in recognizing third-person opportunities and the min-rule in evaluating first-person opportunities will be further examined in the discussion section using analytical methods.

Since Figures 4.4 and 4.5 show that the opportunity beliefs perform differently under the two evaluation rules. We calculate the ranking differences by subtracting the ranking under the max-rule from that under the min-rule. So a positive difference suggests that the specific opportunity belief performance better under the max-rule; a negative difference suggests otherwise. Consider O5 as an example. On average, its ranking difference between



Note. Figure a) illustrates the overall ranking of the seven opportunity beliefs under the max-rule. Figures b)–h) depict the ranking of each opportunity belief under the six cost scenarios.

Figure 4.5: Ranking of opportunity beliefs under the min-rule.

the min-rule (7) and the max-rule (2.5) is 4.5 (= 7 − 2.5) where O5's ranking is 4.5 higher under the max-rule. Following this logic, as O1 consistently ranks the first no difference is observed. O5, O3 and O6 are more likely to rank higher among the seven opportunity beliefs under the max-rule. In turn, the rankings of O1, O2 are higher under the min-rule. This result is very much consistent with the insights derived from Figure 4.3. [The ranking differences of the seven opportunity beliefs with respect to each cost scenario can be found in the Supplementary note. In general, we observe similar patterns across most scenarios.]

4.5 Discussion

The central theme of this chapter is to examine altruistic reciprocity (Axelrod and Hamilton, 1981; Nowak, 2006; Trivers, 1971) and entrepreneurship (McMullen and Shepherd, 2006) in times of extreme environmental events. This is an important topic since these disastrous events disproportionately influence the business landscape. In addition, there is little literature on how these events influence entrepreneurship, altruism, and collective value creation. Our work addresses this limitation by extending the theory of entrepreneurial action into the context of disasters and develop a concept of altruistic entrepreneurship. Our focus is on the dynamic interactions between opportunity recognition beliefs motivated by altruistic reciprocity, opportunity evaluation rules (i.e., the willingness to act) and cost scenarios (i.e., feasibility of taking actions) and their overall impact on collective recovery performance.

Essentially, our simulation outcomes, illustrated in Tables 4.5 and 4.6, suggest that altruistic opportunity beliefs generally facilitate better overall entrepreneurial value creation following disasters than non-altruistic opportunity beliefs. To further support this altruistic entrepreneurship hypothesis, following the lead of complex systems studies (Miller and Page, 2007), we derive some analytic results about the structure and function of altruistic entrepreneurship in times of disasters. Let $\Pr\{\phi_i = 0\} = \theta_0$, $\Pr\{\phi_i = 1\} = \theta_1$, and $\Pr\{\phi_i = 2\} = 1 - \theta_0 - \theta_1 = 1 - \boldsymbol{\theta}$ be the possibilities of an actor having a poor, fair, or good pre-recovery state, respectively. Note that they are somewhat equivalent to the probability of someone encountering a major (f), minor (g), or none ($1-f-g$) disaster. In the standard *von Newmann* neighborhood network, the number of good-state actors, denoted as X, is a random variable, following the binomial distribution, i.e., $X \sim \mathrm{B}(5, 1-\boldsymbol{\theta})$. (A graphic illustration is included in the supplementary note.) The probability of having exactly m good-state actors prior to recovery in the neighborhood is

$$\Pr\{X = m\} = \binom{5}{m}(1-\boldsymbol{\theta})^m \boldsymbol{\theta}^{5-m}, \quad \text{for } m = 0, 1, \cdots, 5.$$

Take O1 as an example. A networked actor adopting O1 is motivated to return to the good state when his/her immediate row-/column-neighbors and self are in the good state prior to recovery activities. Under the min-rule, in addition to the actor self, all the four neighbors, ease, south, west, and north, must be in the good state, i.e., $m = 5$. This restriction is relaxed under the max-rule where $m \in \{3, 4, 5\}$. That is, the good-state actor is willing to take recovery action when at least two of the four neighbors, either row-neighbors (west and east) or column-neighbors (north and south), are in the good state prior to recovery. Following this logic, we get:

Claim 1. *In the von Neumann neighborhood network, under the max-rule ($\psi_{n,k} = \Phi_{n,k}$),*

(i) an actor adopting O1 pursues an entrepreneurial opportunity with the probability of $2(1-\boldsymbol{\theta})^3 - (1-\boldsymbol{\theta})^5$*;*

(ii) an actor adopting O2 pursues an entrepreneurial opportunity with the probability of $1 + 3\boldsymbol{\theta}^4 - 4\boldsymbol{\theta}^3$*;*

(iii) an actor adopting O3 pursues an entrepreneurial opportunity with the probability of $1 - \boldsymbol{\theta}^2 + \theta_1^2(\theta_1^3 + 5\theta_1^2\theta_0 + 5\theta_1\theta_0^2 + 2\theta_0^3)$*;*

(iv) an actor adopting O4 pursues an entrepreneurial opportunity with the probability of $1 - (1-\boldsymbol{\theta})^5$*;*

(v) an actor adopting O5 pursues an entrepreneurial opportunity with the probability of $1 - \boldsymbol{\theta}^5$*;*

(vi) an actor adopting O6 pursues an entrepreneurial opportunity with the probability of $1 - \boldsymbol{\theta}^5$*;*

(vii) an actor adopting O7 pursues an entrepreneurial opportunity with the probability of 1.

Accordingly, we can find the boundary conditions where the actors adopting an altruistic opportunity belief are more likely to take recovery actions than those adopting a non-altruistic belief:

Proposition 1. *Under the max-rule,*

(i) when $\boldsymbol{\theta} > \frac{1}{3}$, actors adopting O3 are more likely to pursue an entrepreneurial opportunity than those adopting O2;

(ii) when $\boldsymbol{\theta} < \frac{1}{2}$, actors adopting O5 and O6 are more likely to pursue an entrepreneurial opportunity than those adopting O4;

(iii) when $\frac{1}{3} < \boldsymbol{\theta} < \frac{1}{2}$, the ranking of the seven opportunity beliefs follows $O1 < O2 < O3 < O4 < O5 = O6 < O7$.

Note that our simulation outcomes in Figure 4.4a support this proposition perfectly. One plausible explanation lies in our parameter setting in Section 4.4.1, where $f = 17/365$ and $g = 134/365$, that satisfies $\frac{1}{3} < f + g < \frac{1}{2}$. In general, Proposition 1 (P1) specifies the impact of extreme events, both major and minor disasters, on the effectiveness of altruistic opportunity beliefs and the resultant likelihood of pursuing an opportunity following disasters. Additionally, because no conditions attached to the better ranking of altruistic opportunity beliefs (O4 to O7), we can conclude that altruistic entrepreneurship under the max-rule is always able to achieve the best value creation for recovery.

Likewise, we can derive the proposition under the min-rule by specifying the action probabilities associated with each opportunity beliefs. Formally,

Claim 2. *In the von Neumann neighborhood network, under the min-rule,* $(\psi_{n,k} = \Theta_{n,k})$

(i) an actor adopting O1 pursues an entrepreneurial opportunity with the probability of $(1-\boldsymbol{\theta})^5$;

(ii) an actor adopting O2 pursues an entrepreneurial opportunity with the probability of $(1-\boldsymbol{\theta})^3(1+3\boldsymbol{\theta})$;

(iii) an actor adopting O3 pursues an entrepreneurial opportunity with the probability of $(1-\boldsymbol{\theta})^2 + \theta_1^3(\theta_0^2 + 3\theta_0\theta_1 + \theta_1^2)$;

(iv) *an actor adopting O4 pursues an entrepreneurial opportunity with the probability of* $1 + (1 - \boldsymbol{\theta})^5 - 2(1 - \boldsymbol{\theta})^3$*;*

(v) *an actor adopting O5 pursues an entrepreneurial opportunity with the probability of* $1 + \boldsymbol{\theta}^5 - 2\boldsymbol{\theta}^3$*;*

(vi) *an actor adopting O6 pursues an entrepreneurial opportunity with the probability of* $1 + \boldsymbol{\theta}^5 - 2\boldsymbol{\theta}^3$*;*

(vii) *an actor adopting O7 pursues an entrepreneurial opportunity with the probability of* 1.

Proposition 2. *Under the min-rule,*

(i) *when* $\boldsymbol{\theta} > \frac{2}{3}$*, actors adopting O3 are more likely to pursue an entrepreneurial opportunity than those adopting O2;*

(ii) *when* $\boldsymbol{\theta} > \frac{1}{2}$*, actors adopting O4 are more likely to pursue an entrepreneurial opportunity than those adopting O5 and O6;*

(iii) *when* $\boldsymbol{\theta} < \frac{\sqrt{17}-1}{4}$*, actors adopting O5 and O6 are more likely to pursue an entrepreneurial opportunity than those adopting O3;*

(iv) *when* $\frac{2}{3} < \boldsymbol{\theta} < \frac{\sqrt{17}-1}{4}$*, the ranking of the seven opportunity beliefs follows* $O1 < O2 < O3 < O5 = O6 < O4 < O7$.

Under the min-rule, the robustness of altruistic opportunity beliefs is dependent upon the number of good-state actors in the neighborhood, or equivalently the probability of disasters. When disasters sway most actors, altruistic entrepreneurship cannot restore the system effectively since actors have doubts on the time lag of receiving repayment, hence are very conservative on pursuing identified opportunities. Note that altruistic reciprocity is considered inherently selfish in a sense that a rational actor strives for (long-term) self benefit derived from reciprocal return (Kenrick et al., 2009; Nowak, 2006). Accordingly, as suggested by Shepherd et al. (2007) and McMullen and Shepherd (2006), such doubt is very likely to obfuscate the evaluation of the first-person opportunity and prevent entrepreneurial actions.

Figure 4.5a reports a very similar ranking pattern to Proposition 2 (P2). For instance, O7 and O4 are the most robust altruistic opportunity beliefs to pursue entrepreneurial value creation. One notable difference in our simulation is the rankings of O5 and O3. A plausible explanation is that among the seven opportunity beliefs, only these two have a possibility of returning a poor state post recovery:

Claim 3. *In the von Neumann neighborhood network, under the min-rule,* $(\psi_{n,k} = \Theta_{n,k})$

(i) an actor adopting O3 returns a poor post-recovery state with the probability of $\theta_0^3 - 3\theta_0^2 + 2\theta_0$*;*

(ii) an actor adopting O5 returns a poor post-recovery state with the probability of $2\theta_0^3 - \theta_0^5$.

Recall that we adopt worst-case-scenario (1st percentile) of entrepreneurial value creation as the performance measure. Therefore, unlike the other five opportunity beliefs, whose worst post-recovery state has a value of 1 (i.e., fair state), O3 and O5 are more likely to return a poor state (0). So O5's low ranking under the min-rule suggest that altruistic entrepreneurship requires aggressive opportunity evaluation methods to launch the action.

Finally, our results statistically demonstrate that the robustness of altruistic opportunity beliefs are further moderated by the high value increment per period and large network size. On the country, the value creation resulting from the non-altruistic beliefs are negatively affected as the value increment increases and/or the network grows large.

4.6 Supplementary Notes

4.6.1 The benefit-to-cost ratio

To determine whether can receive reciprocal benefits, an altruist compares the benefit-cost-ratio, b/c, with the average number of neighbors, $w = 2$ in our study. Specifically, the cost of helping a poor-state or fair-state neighbor is given by the scenarios 1 to 9 in Table 4-7 by counting the frequency of the altruist having good pre-recovery state yet poor or fair post-recovery state. That is, the deteriorate state post recovery indicates the altruist's cost. On the other hand, the scenarios 10-27 then illustrate the possible benefits that can be returned by the recipients – we count the frequency of the altruist having a poor or fair pre-recovery state yet good post-recovery state. Formally,

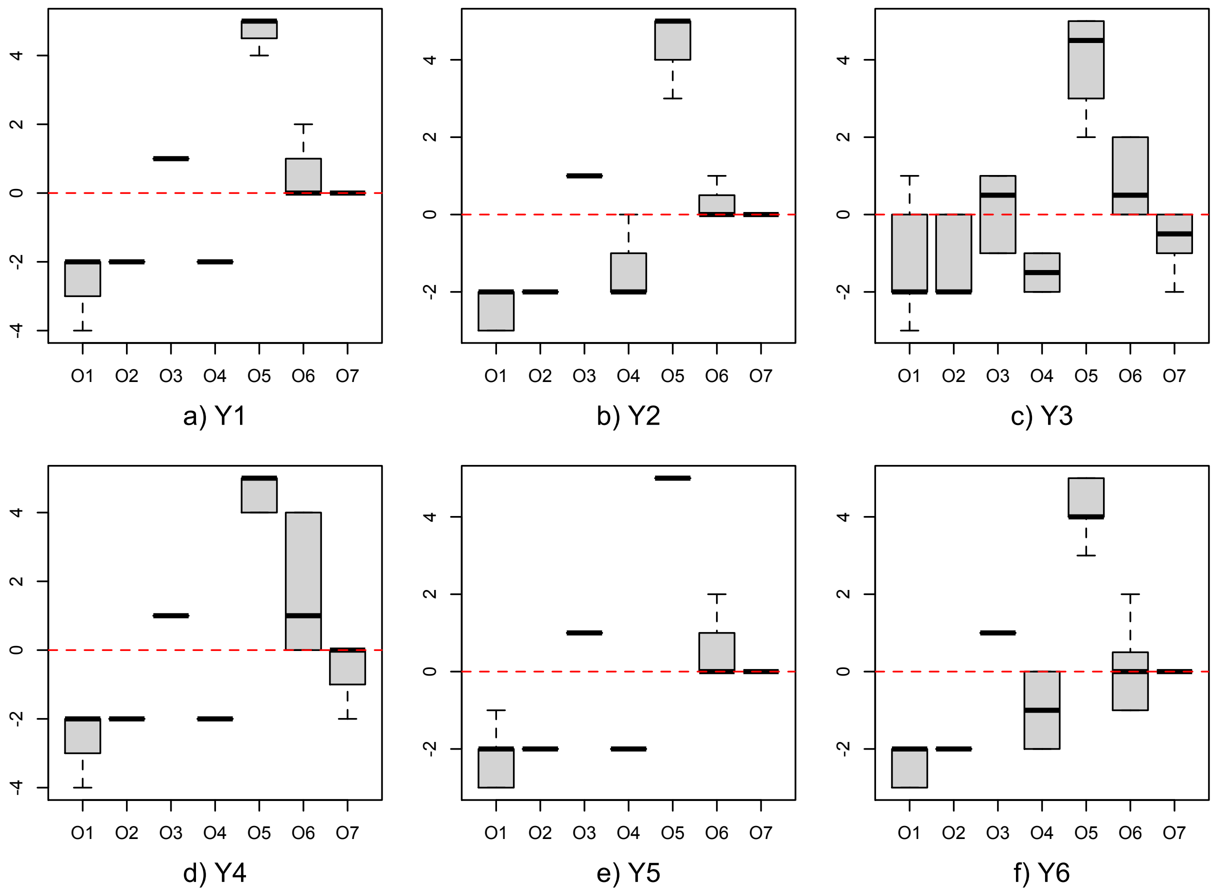
$$\frac{b}{c} = \frac{\text{The number of } \{\phi_{n,k} \neq 2, \psi_{n,k} = 2\}/\text{Total number of benefit-related scenarios}}{\text{The number of } \{\phi_{n,k} = 2, \psi_{n,k} \neq 2\}/\text{Total number of cost-related scenarios}}.$$

Table 4.7: Discovering entrepreneurial opportunities for recovery

Scenario	$\phi_{n-1,k}(t)$ ($\phi_{n,k-1}(t)$)	$\phi_{n,k}(t)$	$\phi_{n+1,k}(t)$ ($\phi_{n,k+1}(t)$)	$h_{n,k}(t)(v_{n,k}(t))$						
				O1	**O2**	**O3**	**O4**	**O5**	**O6**	**O7**
1	0	2	0	1	1	0	2	2	2	2
2	0	2	1	1	1	0	2	2	2	2
3	0	2	2	1	2	0	2	2	2	2
4	1	2	0	1	1	1	2	2	2	2
5	1	2	1	1	1	1	2	2	2	2
6	1	2	2	1	2	1	2	2	2	2
7	2	2	0	1	2	2	2	2	2	2
8	2	2	1	1	2	2	2	2	2	2
9	2	2	2	2	2	2	1	2	2	2
10	0	1	0	1	1	0	2	1	1	2
11	0	1	1	1	1	0	2	1	1	2
12	0	1	2	1	1	0	2	2	2	2
13	1	1	0	1	1	2	2	1	1	2
14	1	1	1	1	1	2	2	1	1	2
15	1	1	2	1	1	2	2	2	2	2
16	2	1	0	1	1	2	2	2	2	2
17	2	1	1	1	1	2	2	2	2	2
18	2	1	2	1	2	2	2	2	2	2
19	0	0	0	1	1	1	2	1	0	2
20	0	0	1	1	1	1	2	1	1	2
21	0	0	2	1	1	1	2	2	2	2
22	1	0	0	1	1	1	2	1	1	2
23	1	0	1	1	1	1	2	1	1	2
24	1	0	2	1	1	1	2	2	2	2
25	2	0	0	1	1	2	2	2	2	2
26	2	0	1	1	1	2	2	2	2	2
27	2	0	2	1	2	2	2	2	2	2

4.6.2 Cost scenario analysis on the opportunity belief ranking difference

Figure 4.6 illustrates the ranking differences of the seven opportunity beliefs with respect to each cost scenario can be found in the Supplementary note. In general, we observe similar patterns across most scenarios.



Note. A larger value on the y-axis indicates better ranking under the max-rue, where 0 represents the same performance under the two opportunity evaluation rules.

Figure 4.6: The boxplot of opportunity beliefs ranking difference under the six cost scenarios.

4.6.3 The state distribution table

Figure 4.7 illustrate the distribution of good-state actors in the standard *vonNewmann* neighborhood. We calculate the likelihood of recovery action under each opportunity belief accordingly.

O1. Under the max-rule, an actor employing O1 will act entrepreneurially in scenarios s1 – s5, s7, and s12 in Figure 4.10. So, we derive

$$\begin{aligned}\Pr\{\psi_{n,k}=2|\Phi\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}+\underbrace{4(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 – s5}}+\underbrace{2(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s7, s12}}\\ &= 2(1-\theta_0-\theta_1)^3-(1-\theta_0-\theta_1)^5.\end{aligned}$$

In contrast, under the min-rule, the actor will only take recovery action when all the five firms in the neighborhood are in the good state (scenario s1 in Figure 4.10), formally,

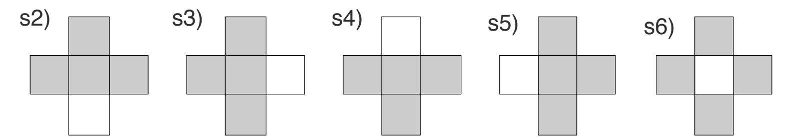
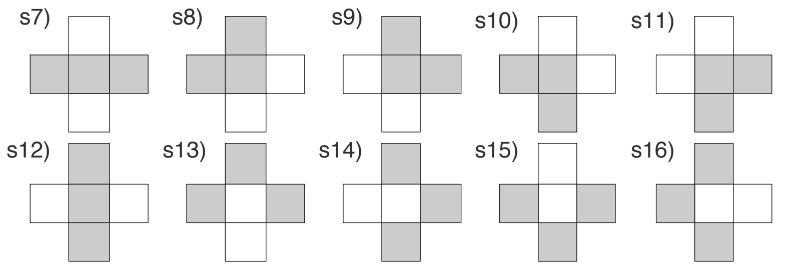
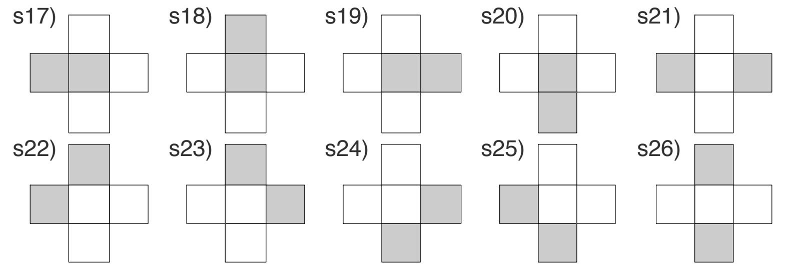
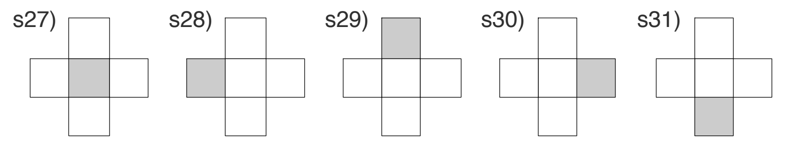
$$\Pr\{\psi_{n,k}=2|\Theta\}=\underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}.$$

O2. Under the max-rule, an actor employing O2 will act entrepreneurially in scenarios s1 – s21, and s26 in Figure 4.10. So, we derive

$$\begin{aligned}\Pr\{\psi_{n,k}=2|\Phi\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}+\underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 – s6}}+\\ &\quad \underbrace{10(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s7 – s16}}+\underbrace{6(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3}_{\text{s17 – s21, s26}}\\ &= 1-4(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3-5(1-\theta_0-\theta_1)(\theta_0+\theta_1)^4-(\theta_0+\theta_1)^5\\ &= 1+3(\theta_0+\theta_1)^4-4(\theta_0+\theta_1)^3.\end{aligned}$$

In contrast, under the min-rule, the actor will take recovery action in scenarios s1 – s6 and s8 – s11 in Figure 4.10, formally,

$$\begin{aligned}\Pr\{\psi_{n,k}=2|\Theta\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}+\underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 – s6}}+\underbrace{4(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s8 – s11}}\\ &= (1-\theta_0-\theta_1)^3[1+3(\theta_0+\theta_1)].\end{aligned}$$

Probability	Illustration
$\binom{5}{5}(1-\theta_0-\theta_1)^5$	
$\binom{5}{4}(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)$	
$\binom{5}{3}(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2$	
$\binom{5}{2}(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3$	
$\binom{5}{1}(1-\theta_0-\theta_1)(\theta_0+\theta_1)^4$	
$\binom{5}{0}(\theta_0+\theta_1)^5$	

Note. The first row shows the probability of having five good-state actors prior to recovery in the neighborhood, the second for four good-state actors, the third for three good-state actors, the fourth for two good-state actors, the fifth for one good-state actor, and the sixth for no good-state actors in the neighborhood.

Figure 4.7: The state distribution of networked actors in the *von Neumann* neighborhood.

O3. Under the max-rule, an actor employing O3 will act entrepreneurially in scenarios s1 – s10, s12 – s18, s21 – s23, s25 – s26, s28 – s29, and s32 in Figure 4.10. So, we derive

$$\begin{aligned}
\Pr\{\psi_{n,k} = 2|\Phi\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}} + \underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 – s6}} + \underbrace{9(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s7 – s10, s12 – s16}} + \\
&\quad \underbrace{7(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3}_{\text{s17, s18, s21 – s23, s25, s26}} + \underbrace{2(1-\theta_0-\theta_1)(\theta_0+\theta_1)^4}_{\text{s28 – s29}} + \\
&\quad \underbrace{(\theta_1^5 + 5\theta_1^4\theta_0 + 5\theta_1^3\theta_0^2 + 2\theta_1^2\theta_0^3)}_{\text{a subset of s32}} \\
&= 1 - (\theta_0+\theta_1)^2 + \theta_1^2(\theta_1^3 + 5\theta_1^2\theta_0 + 5\theta_1\theta_0^2 + 2\theta_0^3).
\end{aligned}$$

In contrast, under the min-rule, the actor will take recovery action in scenarios s1 – s3, s6, s8, s13, s16, s22, and s32 in Figure 4.10, formally,

$$\begin{aligned}
\Pr\{\psi_{n,k} = 2|\Theta\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}} + \underbrace{3(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2, s3, s6}} + \\
&\quad \underbrace{3(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s8, s13, s16}} + \underbrace{(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3}_{\text{s22}} \\
&\quad \underbrace{(\theta_1^5 + 3\theta_1^4\theta_0 + \theta_1^3\theta_0^2)}_{\text{a subset of s32}} \\
&= (1-\theta_0-\theta_1)^2 + \theta_1^3(\theta_0^2 + 3\theta_0\theta_1 + \theta_1^2). \\
\Pr\{\psi_{n,k} = 0|\Theta\} &= \theta_0^3 - 3\theta_0^2 + 2\theta_0.
\end{aligned}$$

O4. Under the max-rule, an actor employing O4 will act entrepreneurially in all scenarios except for s1 in Figure 4.10. So, we derive

$$\Pr\{\psi_{n,k} = 2|\Phi\} = 1 - \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}.$$

In contrast, under the min-rule, the actor will take recovery action in scenarios s6, s8 – s11, s13 – s16, and s17 – s32 in Figure 4.10, formally,

$$\begin{aligned}
\Pr\{\psi_{n,k} = 2|\Theta\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}} + \underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 – s6}} + \underbrace{4(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s8 – s11}} \\
&= 1 + (1-\theta_0-\theta_1)^5 - 2(1-\theta_0-\theta_1)^3.
\end{aligned}$$

O5. Under the max-rule, an actor employing O5 will act entrepreneurially in all scenarios except for s32 in Figure 4.10. So, we derive

$$\begin{aligned}\Pr\{\psi_{n,k}=2|\Phi\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}+\underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 -- s6}}+\\ &\quad \underbrace{10(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s7 -- s16}}+\underbrace{10(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3}_{\text{s17 -- s26}}+\\ &\quad \underbrace{5(1-\theta_0-\theta_1)(\theta_0+\theta_1)^4}_{\text{s27 -- s31}}+\\ &= 1-(\theta_0+\theta_1)^5.\end{aligned}$$

In contrast, under the min-rule, the actor will take recovery action in scenarios s1 – s6 and s8 – s11 in Figure 4.10, formally,

$$\begin{aligned}\Pr\{\psi_{n,k}=2|\Theta\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}+\underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 -- s6}}+\underbrace{10(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s7 -- s16}}+\\ &= \underbrace{8(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3}_{\text{s17 -- s20, s22 -- s25}}+\underbrace{(1-\theta_0-\theta_1)(\theta_0+\theta_1)^4}_{\text{s27}}\\ &= 1+(\theta_0+\theta_1)^5-2(\theta_0+\theta_1)^3.\\ \Pr\{\psi_{n,k}=0|\Theta\} &= \theta_0^5+4\theta_0^4(1-\theta_0)+2\theta_0^3(1-\theta_0)^2\\ &= 2\theta_0^3=\theta_0^5.\end{aligned}$$

O6. Under the max-rule, an actor employing O5 will act entrepreneurially in all scenarios except for s32 in Figure 4.10. So, we derive

$$\begin{aligned}\Pr\{\psi_{n,k}=2|\Phi\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}}+\underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 -- s6}}+\\ &\quad \underbrace{10(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s7 -- s16}}+\underbrace{10(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3}_{\text{s17 -- s26}}+\\ &\quad \underbrace{5(1-\theta_0-\theta_1)(\theta_0+\theta_1)^4}_{\text{s27 -- s31}}+\\ &= 1-(\theta_0+\theta_1)^5.\end{aligned}$$

In contrast, under the min-rule, the actor will take recovery action in scenarios s1 – s6, s7

– 16, s17 – s20, s22 – s25, and s27 in Figure 4.10, formally,

$$
\begin{aligned}
\Pr\{\psi_{n,k} = 2|\Theta\} &= \underbrace{(1-\theta_0-\theta_1)^5}_{\text{s1}} + \underbrace{5(1-\theta_0-\theta_1)^4(\theta_0+\theta_1)}_{\text{s2 – s6}} + \underbrace{10(1-\theta_0-\theta_1)^3(\theta_0+\theta_1)^2}_{\text{s7 – s16}} + \\
&= \underbrace{8(1-\theta_0-\theta_1)^2(\theta_0+\theta_1)^3}_{\text{s17 – s20, s22 – s25}} + \underbrace{(1-\theta_0-\theta_1)(\theta_0+\theta_1)^4}_{\text{s27}} \\
&= 1 + (\theta_0+\theta_1)^5 - 2(\theta_0+\theta_1)^3.
\end{aligned}
$$

O7. Under the max-rule, an actor employing O5 will act entrepreneurially in all scenarios in Figure 4.10. So, we derive

$$\Pr\{\psi_{n,k} = 2|\Phi\} = 1.$$

Likewise, under the min-rule, the actor will take recovery action in all scenarios as well,

$$\Pr\{\psi_{n,k} = 2|\Theta\} = 1.$$

4.6.4 Proofs

Proofs of Proposition 1. For **part (i)**, given O3's associated action probability is bounded by $[1-\boldsymbol{\theta}^2, 1-\boldsymbol{\theta}^2+\boldsymbol{\theta}^5]$, we make a comparison between the lower bound of O3 and O2 and get

$$(1-\boldsymbol{\theta}^2) - [1-\boldsymbol{\theta}^3 - 3\boldsymbol{\theta}^3(1-\boldsymbol{\theta})] = \boldsymbol{\theta}^2 \underbrace{(1-\boldsymbol{\theta})}_{+ve}(3\boldsymbol{\theta}-1) > 0 \Leftrightarrow \boldsymbol{\theta} > \frac{1}{3}.$$

For **part (ii)**, the action probability associated with O5 and O6 are the same according to Claim 1. We obtain the condition that O5 (or O6) outperforms O4 by

$$(1-\boldsymbol{\theta}^5) - [1-(1-\boldsymbol{\theta})^5] = (1-2\boldsymbol{\theta}) \underbrace{[(1-\boldsymbol{\theta})^4 + (1-\boldsymbol{\theta})^3\boldsymbol{\theta} + (1-\boldsymbol{\theta})^2\boldsymbol{\theta}^2 + (1-\boldsymbol{\theta})\boldsymbol{\theta}^3 + \boldsymbol{\theta}^4]}_{+ve} > 0$$
$$\Leftrightarrow \boldsymbol{\theta} < \frac{1}{2}.$$

For **part (iii)**, we compare the action likelihood associated with each opportunity belief in pairs. For instance, O2 ranks higher than O1 due to a larger probability of pursuing an entrepreneurial opportunity:

$$[1-\boldsymbol{\theta}^3-3\boldsymbol{\theta}^3(1-\boldsymbol{\theta})]-[2(1-\boldsymbol{\theta})^3-(1-\boldsymbol{\theta})^5] = \underbrace{(1-\boldsymbol{\theta})}_{+ve}[\boldsymbol{\theta}^2\underbrace{(1-\boldsymbol{\theta})(6-\boldsymbol{\theta})}_{+ve}+(1+\boldsymbol{\theta})\underbrace{(2-\boldsymbol{\theta})}_{+ve}] > 0.$$

Likewise, O4 outperforms O3 as the action probability associated with O4 exceeds the upper bound of that with O3,

$$[1-(1-\boldsymbol{\theta})^5]-(1-\boldsymbol{\theta}^2+\boldsymbol{\theta}^5) = \underbrace{(1-\boldsymbol{\theta})}_{+ve}[5\boldsymbol{\theta}^3+\underbrace{(1-\boldsymbol{\theta})}_{+ve}(1+5\boldsymbol{\theta})] > 0.$$

Together with the results in parts (i) and (ii), the result follows.

Proofs of Proposition 2. For **part (i)**, given O3's associated action probability is bounded by $[(1-\boldsymbol{\theta})^2, (1-\boldsymbol{\theta})^2+\boldsymbol{\theta}^5]$, we make a comparison between the lower bound of O3 and O2 and get

$$(1-\boldsymbol{\theta})^2-(1-\boldsymbol{\theta})^3(1+3\boldsymbol{\theta}) = \boldsymbol{\theta}(1-\boldsymbol{\theta})^2(3\boldsymbol{\theta}-2) > 0 \Leftrightarrow \boldsymbol{\theta} > \frac{2}{3}.$$

For **part (ii)**, the action probability associated with O5 and O6 are the same according to Claim 2. We obtain the condition that O4 outperforms O5 (or O6) by

$$[1+(1-\boldsymbol{\theta})^5-2(1-\boldsymbol{\theta})^3]-[1+\boldsymbol{\theta}^5-2\boldsymbol{\theta}^3] > 0 \Leftrightarrow \boldsymbol{\theta} > \frac{1}{2}.$$

For **part (iii)**, we compare the O5's (or O6's) action probability with the upper bound of O3

$$[1+\boldsymbol{\theta}^5-2\boldsymbol{\theta}^3]-[(1-\boldsymbol{\theta})^2+\boldsymbol{\theta}^5] = \boldsymbol{\theta}(-2\boldsymbol{\theta}^2-\boldsymbol{\theta}+2) > 0 \Leftrightarrow \boldsymbol{\theta} < \frac{\sqrt{17}-1}{4}.$$

For **part (iv)**, we compare the action likelihood associated with each opportunity belief in pairs. For instance, O2 ranks higher than O1 due to a larger probability of pursuing an entrepreneurial opportunity:

$$(1-\boldsymbol{\theta})^3(1+3\boldsymbol{\theta})-(1-\boldsymbol{\theta})^5 = \boldsymbol{\theta}\underbrace{(1-\boldsymbol{\theta})^3}_{+ve}\underbrace{(5-\boldsymbol{\theta})}_{+ve} > 0.$$

Likewise, O4 outperforms O3 as the action probability associated with O4 exceeds the upper bound of that with O3,

$$[1-(1-\boldsymbol{\theta})^5]-(1-\boldsymbol{\theta}^2+\boldsymbol{\theta}^5) = \underbrace{(1-\boldsymbol{\theta})}_{+ve}[5\boldsymbol{\theta}^3+\underbrace{(1-\boldsymbol{\theta})}_{+ve}(1+5\boldsymbol{\theta})] > 0.$$

Together with the results in parts (i), (ii), and (iii), the result follows.

Chapter 5

Who sways whom: The spatiotemporal dynamics of entrepreneurial action

5.1 Introduction

An entrepreneurial opportunity such as the launch of new products, services or processes, the development of new business models, and the creation of new organizational routines, typically provides a more efficient way of utilizing resources for value creation than current existing practices (Keyhani et al., 2015; Shepherd and Patzelt, 2013). A number of networked *actors* (i.e., community members) – individuals, organizations, or firms – who may act entrepreneurially will be alerted to this opportunity via their business or social network and exploit it for benefits via their entrepreneurial *actions* (McMullen and Shepherd, 2006; Phan and Chambers, 2013). In this sense, entrepreneurship is a spatiotemporal process of identification, evaluation, and exploitation of opportunities for potential value creation arising from direct and indirect interactions among potential actors networked with each other. The dynamic process involves making sense of the feedback from spatially interdependent others to identify opportunities (third person opportunity), evaluating the feasibility and desirability of identified opportunities (first person opportunity), and engaging or disengaging from action by mobilizing resources and efforts with uncertain outcomes and payoffs (entrepreneurial action). In short, the entrepreneurial action emerges from the interactions among potential actors over not only *time* but also *space*.

Evidence indicates that entrepreneurs are intimately embedded in a broader business (and social) network and benefit from their connections with other entrepreneurs for the discovery of entrepreneurial opportunities (Klepper and Sleeper, 2005; Markman et al., 2005; Parker, 2008). A notable example is the "open government data" initiatives in America. By 2009 big data have made big difference in business sectors. Pioneers like Google and Microsoft have identified and exploited significant amount of entrepreneurial opportunities to unlock new forms of value creation Keyhani et al., 2015. Their successful lessons later convinced the government, the original gather of mass data (i.e., information hub), to release the data to private sectors. Action was taken; on 21 January 2009, President Barack Obama issued a presidential memorandum authorizing public access of government data to the most extent (WhiteHouse, 2009). Google and Microsoft then took advantage of these rich data to identify and pursue subsequent opportunities. In parallel, they have been keen to making government data more open, transparent, and easily accessed to communities of web developers and other users (WashingtonPost, 2009; Micosoft, 2014). As a result, those developers do not need to collect or control mass data, could still utilize open government data for exploring and then exploiting entrepreneurial opportunities. Successful ones may be acquired by the pioneer firms later (Businessweek, 2014). In this sense, the open government data initiative is an evolving spatiotemporal process where the pioneers play a central role in engaging the government and developers to entrepreneurial activities: they are the hub of this network. So *network does matter for entrepreneurial action.*

The aforementioned case demonstrates that network connections facilitate the feedback from exploitation of an existing opportunity to discovery of subsequent opportunities over space and over time. In any system, networked actors continuously modify the identification, evaluation, and exploitation of opportunities based on connected others' behavior. An actor's entrepreneurial action may increase the feasibility and desirability of subsequent opportunities and provide such information to other actors through network connections (Shepherd and Patzelt, 2013). In the open data case, the government and pioneering firms' entrepreneurial actions make the opportunity exploration of big data feasible and desirable to web developers and other potential users. The role of network here is to determine the magnitude of feedback one's action could possible generate, in terms of how many (i.e., the number of connected others) and how much (i.e., the degree of connections).

The underlying mechanism of entrepreneurial process in a networked system is the feedback loop from an exploitation of an existing opportunity to the recognition and evaluation of subsequent opportunities (Shepherd and Patzelt, 2013). Loosely speaking, entrepreneurial action displays spatial and contagious patterns, that is, how the actors are connected and influenced in the system – who sways whom, shortly. In the graph theory sense, it refers to both spatial and temporal interdependence between actors during repeated interactions (Barabási, 2009; Newman et al., 2001; Nowak, 2006; Suweis et al., 2013; Vazquez et al., 2007). That is, one's (her) entrepreneurial action is likely to impact a connected actor's (his) decision on discovering an opportunity (i.e., space dimension), as well as provide information and experience to herself on exploiting subsequent opportunities (i.e., time dimension). In other words, her subsequent entrepreneurial-action decision is spatially dependent on his feedback and temporally dependent on her past decisions (McMullen and Dimov, 2013; Shepherd and Patzelt, 2013).

Graph theory has been widely applied to formalize spatial feedback processes of human behavior, such as cooperation in the evolutionary literature (e.g., Lieberman et al. (2005); Ohtsuki et al. (2006); Santos et al. (2008); Szabó and Fáth (2007), disease spreading in the epistemology literature (e.g., Keeling (1999); Kretzschmar and Morris (1996)), and innovation in the business literature (e.g., Schilling and Phelps, 2007; Uzzi and Spiro, 2005). Graph theorists generalize *network structure* by arranging actors on a graph, where each node (or vertex) represents an actor, and the arcs (or edges, links) depict who interacts with whom (Lieberman et al., 2005; Ohtsuki et al., 2006; Suweis et al., 2013). Following this logic, network structure models the feedback system within which actors capture value from opportunity exploitation to enhance recognition of subsequent opportunities.

On the other hand, the entrepreneurial action theory including McMullen and Shepherd (2006), Shepherd and Patzelt (2013), Shepherd et al. (2007), and Choi et al. (2008), explores the temporal action process of identification, evaluation, and exploitation of a possible opportunity in pursuit of value creation. Yet three types of uncertainty will obfuscate the perceived need to act; they are state uncertainty, effect uncertainty, and response uncertainty (McMullen and Shepherd, 2006; Milliken, 1987). State uncertainty refers to an inability to predict the future state of environmental components (e.g., whether a connected actor will take entrepreneurial action and provide feedback to the focal actor under market imperfection). Effect uncertainty refers to an inability to predict the impact of a future state of the environment (e.g., knowing that turbulent environment is naturally value-creating or value-destroying does not mean that the actor know how it will impacts him/her). Finally, response uncertainty refers to the inability to specify response options and/or predict the likely consequences of a response choice (e.g., whether a perceived need to act will turn to action). In this sense, the temporal process of entrepreneurial action is to make action decisions under those three types of uncertainty over time.

In this chapter, we develop a graph-theoretic model to study the spatiotemporal dynamics of entrepreneurial action. Our model includes a number of heterogeneous actors in a networked system; and, they need to identify, evaluate and exploit opportunities for value creation. At the temporal dimension, we use the random utility framework, pioneered by Luce (1959) and McFadden (1974), to operationalize the decision-making process (i.e., the behavioral rule in graph theory language) of entrepreneurial action under uncertainty conceptualized by McMullen and Shepherd (2006), Milliken (1987), Shepherd and Patzelt (2013), Grégoire et al. (2010), Shepherd et al. (2007), and Shepherd and Patzelt (2011). In particular, an actor's perceived need to act is influenced by his/her opportunity-recognition belief on the connection's entrepreneurial-action decision for possible feedback under market imperfection (Shepherd et al., 2007). So, entrepreneurial action will be the outcomes of temporally and spatially dynamical interactions between actors' entrepreneurial-action decisions as well as the realization of uncertainties to their networked system (McMullen and Dimov, 2013; Yang and Chandra, 2013).

At the spatial dimension, we investigate six distinctive structures of network that have been observed in diverse domains: the *square lattice* network (Hauert and Szebó, 2003), which has been widely studied in biology and evolutionary literatures, the *pack* network

(Yayavaram and Ahuja, 2008), which captures the key characteristics in product and organization design, the *small-world* network (Watts and Strogatz, 1998) and two extreme cases, the *random* graph and the *ring lattice* network, which are widely adopted in epidemiological studies, and the *scale-free* network (Barabási and Albert, 1999), which is a typical structure for technological systems, such as world-wide web and computer virus infections. We believe that these six network structures should cover most spatial patterns in the real world that potential entrepreneurial actors could possibly be embedded in for identifying, evaluating, and exploiting opportunities.

Our formal analysis provides a clear view on entrepreneurial action as a spatiotemporal dynamical process: A shift in the network structure can significantly change the total number of entrepreneurial action taken by all actors in a networked system. The scale-free network, square lattice network and pack network generate more entrepreneurial actions than the other three networks under uncertainty. We further show that the impacts of the ring lattice network, random network, and small-world network on entrepreneurial action are sensitive to actors' opportunity-recognition belief. Specifically, they generate the most entrepreneurial actions when actors' opportunity-recognition belief follows a martingale – the actors' expectation of receiving entrepreneurial-action feedback from connections in the next period is equal to the present observed feedback. In addition, they are more likely to foster entrepreneurial action under optimistic opportunity-recognition belief – receiving feedback from connections at each time period – over pessimistic opportunity-recognition belief – receiving no feedback from connection at each time period. We conclude that there is a close relationship between the network structure and the dynamics of entrepreneurship.

5.2 Model

Following the notations in Chapter 2, a weighted directed graph $(\mathbf{\Omega}, \mathcal{N}, \mathbf{\Lambda})$ is a collection of n "nodes" $\mathbf{\Omega} = \{\omega_1, \omega_2, \cdots, \omega_n\}$, the "arcs" $\mathcal{N} = \{\mathbb{I}_{ij}(G)\}$ that are directed connections from node i to node j embedded in certain network structure G, and the "arcs weights" , where $i, j \in \{1, 2, \cdots, n\}$. For any ordered pair of nodes (i, j), $\mathbb{I}_{ij}(G) \in \{0, 1\}$. We have

$\mathbb{I}_{ij}(G) = 1$ only if a directed link is drawn from node i to node j, denoted as $i \sim j$; in other words, i is j's neighbor. Then, $0 \leq \lambda_{ij} \leq 1$ is a measure of their connection weight, with larger values leading to stronger connection between nodes. A graph is said to be weighted and directed when the arcs and arcs weights are asymmetric, i.e., $\lambda_{ij} \neq \lambda_{ji}$ and $\mathbb{I}_{ij}(G) \neq \mathbb{I}_{ji}(G)$. (Since this study uses the weighted directed graph only, the following sections will use graph/network and weighted directed graph interchangeably.)

In our model, we refer to *actors* – potential entrepreneurial individuals, organizations, or firms – as nodes, to *connections* – business and/or social relations – as arcs, and to anti-*friction* – the degree of feedback against friction arising from imperfection in the economy, such as transactional costs and barriers to trade (e.g., Chatain and Zemsky, 2011) – as arcs weights. In other words, we depict the phenomenon of entrepreneurship as the form of interconnected actors who may act entrepreneurially under market imperfection on a graph. The graph is assumed to be fixed for the duration of analysis. Consider a network of n actors pursuing possible opportunities for value creation. An *entrepreneur* is a networked actor who acts upon opportunities and her/his action creates value for self and other networked actors to whom s/he is connected. A *non-entrepreneur* is a networked actor who does not act upon opportunities, but s/he may receive value from the neighboring actors acting entrepreneurially.

Our model possesses the following two properties in graph theory: (1) space dynamical property that depicts a network structure in which the actors attain feedback from connected other's entrepreneurial action; (2) time dynamical property that depicts the process of forming entrepreneurial action for each networked actor. Consequently, we are able to infer the entrepreneurial action dynamics of networked actors through the number and the type, entrepreneur or non-entrepreneur, of their connections. The goal of this paper is to operationalize these two properties so as to provide a formalism of entrepreneurial action theory using weighted directed networks.

5.2.1 Spatial feedback process to recognize third person opportunity

In this chapter, we discuss the structural features of six well-established networks, $G = 1, 2, \cdots, 6$, under the same total number of connection where $M = 4n$, so as to investigate the spatiotemporal dynamics of entrepreneurial action. Specifically, they are *square lattices* ($G = 1$), *packs* ($G = 2$), *ring lattices* ($G = 3$), *random* ($G = 4$), *small-world* ($G = 5$), and *scale-free* ($G = 6$). The illustration of these network structures can be found in Figure 5.1. Herein, we provide a verbal description of each structure based on the in-degree and out-degree distributions, together with a graphic illustration for visualization, a symbolic illustration, and a numerical illustration of structure matrix $\mathcal{N}$ for $n = 12$, as well as some applications of the network structure in literature. (Detailed explanation and the algorithms to construct the network with each structure are specified in Chapter 2.)

The six network structures explored depict different who-connects-to-whom patterns, which affects the feedback process of networked actors in reaching interdependent entrepreneurial-action decisions (e.g., Albert et al., 2000; Parker, 2008; Rivkin and Siggelkow, 2007; Szabó and Fáth, 2007). For instance, in a square lattice network, actors are connected on a checkerboard-like grid with the edges wrapped around to form a torus; so each of them will look for feedback from four neighbors to the east, south, west, and north. In a pack network, actors exist in packs where the possible feedback comes from the other three pack mates and one actor outside the pack. In a ring lattice network, actors are arranged in a circle so that entrepreneurial actions from the two adjacent neighbors in both directions are likely to modify their opportunity recognition. If we replace some of those local connections by random connections, we say actors live on a small-world network. At the extreme condition, a random graph rewires all local connections to be random. And in a scale-free network, a small number of actors have significantly large connections and work as a hub of the network, whose action will fed back the most entrepreneurial spillover into the system. With these six network structures, we next formulate the entrepreneurial action process for each actor over time.

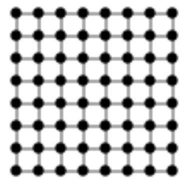
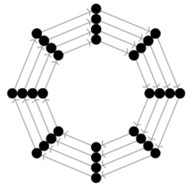
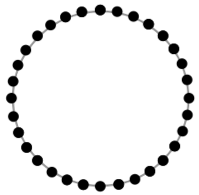
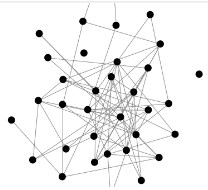
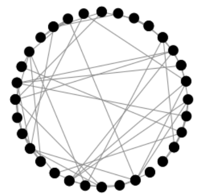
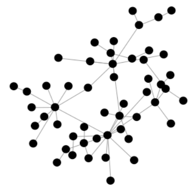
G	Graph	Degree Distribution and Meaning	Graphic Illustration	Symbolic Illustration	Numeric Illustration $\mathcal{N}_{12\times12}(\cdot)$	Application
1	Square Lattices	$f(\kappa_{(out)}) = \psi(\kappa_{(out)} - \kappa_{(out),0})$ *and* $f(\kappa_{(in)}) = \psi(\kappa_{(in)} - \kappa_{(in),0})$.* We consider the standard *von Neumann* neighborhood including four neighbors to the east, south, west, and north. A spatial lattice network characterizes a system where the behavior of each actor depends much more upon the behavior of its nearest connections than that of distant connections.		Suppose the lattice has r row and c columns, where $r, c > 1$ are integers and $r \times c = n$. (1) For actor i who is located at column 1, i.e., $i-1$ is a positive divisor of r, or $(i-1)\|r$, $\mathbb{I}_{ij}(1) = 1$ if $j = i + r - 1$; (2) For actor i who is located at column $c \neq 1$, i.e., $i-1$ does not evenly divide r but leaves a remainder, $\mathbb{I}_{ij}(1) = 1$ if $j = i - 1$; (3) For actor i who is located at row 1, i.e., $i \leq c$, $\mathbb{I}_{ij}(1) = 1$ if $j = i + (r-1) \times c$; (4) For actor i who is located at row $r \neq 1$, $\mathbb{I}_{ij}(1) = 1$ if $j = i - c$, $\mathbb{I}_{ij}(1) = 0$ otherwise.	$\begin{bmatrix} 0&1&0&1&1&0&0&0&1&0&0&0 \\ 1&0&1&0&0&1&0&0&0&1&0&0 \\ 0&1&0&1&0&0&1&0&0&0&1&0 \\ 1&0&1&0&0&0&0&1&0&0&0&1 \\ 1&0&0&0&0&1&0&1&1&0&0&0 \\ 0&1&0&0&1&0&1&0&0&1&0&0 \\ 0&0&1&0&0&1&0&1&0&0&1&0 \\ 0&0&0&1&1&0&1&0&0&0&0&1 \\ 1&0&0&0&1&0&0&0&0&1&0&1 \\ 0&1&0&0&0&1&0&0&1&0&1&0 \\ 0&0&1&0&0&0&1&0&0&1&0&1 \\ 0&0&0&1&0&0&0&1&1&0&1&0 \end{bmatrix}$	Evolutionary graph theory on cooperation (Hauert and Szabó, 2003; Lieberman et al., 2005; Ohtsuki et al., 2006)
2	Packs	$f(\kappa_{(out)}) = \psi(\kappa_{(out)} - \kappa_{(out),0})$ *and* $f(\kappa_{(in)}) = \psi(\kappa_{(in)} - \kappa_{(in),0})$.* Four actors form cliques (i.e., packs) for entrepreneurial decision-making such that actors within each clique all connect with each other but are relatively weakly connected to actors in other cliques. In the short run, the dynamics of one clique is approximately independent of another clique, whereas the long-run dynamics of any clique depends on all other cliques in an aggregate way.		Suppose one pack J_q has 4 actors, where $q = 1, 2, \cdots, n/4$. If actors i and j are in the same pack $(i, j \in J_q)$, then $\mathbb{I}_{ij}(2) = 1$; if they are not in the same pack, i.e., $i \in J_q$ and $j \in J_{q' \neq q}$, then for $i \leq n-4$, $\mathbb{I}_{ij}(2) = \begin{cases} 1 & \text{if } j = i+4 \\ 0 & \text{otherwise} \end{cases}$, for $i > n-4$, $\mathbb{I}_{ij}(2) = \begin{cases} 1 & \text{if } j = i+4-n \\ 0 & \text{otherwise} \end{cases}$.	$\begin{bmatrix} 0&1&1&1&0&0&0&0&0&0&0&0 \\ 1&0&1&1&0&1&0&0&0&0&0&0 \\ 1&1&0&1&0&0&1&0&0&0&0&0 \\ 1&1&1&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&1&1&1&1&0&0&0 \\ 0&0&0&0&1&0&1&1&0&1&0&0 \\ 0&0&0&0&1&1&0&1&0&0&1&0 \\ 0&0&0&0&1&1&1&0&0&0&0&1 \\ 1&0&0&0&0&0&0&0&0&1&1&1 \\ 0&1&0&0&0&0&0&0&1&0&1&1 \\ 0&0&1&0&0&0&0&0&1&1&0&1 \\ 0&0&0&1&0&0&0&0&1&1&1&0 \end{bmatrix}$	Product and organization design (Ethiraj and Levinthal, 2004; Yayavaram and Ahuja, 2008)
3	Ring Lattices	$f(\kappa_{(out)}) = \psi(\kappa_{(out)} - \kappa_{(out),0})$ *and* $f(\kappa_{(in)}) = \psi(\kappa_{(in)} - \kappa_{(in),0})$.* Each actor connects to its adjacent neighbors on either side of it. A ring lattice network describes a sequentially interdependent system: actors are in series where the behavioral output of one actor becomes the input to another one.		For $i < n$, $\mathbb{I}_{ij}(3) = \mathbb{I}_{ji}(3) = \begin{cases} 1 & \text{if } j = i+1 \\ 0 & \text{otherwise} \end{cases}$, for $i = n$, $\mathbb{I}_{ij}(3) = \mathbb{I}_{ji}(3) = \begin{cases} 1 & \text{if } j = i+1-n \\ 0 & \text{otherwise} \end{cases}$; for $i < n-1$, $\mathbb{I}_{ij}(3) = \mathbb{I}_{ji}(3) = \begin{cases} 1 & \text{if } j = i+2 \\ 0 & \text{otherwise} \end{cases}$, for $i \geq n-1$, $\mathbb{I}_{ij}(3) = \mathbb{I}_{ji}(3) = \begin{cases} 1 & \text{if } j = i+2-n \\ 0 & \text{otherwise} \end{cases}$.	$\begin{bmatrix} 0&1&1&0&0&0&0&0&0&0&1&1 \\ 1&0&1&1&0&0&0&0&0&0&0&1 \\ 1&1&0&1&1&0&0&0&0&0&0&0 \\ 0&1&1&0&1&1&0&0&0&0&0&0 \\ 0&0&1&1&0&1&1&0&0&0&0&0 \\ 0&0&0&1&1&0&1&1&0&0&0&0 \\ 0&0&0&0&1&1&0&1&1&0&0&0 \\ 0&0&0&0&0&1&1&0&1&1&0&0 \\ 0&0&0&0&0&0&1&1&0&1&1&0 \\ 0&0&0&0&0&0&0&1&1&0&1&1 \\ 1&0&0&0&0&0&0&0&1&1&0&1 \\ 1&1&0&0&0&0&0&0&0&1&1&0 \end{bmatrix}$	Loop-based plant layout (Asef-Vaziri and Laporte, 2005) Value/Logistic chain (Kumar and van Dissel, 1996)
4	Random	$f(\kappa_{(out)}) = \dfrac{z_1^{\kappa_{(out)}} e^{-z_1}}{\kappa_{(out)}!}$ *and* $f(\kappa_{(in)}) = \dfrac{z_2^{\kappa_{(in)}} e^{-z_2}}{\kappa_{(in)}!}$, where z_1 and z_2 are the values of the mean out-degree and mean in-degree of the network. A random graph $G_{n,M}$ consists of n actors and M acrs, where the connections between actors are drawn randomly. Consequently, every actor does not necessarily have the same number of out- and in-degrees as actors embedded in regular networks.		For any ordered pair of actors (i, j) and $i \nsim j$, $\mathbb{I}_{ij}(4) = 1$, s.t. $M = \sum_{i=1}^{n} \sum_{j=1}^{n} \mathbb{I}_{ij}(4) = 4n$.	$\begin{bmatrix} 0&1&0&0&0&1&0&1&0&0&0&0 \\ 1&0&1&0&0&0&1&0&0&1&0&1 \\ 0&1&0&0&1&1&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&1&0&0&1&1&1&0 \\ 1&0&1&0&1&0&1&0&0&1&1&1 \\ 0&1&0&0&0&1&0&1&0&1&0&0 \\ 1&0&0&0&0&0&1&0&1&0&0&1 \\ 0&0&0&0&1&0&0&1&0&0&0&0 \\ 0&1&0&0&1&1&1&0&0&0&1&1 \\ 0&0&0&0&1&1&0&0&0&1&0&1 \\ 0&1&0&0&0&1&0&1&0&1&1&0 \end{bmatrix}$	Epidemiology (Kretzschmar and Morris, 1996) Ecological food web (Williams and Martinez, 2000)
5	Small-world	Following Watts and Strogatz (1998), a small-world network is created from a ring lattice network by randomly rewiring a fraction α of connections in a way that conserve the out- and in-degree for each actor. In the limit $\alpha \to 0$ the depicted network is equivalent to a ring lattice network. If all connections are randomly rewired ($\alpha = 1$), we derive a random graph. That is, the small-world network interpolates between the ring lattice network and the random graph. Shortly, most actors embedded in the small-world network are connected to the adjacent neighbors, yet a few have distant connections.		(1) With a probability of α, actor i connects to a non-first-order neighbor j randomly. That is, for an ordered pair of actors (i, j) and $i \nsim j$, $\text{Prob}\{\mathbb{I}_{ij}(5) = 1\} = \alpha$; (2) With a probability of $1-\alpha$, node i connects to its neighbor j, i.e., for $i < n$, $\text{Prob}\{\mathbb{I}_{ij}(5) = 1\} = \begin{cases} 1-\alpha & \text{if } j = i+1 \\ 0 & \text{otherwise} \end{cases}$, for $i = n$, $\text{Prob}\{\mathbb{I}_{ij}(5) = 1\} = \begin{cases} 1-\alpha & \text{if } j = i+1 \\ 0 & \text{otherwise} \end{cases}$.	$\begin{bmatrix} 0&1&0&0&1&0&0&0&1&0&1&1 \\ 1&0&1&0&0&0&0&0&0&0&0&0 \\ 0&1&0&1&0&1&1&0&0&0&0&0 \\ 0&0&1&0&0&0&1&0&0&1&0&0 \\ 1&0&0&0&0&1&0&1&0&0&1&1 \\ 0&0&1&0&1&0&1&0&1&0&0&0 \\ 0&0&1&1&0&1&0&0&0&1&0&0 \\ 0&0&0&0&1&0&0&0&1&0&0&1 \\ 1&0&0&0&0&1&0&1&0&1&1&0 \\ 0&0&0&1&0&0&1&0&1&0&1&0 \\ 1&0&0&0&1&0&0&0&1&1&0&1 \\ 1&0&0&0&1&0&0&1&0&0&1&0 \end{bmatrix}$	Strategic alliance network (Schilling and Phelps, 2007) Board interlocks networks (Newman et al., 2001) Collaboration networks of scientists (Newman, 2001) Power grid of the western U.S. (Watts and Strogatz, 1998)
6	Scale-free	$f(\kappa_{(out)}) \propto \kappa_{(out)}^{-\gamma_{out}}$ *and* $f(\kappa_{(in)}) \propto \kappa_{(in)}^{-\gamma_{in}}$, where typically $2 < \gamma_{out}, \gamma_{in} < 3$. In a scale-free network, the out- and in-degree distributions have power-law tails, indicating that some actors have significantly larger connections than others. This distinctive phenomenon is practically absent in random graphs and Watts-Strogatz small-world networks. Comparing to the other five networks, we have a larger chance to find highly connected actors in a scale-free network.		Actor i connects preferentially to actors that have large connections. Given this condition, the probability of an actor j is picked is $\kappa_j / \sum_j \kappa_j$, where κ_j is the degree of actor j and $\sum_j \kappa_j$ is the total number of connections in the network at the current point. Formally, $\text{Prob}\{\mathbb{I}_{ij}(6) = 1\} = \kappa_j / \sum_j \kappa_j$.	$\begin{bmatrix} 0&1&1&1&1&1&1&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&1&0&1&0&0&0 \\ 0&0&0&0&0&0&0&1&0&1&1&1 \\ 0&0&0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&0&1&0&0&0 \end{bmatrix}$	World-Wide Web (Albert et al., 1999) Physical Internet (Faloutsos et al., 1999) Transportation network (Banavar et al., 1999) Citation network (Redner, 1998)

Figure 5.1: Network structure illustration

5.2.2 Temporal action process to evaluate and exploit first person opportunity

Following the lead of McMullen and Shepherd (2006) and Keyhani et al. (forthoming), taking an *entrepreneurial action* or not for actor i at time t can be viewed as the realization of a Bernoulli random variable, taking value 1 with success probability $p_{i,t}$ and value 0 with failure probability $1 - p_{i,t}$. The probability $p_{i,t}$ is always within a range of 0 to 1, i.e., $p_{i,t} \in [0, 1]$. Then a formal notation of entrepreneurial action launched by actor i at time t is

$$z_{i,t} = \mathbf{1}(p_{i,t} - \underbrace{\varepsilon_{i,t}}_{\textit{response uncertainty}} \geq 0) \quad \text{for } t = 1, 2, \cdots, T \text{ and } i = 1, 2, \cdots, n,$$

where $\mathbf{1}(\cdot)$ is the indicator function, and $\varepsilon_{i,t}$ is the response uncertainty associated with the action decision. So $z_{i,t} \in \{0, 1\}$ indicates whether or not actor i takes entrepreneurial action at time t. The success probability $p_{i,t}$ is the likelihood of entrepreneurial action taken by actor i at time t. Notice that a high success probability $p_{i,t}$ is likely to associated with, but cannot guarantee, an entrepreneurial action ($z_{i,t} = 1$) under response uncertainty $\varepsilon_{i,t}$, which is a floating point number uniformly distributed between 0 and 1. In other words, $\varepsilon_{i,t}$ impedes action by obfuscating the possibility for action. Our entrepreneurial-action formulation is thus consistent with studies on the role of (response) uncertainty that plays in preventing actors from acting entrepreneurially (Autio et al., 2013; Keh et al., 2002; Lipshitz and Strauss, 1997; McMullen and Shepherd, 2006; Milliken, 1987; Shepherd et al., 2007).

In line with the general and widely adopted practice in the economics and econometrics literatures on decision-making behavior and process (e.g., Luce, 1959; McFadden, 1974), the likelihood of entrepreneurial action taken by actor i at time t takes the logit form

$$p_{i,t} = \frac{\exp(\mathbb{E}[\omega_{i,t}])}{1 + \exp(\mathbb{E}[\omega_{i,t}])}.$$

As such, we map the original success probability $p_{i,t}$, which is bounded by 0 and 1, to the real line of value created by entrepreneurial action. Following Bradley et al. (2011) and Wiklund and Shepherd (2003), potential value creation from exploiting an identified and evaluated opportunity or not (i.e., taking an entrepreneurial action or not) is modeled as an expected utility function consisting of the value possessed by networked actors: for actor i at time t,

$$\mathbb{E}[\omega_{i,t}] = \omega_{i,t-1} + \sum_{j \sim i} \mathbb{E}[\lambda_{ji,t}]\omega_{j,t-1} - \sum_{i \sim j} \mathbb{E}[\lambda_{ij,t}]\omega_{i,t-1} \tag{5.1}$$

where $\omega_{i,t-1}$ is the value that the actor i has generated before time t, $j \sim i$ is a set of actors j ($\neq i$) who connect to actor i, $i \sim j$ is a set of actors j whom actor i connects to, and $\mathbb{E}[\lambda_{ij,t-1}]$ is the opportunity-recognition belief on the degree of feedback against friction between the neighboring actors around actor i at time t. Following this logic, our formulation in Equation 5.1 is consistent with Shepherd et al. (2007) that an entrepreneurial-action decision is based on priori beliefs on opportunities, not necessarily facts. In this chapter, we consider three scenarios of opportunity-recognition beliefs; they are

$$\mathbb{E}[\lambda_{ji,t}] = \begin{cases} \lambda_{ji,t-1} & \text{if actor } i\text{'s opportunity-recognition belief is a martingale,} \\ \lambda_{ji,0} & \text{if actor } i \text{ has an optimistic opportunity-recognition belief,} \\ 0 & \text{if actor } i \text{ has a pessimistic opportunity-recognition belief,} \end{cases}$$

where $\forall t : \lambda_{ji,t-1} \in \{\lambda_{ji,0}, 0\}$. Specifically, in a martingale scenario, actor i believes that the degree of entrepreneurial feedback from a neighbor j in the next time period is the same as the present observed degree; in an optimism scenario, the actor relies on the initial feedback information received at time 0 (We call it an optimistic belief because it implies that actor j will always take entrepreneurial action at each time period and provide feedback to actor i, explained later in Equation 5.2); in a pessimism scenario, the actor will not expect any feedback from others' entrepreneurial actions. Since opportunities may take the forms of possible feedback from other actors' entrepreneurial actions in a networked system (Gaimon and Bailey, 2013; Keyhani et al., 2015; Parker, 2008; Shepherd and Patzelt, 2013), the opportunity-recognition belief in our model depicts an actor's awareness of a *third-person* opportunity arising from entrepreneurial action launched by connected actors under market imperfection. The optimism scenario is associated with the most number of entrepreneurial opportunities, followed by the martingale scenario and finally the pessimism scenario.

After recognizing a third-person opportunity, an actor next develops and employs a collection of knowledge, skills, abilities and resources to evaluate and exploit it in pursuit of potential value creation (Gaimon and Bailey, 2013; Joglekar and Lévesque, 2013; Mũnoz C. et al., 2011). Similar to the modeling rationale in Haynie et al. (2009) and Keyhani et al. (2015), Equation 5.1 describes that for actor i at time t, the opportunity-evaluation outcome depends on not only her/his existing value, $\omega_{i,t-1}$, but also the expected value creation derived from the interactive feedback from adjacent actors, $\omega_{j,t-1}$ for $j \sim i$. This cost-benefit calculus later tells whether an identified opportunity worths pursuing, i.e., a *first person* opportunity. So, our model provides a way of formalizing the verbal arguments of third-person and first-person opportunities in the entrepreneurial action literature.

For a collection of n networked actors, the expected potential value creation at time t is

$$\mathbb{E}[\boldsymbol{\Omega}_t] = \underbrace{\mathbb{E}[(\boldsymbol{\Lambda}_t + \mathbf{D}_t)]}_{\textit{spatial effect}} \underbrace{\boldsymbol{\Omega}_{t-1}}_{\textit{temporal effect}}$$

where $\boldsymbol{\Omega}_{t-1}$ is a vector of n actors' created value at time $t-1$, $\boldsymbol{\Lambda}_t$ is the anti-friction matrix at time t, and $\mathbf{D}_t = \text{diag}\{1 - \sum_{1\sim j} \lambda_{1j}, 1 - \sum_{2\sim j} \lambda_{2j}, \cdots, 1 - \sum_{n\sim j} \lambda_{nj}\}$. In other words, we formulate the dynamic interplay between spatial feedback process rooted in network structure and temporal entrepreneurial action process.

After actors make entrepreneurial-action decisions at time t following the realization of Bernoulli process $z_{i,t}\,(p_{i,t})$, at time t, actor i's actual entrepreneurial feedback from a neighboring actor j as

$$\lambda_{ji,t}(z_{j,t}) = \begin{cases} \lambda_{ji,0} & \text{if } z_{j,t} = 1, \\ 0 & \text{otherwise.} \end{cases} \tag{5.2}$$

The rationale behind this equation is that actor j not taking action at time t ($z_{j,t} = 0$) will not create valuable feedback for actor i's opportunity discovery, following the entrepreneurship literature such as Keyhani et al., 2015. Then actor i's value at time t is updated following the equation

$$\omega_{i,t} = \omega_{i,t-1} + \sum_{j\sim i} \lambda_{ji,t}\omega_{j,t-1} - \sum_{i\sim j} \lambda_{ij,t}\omega_{i,t-1}. \tag{5.3}$$

In summary, Equations 5.1 to 5.3 suggest an iterative scheme for making entrepreneurial-action decisions in a networked system, as does Shepherd et al. (2007) and Grégoire et al. (2010). Set $t = 0$, $\mathbf{\Omega}_0$ and $\mathbf{\Lambda}_0$ be initial inputs for potential value creation. Now iterate between

Step 1. Solve $\mathbb{E}[\mathbf{\Omega}_1]$ and the resultant $\mathbf{z}_1(\mathbf{p}_1)$ to give $\mathbf{\Lambda}_1$,

Step 2. Update $\mathbf{\Omega}_1$. Set $t \to t + 1$ and return to Step 1.

5.2.3 Operationalization

The operationalization of the proposed model framework is as follows. We specify a network structure $G \in \{1, \cdots, 6\}$ in which n actors are embedded, as well as their opportunity-recognition belief. At time $t \in \{1, \cdots, T\}$ each actor makes an interdependent decision by taking account of the decisions of neighboring actors around the focal actor. To illustrate the complexity of entrepreneurial decision-making, we break down the symmetry of actors by introducing heterogeneity in actor types (possessed value, $\mathbf{\Omega}$, and degree of feedback against friction, $\mathbf{\Lambda}$), as does Rivkin and Siggelkow (2007). Specifically, we impose differences among actors on their value possessed at time 0,

$$\omega_{i,0} = \mu_\omega + \varepsilon_\omega \quad \text{where } \varepsilon_\omega \sim N(0, \sigma_\omega^2).$$

Parameter μ_ω is the average value controled by networked actors at the beginning. Standard normal random variable ε_ω with variance σ_ω^2 captures the variability among the actors' initial values. Asymmetric anti-friction matrix at time 0 (i.e., $\lambda_{ij,0} \neq \lambda_{ji,0}$) is modeled as

$$\lambda_{ij,0} = \mu_\lambda + \varepsilon_\lambda \quad \text{where } \varepsilon_\lambda \sim N(0, \sigma_\lambda^2).$$

Parameter μ_λ is the actors' average degree of feedback against friction under market imperfection. Standard normal random variable ε_λ with variance σ_λ^2 captures heterogeneous degree of feedback against friction and is censored so that the value of $\lambda_{ij,0}$ is between 0 and 1. (We can then use sensitivity analysis on parameters ε_ω and ε_λ to examine the impact of networked actors' inherent differences on their spatiotemporal dynamics of entrepreneurial actions.)

Subsequently, the simulation starts to be executed until time T is reached. With each time tick (time is discrete in our setting), the actors evaluate the identified entrepreneurial opportunities following Equation 5.1 and eventually make entrepreneurial-action decisions according to the realization of Bernoulli random variables $\{z_{i,t}\}$.

At each time t, we are interested in the number of entrepreneurial actions in the network, i.e., the *entrepreneurial action ratio*, δ_t,

$$\delta_t \equiv \frac{1}{n}\sum_{i=1}^{n} z_{i,t}$$

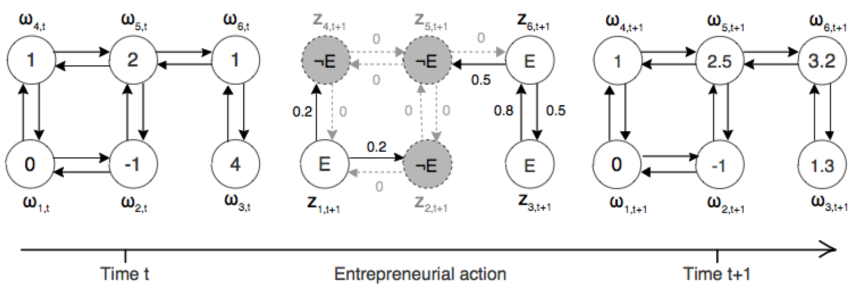
such that $0 \leq \delta_t \leq 1$. We use this measure to evaluate the impact of network structure, the dynamic effect of opportunity-recognition belief, and the efficacy of starting value and degree of feedback against friction. The simulation of the proposed model was carried out in Netlogo, which is one of major platforms to conduct research in computational social science and network science (Miller and Page, 2007).

5.2.4 Illustration

In this section, we illustrate a stylized example for the proposed formal model of entrepreneurial action dynamics. Consider six actors embedded in a network with 12 connections in total, i.e., $\mathbf{\Omega} = \{\omega_1, \cdots, \omega_6\}$ and $M = 12$. To make it simple for the illustration purpose, we set $\lambda_{ij} = \lambda_i$ for all $j \sim i$ and $\lambda_{i,t} = \lambda_{i,0}$. The martingale scenario of opportunity-recognition belief is applied. The spatiotemporal dynamics of entrepreneurial action is investigated in two graphs: a random graph in the left panel and a regular network in the right panel, shown in Figure 5.2. The two graphs have different structure matrices so that the 12 connections are distributed in a different manner.

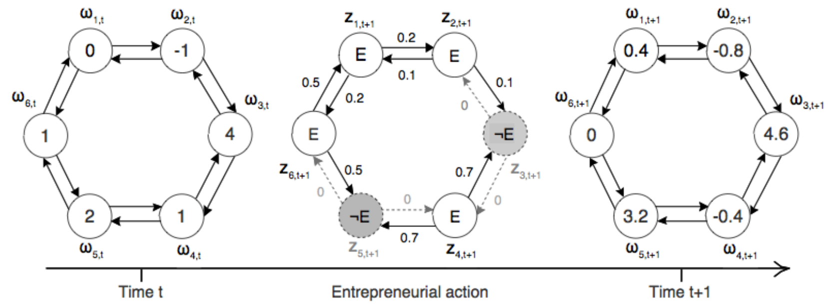
In the left panel, the actors have different out- and in-degrees, as described in the structure matrix $\mathcal{N}$. Specifically, actors 1, 2, 4, 6 each has two neighbors ($\kappa_{i,(out)} = \kappa_{i,(in)} = \kappa_i = 2$, for $i = 1, 2, 4, 6$), whereas actors 3 and 5 have one neighbor and three neighbors, respectively ($\kappa_3 = 1$ and $\kappa_5 = 3$). The table at bottom depicts the process that each actor interacts with neighboring actors and makes corresponding decisions on entrepreneurial action. To evaluate a potential opportunity for value creation at time t, actor i first evaluates

$$\mathcal{N} = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \end{bmatrix} \quad \mathbf{\Lambda_0} = \begin{bmatrix} 0 & .2 & 0 & .2 & 0 & 0 \\ .1 & 0 & 0 & 0 & .1 & 0 \\ 0 & 0 & 0 & 0 & 0 & .8 \\ .7 & 0 & 0 & 0 & .7 & 0 \\ 0 & .1 & 0 & .1 & 0 & .1 \\ 0 & 0 & .5 & 0 & .5 & 0 \end{bmatrix}$$



	$\lambda_{i,t}$	$\omega_{i,t}$	$\mathbb{E}[\omega_{i,t+1}]$	$p_{i,t+1}$	$\varepsilon_{i,t+1}$	$z_{i,t+1}$	$\lambda_{i,t+1}$	$\omega_{i,t+1}$
1	0.2	0	0.6	0.646	*0.503*	**1**	0.2	0
2	0.1	−1	−0.6	0.354	*0.739*	**0**	0	−1
3	0.8	4	1.3	0.786	*0.365*	**1**	0.8	1.3
4	0.7	1	−0.2	0.450	*0.535*	**0**	0	1
5	0.1	2	2.5	0.924	*0.977*	**0**	0	2.5
6	0.5	1	3.4	0.968	*0.171*	**1**	0.5	3.2

$$\mathcal{N} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad \mathbf{\Lambda_0} = \begin{bmatrix} 0 & .2 & 0 & 0 & 0 & .2 \\ .1 & 0 & .1 & 0 & 0 & 0 \\ 0 & .8 & 0 & .8 & 0 & 0 \\ 0 & 0 & .7 & 0 & .7 & 0 \\ 0 & 0 & 0 & .1 & 0 & .1 \\ .5 & 0 & 0 & 0 & .5 & 0 \end{bmatrix}$$



	$\lambda_{i,t}$	$\omega_{i,t}$	$\mathbb{E}[\omega_{i,t+1}]$	$p_{i,t+1}$	$\varepsilon_{i,t+1}$	$z_{i,t+1}$	$\lambda_{i,t+1}$	$\omega_{i,t+1}$
1	0.2	0	0.4	0.599	*0.503*	**1**	0.2	0.4
2	0.1	−1	2.4	0.917	*0.739*	**1**	0.1	−0.8
3	0.8	4	−1.9	0.130	*0.365*	**0**	0	4.6
4	0.7	1	3	0.953	*0.535*	**1**	0.7	−0.4
5	0.1	2	2.8	0.943	*0.977*	**0**	0	3.2
6	0.5	1	0.2	0.550	*0.171*	**1**	0.5	0

Figure 5.2: Entrepreneurial action dynamics on directed network

the expected value at time $t+1$, $\mathbb{E}[\omega_{i,t+1}]$, following Equation 5.1. Next, actor i assesses the probability of taking entrepreneurial action, $p_{i,t+1}$ and the resulting decision of acting entrepreneurially or not follows the realization of a Bernoulli process at time t, $z_{i,t+1}(p_{i,t})$. In general, according to the entrepreneurship literature (and the random utility framework in the econometrics and statistics literature), actor i with a better outcome of opportunity evaluation (i.e., higher probability $p_{i,t+1}$) is more likely to take entrepreneurial action from time t to time $t+1$. For instance, actor 6 with $p_{6,t+1} = 0.968$ (> 0.171, an uniform random number of response uncertainty to decide the realization of a Bernoulli random variable, see Miller and Page, 2007) will act, denoted as E, whereas actor 2 with $p_{2,t+1} = 0.354$ (< 0.739) will not act at time $t+1$, denoted as $\neg$E. It is noticeable that our random-utility based formulation allows actors take action under low probabilities or take non-action under high probabilities due to some randomness, in line with the entrepreneurship literature on uncertainty and risk (Myerson, 2004; Nair et al., 2009). Actor 5, for example, decides not to act upon an opportunity even at $p_{5,t+1} = 0.924$ (< 0.977). So, our model successfully captures the phenomena of entrepreneurial action dynamics under response uncertainty. The entrepreneurial action ratio at time $t+1$ is $\delta_{t+1} = 3/6 = 0.5$, i.e., three out of six actors acting. Finally, according to Equation 5.3, all actors update their possessed value as $\omega_{i,t+1}$, $i = 1, 2, \cdots, 6$, when the actual degree of feedback are known upon the entrepreneurial-action decisions.

When the network structure for these six actors is a regular network, see the right panel of Figure 5.2, the entrepreneurial action dynamics changes dramatically. Herein, each actor is connected to the two most adjacent neighboring actors ($\kappa_i = 2$ for $i = 1, \cdots, 6$). We can see that most actors significantly modify the expectation towards potential value creation if exercising entrepreneurial-action decisions. Take actor 3 as an example. The probability of taking entrepreneurial action for this actor from time t to time $t+1$ drops from 0.786 to 0.130, which ultimately leading to a non-action decision. At the network dimension, the entrepreneurial action ratio increases, i.e., $\delta_{t+1} = 4/6 = 0.67$, comparing to 0.5 in the random graph. Note that the only difference between the two panels is network structure.

Thus, network structure is fully responsible for the changes in the entrepreneurial action dynamics for potential value creation.

In the subsequent sections, we follow the best practice of developing management and organizational theory through simulation experiments (Davis et al., 2007; Harrison et al., 2007; Miller and Page, 2007).

5.3 Analysis

We analyze our model in two stages. First we conduct a base case analysis to investigate the role of six network structure in entrepreneurial action dynamics. They are examined under three scenarios – martingale, optimism, and pessimism for opportunity-recognition belief. To understand the sensitivity of model parameters, we next resort to an extensive numerical analysis via a careful experimental design to illustrate their effects on entrepreneurial action over time and space.

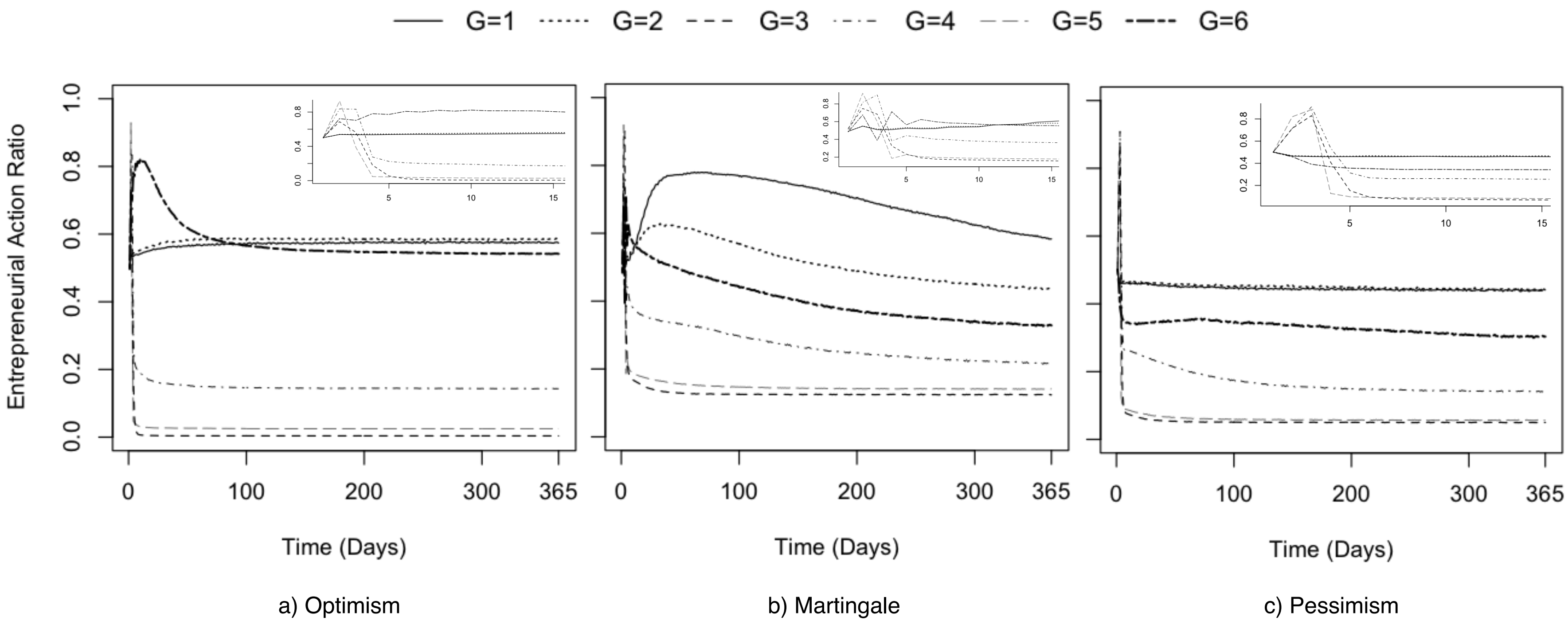
5.3.1 Base case

Without loss of much generality, we set the actors' starting value from a standard normal distribution with variance 1, i.e. $\omega_{i,0} \sim N(0,1)$, and the degree of feedback against friction is drawn from a truncated normal distribution with mean $\mu_\lambda = 0.2$ and variance $\sigma_\lambda^2 = 0.04$, ranging from 0 to 1. Table 5.1 summarizes the parameter values used in the base case.

Table 5.1: Parameter values in base case setting

Parameter	Values	Meaning
G	{1, 2, 3, 4, 5, 6}	Six network structures (as illustrated in Figure 5.1)
α [†]	0.4	Rewiring probability in small-world networks
n	480	Total number of actors on the network
$\omega_{i,0}$	$N(0,1)$	Value possessed at time 0
$\lambda_{ij,0}$	$TN(0.2, 0.2)$	Degree of feedback between actor pairs ($0 \leq \lambda_{ij,0} \leq 1$)

[†] Our results are insensitive to the choice of α, consistent with the findings in Rivkin and Siggelkow (2007). Results for $\alpha = 0.1, 0.2, \cdots, 0.9$ are available in the supplementary notes.



Note. For each network structure, the main figure illustrates the time plots of entrepreneurial action ratio over one-year time (365 days). To take a close look at the changes at the early days, we include a small figure at the corner, showing the time plot over a short starting period. Note that entrepreneurial action ratio mostly starts from 0.5 across all networks due to our setting of initial possessed value. Each result is an average over 200 runs.

Figure 5.3: Base case of entrepreneurial action ratio on graphs

Figure 5.3 vividly depicts that *network structures generate heterogeneous impacts on the dynamics of entrepreneurial action.* In general, we observe that a larger number of actors act entrepreneurially in square lattice ($G = 1$) network, pack ($G = 2$) network, and scale-free ($G = 6$) network so that the entrepreneurial action ratios in these three network structures are relatively high. The results are consistent among the three scenarios of opportunity-recognition belief. For instance, in a pack network, over 40-percent of actors take entrepreneurial action in each time period. On the contrary, only a small number of actors (less than 20-percent) are motivated to act entrepreneurially when they are embedded in ring lattice ($G = 3$) network, random ($G = 4$) graph, and small-world ($G = 5$) network. Those three network structures act as suppressors of entrepreneurship.

Additionally, the impact of each network structure on entrepreneurial action dynamics varies across the three scenarios of actors' opportunity-recognition belief. As illustrated in Figure 5.3, actors embedded in pack ($G = 2$) network and scale-free ($G = 6$) network are most likely to take entrepreneurial actions when they have optimistic belief. Likewise, when actors hold pessimistic opportunity-recognition belief, they may overlook potential feedback from others' entrepreneurial actions, resulting in relatively low entrepreneurial action ratios in these two networks. The results are consistent with our expectation that entrepreneurial action ratio increases in the number of third-person opportunities. However, for actors embedded in the other four networks, they are most likely to act entrepreneurially under the martingale scenario. That is, opportunity-recognition belief derived from the recent observed entrepreneurial feedback are more effective to identify third-person opportunities that are feasible and desirable to be exploited for value creation in square lattice ($G = 1$) network, ring lattice ($G = 3$) network, random ($G = 4$) graph, and small-world ($G = 5$) network. These observations suggest that networked actors' decisions on entrepreneurial action are regulated by heir opportunity-recognition beliefs and network structure which they are embedded in.

In the following sections, we develop a three-level full factorial design to examine the impact of network structure under various combinations of key model parameters and to check the robustness of results from the base case. The parameter values used in our experiment are listed in Table 5.2. In total, we examine $81(= 3^4)$ parameter instances consisting a wide range of possible scenarios. We run each parameter instance 100 times to achieve statistical reliability for inference. We investigate the spatiotemporal dynamics of entrepreneurial action under three opportunity-recognition belief scenarios, optimism, martingale, and pessimism, respectively. This gives a total of 8100 experiments for each network structure under each opportunity-recognition belief scenario. Under each scenario, we explain how differences in the degree of feedback against friction and initial possessed value change the entrepreneurial action dynamics in each network structure.

Table 5.2: Parameter values in experiments

Parameter	Values	Meaning
μ_{λ_0}	{0.2, 0.5, 0.8}	Average degree of feedback against friction
σ_{λ_0}	{0.2, 0.5, 0.8}	Standard deviation of degree of feedback among networked actors
μ_{ω_0}	{-5, 0, 5}	Average value possessed at time 0
σ_{ω_0}	{1, 5, 10}	Standard deviation of possessed value among networked actors

5.3.2 Experiment under the optimism scenario

When actors hold optimistic opportunity-recognition belief, Figure 5.4 plots the ranking outcomes on the entrepreneurial action ratio, among the network structures, at the end of the simulation time. Rank 1 indicates the highest entrepreneurial action ratio and rank 6 indicates the lowest ratio among all the six network structures. In general, the number of entrepreneurial actions are the most in pack ($G = 2$) network and square lattice ($G = 1$) network, followed by scale-free ($G = 6$) network and random ($G = 4$) graph, and the least in small-world ($G = 5$) network and ring lattice ($G = 3$) network.

To further elaborate the impact of network structure, in Table 5.3 we summarize the degree of feedback and possessed value against the entrepreneurial action ratios under various experimental scenarios. Looking down each column of the table, i.e., holding fixed the

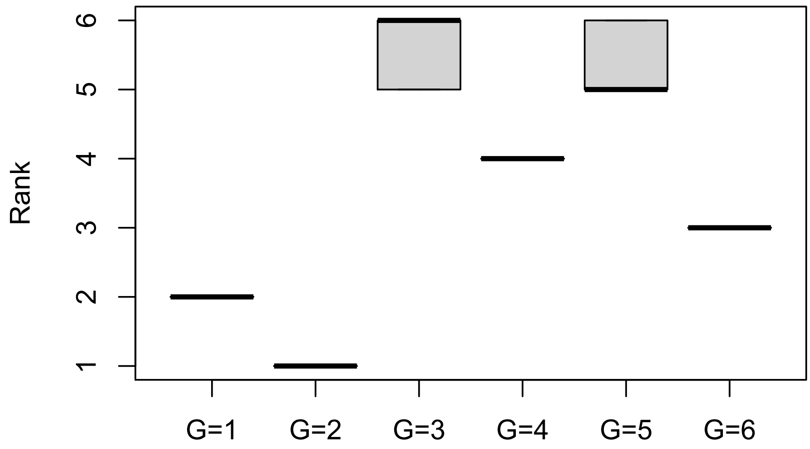


Figure 5.4: Rank of network structures under the optimism scenario

Table 5.3: Entrepreneurial action dynamics under the optimism scenario

	μ_{λ_0}			σ_{λ_0}			μ_{ω_0}			σ_{ω_0}		
	L {0.2}	M {0.5}	H {0.8}	L {0.2}	M {0.5}	H {0.8}	L {−5}	M {0}	H {5}	L {1}	M {5}	H {10}
$G = 1$	45.58	24.78	8.44	29.98	25.80	23.04	25.82	26.24	26.74	26.26	26.28	26.27
	(0.13)	(0.05)	(0.06)	(0.25)	(0.15)	(0.07)	(0.17)	(0.17)	(0.18)	(0.17)	(0.18)	(0.18)
$G = 2$	50.57	32.68	13.63	32.61	32.63	31.63	31.69	32.30	32.90	32.23	32.31	32.33
	(0.10)	(0.04)	(0.10)	(0.25)	(0.15)	(0.07)	(0.16)	(0.17)	(0.18)	(0.17)	(0.17)	(0.18)
$G = 3$	0.39	0.28	0.22	0.28	0.31	0.31	0.28	0.46	0.15	0.17	0.31	0.42
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$G = 4$	7.36	2.87	2.30	6.44	3.08	3.01	3.63	4.02	4.87	4.42	4.29	3.82
	(0.06)	(0.01)	(0.01)	(0.06)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$G = 5$	1.06	0.35	0.25	0.91	0.39	0.36	0.45	0.67	0.54	0.37	0.69	0.60
	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$G = 6$	36.97	19.19	9.30	27.06	20.35	18.06	21.86	21.92	21.70	22.07	21.64	21.76
	(0.15)	(0.07)	(0.05)	(0.22)	(0.12)	(0.07)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)

Note. The entrepreneurial action ratio (in percentage value $\delta \times 100$) is based on an average of 100 runs of 81 experiments. Standard deviations are in parentheses.

experimental parameters, we shadow the network structure in grey as it is associated with a higher entrepreneurial action ratio than the others. Specifically, actors embedded in pack ($G = 2$) network, square lattice ($G = 1$) network, and scale-free ($G = 6$) network are much more likely to take entrepreneurial actions than those embedded in the other three networks in all experimental scenarios, consistent the findings in the base case. Further, packs are associated with the largest number of actors who acting entrepreneurially among the top three network structures. Square lattices and scale-free are effective in fostering entrepreneurial action when the average degree of feedback (parameter μ_{λ_0}) against friction is low and high, respectively. On the contrary, random ($G = 4$) graph, small-world ($G = 5$) network, and ring lattice ($G = 3$) network facilitate a small number of entrepreneurial actions in pursuit of potential value creation. As shown in Table 5.3, no greater than 1% of actors acting entrepreneurially when they are embedded in ring lattice network and small-world network.

Looking across each row of the table, we find that the parameters impact the entrepreneurial action dynamics in a consistent way across the six network structures under the optimism scenario. The mean degree of feedback, parameter μ_{λ_0}, and the standard deviation, parameter σ_{λ_0}, have more significant effect on the entrepreneurial action ratio than the parameters μ_{ω_0} and σ_{ω_0} for the initial possessed value. Specifically, the degree of feedback parameters negatively affect the number of actors acting entrepreneurially. The networked actors achieve the most entrepreneurial actions when their degrees of feedback against friction are distributed with a low mean and low standard deviation. We plot the interaction effect of the two parameters for each network structure in the top panel of Figure 5.5. When the average degree of feedback is low ($\mu_{\lambda_0} = 0.2$, circles overlayed by a dashed line), the entrepreneurial action ratio in most network structures decreases significantly as the standard deviation increases (with an exception of concave downwards in ring lattices). In contrast, when the average degree of feedback against friction is high ($\mu_{\lambda_0} = 0.8$, squares overlayed by a dotted line), the entrepreneurial action ratio slightly improved in the standard deviation. So, while a low mean degree of feedback is always associated with a larger number of entrepreneurial actions than a high mean, the advantage diminishes as the variability among the actors increases.

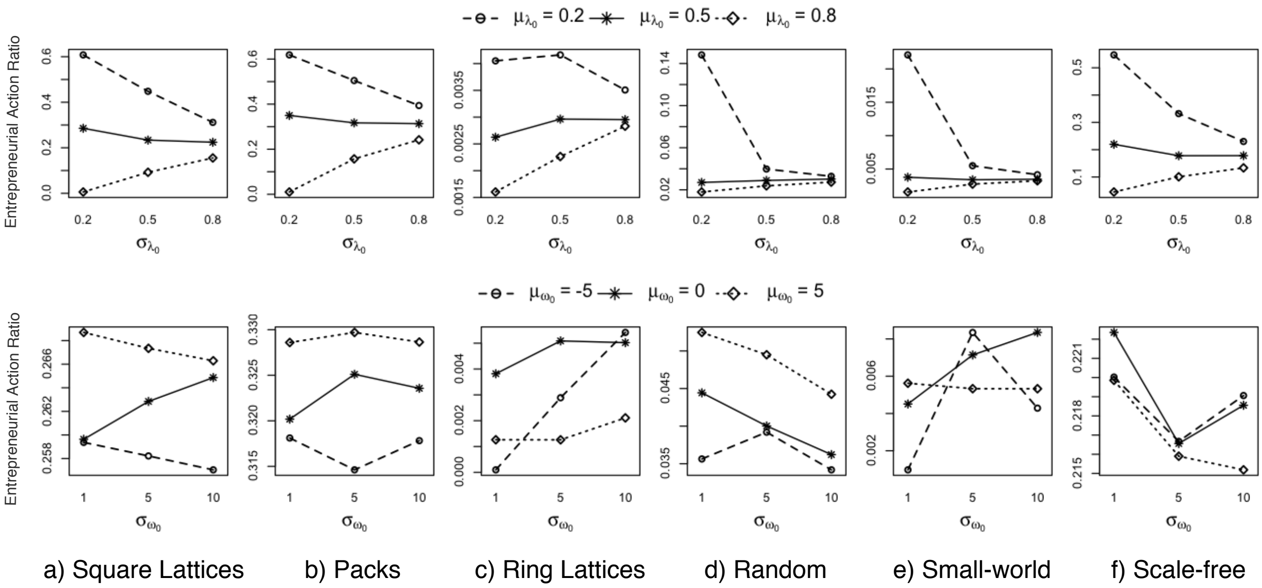


Figure 5.5: Interaction plot of experimental parameters under the optimism scenario

The bottom panel of Figure 5.5 shows a mixed marginal impact of actors' initial possessed value on the entrepreneurial action ratio. In square lattice network, pack network, and random graph, actors possessing higher starting value ($\mu_{\omega 0} = 5$, squares overlaid by a dotted line) are marginally more likely to act entrepreneurially. When actors are embedded in ring lattice network, small-world network, In contrast, high initial possessed value does not give actors advantages in taking entrepreneurial actions. Note that impact of possessed value (parameter ω_0) is not significant across all network structures. So, we will focus our analysis on the degree of feedback against friction impacting entrepreneurial action dynamics in various network structures.

In summary, under the optimism scenario, pack network and square lattice network favor entrepreneurial action for the actors sharing low degree of feedback against friction, and pack network and scale-free network for the actors sharing high degree of feedback. The number of entrepreneurial actions is relatively high when actors have small variation in their degrees of feedback under market imperfection.

5.3.3 Experiment under the martingale scenario

When actors adjust their opportunity-recognition beliefs based on the entrepreneurial feedback from the previous period, i.e., opportunity-recognition beliefs following a martingale, Figure 5.6 plots the ranking outcomes of network structures on entrepreneurial action ratio. We observe that scale-free ($G = 6$) network ranks the first, the small-world ($G = 5$) the last, and the other four network structures in the middle. That is, the ranking of network structures are largely dispersed under the martingale scenario. We next carefully examine the conditions moderating the rankings of network structures.

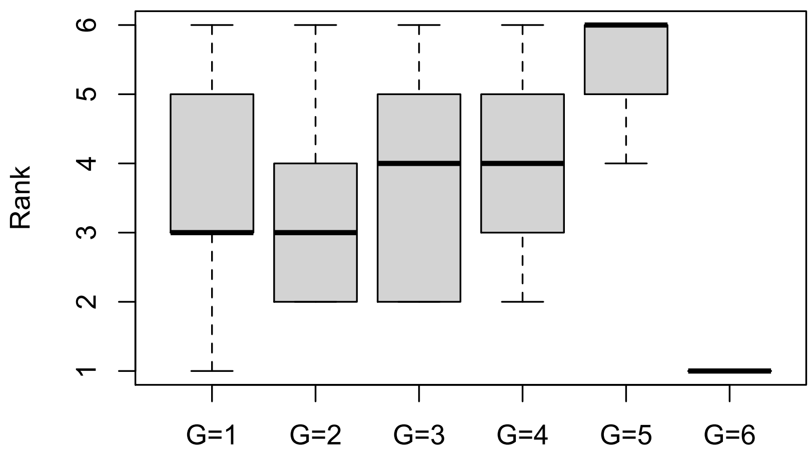


Figure 5.6: Rank of network structures under the martingale scenario

In Table 5.4 we summarize the entrepreneurial action ratio in the six network structures, at the end of the simulation time, in the presence of various experimental parameter combinations. Looking down each column of the table, we find in general that actors embedded in scale-free ($G = 6$) network, square lattice ($G = 1$) network, and pack ($G = 2$) network are more likely to take entrepreneurial actions than actors embedded in the other three networks. However, their leading edge is very narrow (mostly less than 10% differences) under the martingale scenario in comparison to that under the optimism scenario (up to 50% differences) in Section 5.3.2. In particular, when the average degree of feedback against friction is high, i.e., $\mu_{\lambda_0} = 0.8$, ring lattice ($G = 3$) ranks the second, random ($G = 4$) the third, and small-world ($G = 5$) the forth, surpassing square lattices and packs. So, the role of networks structure is dependent on the degree of feedback under the martingale scenario.

Specifically, both the mean degree of feedback (parameter μ_{λ_0}) and the standard deviation (parameter σ_{λ_0}) generate adverse impacts on the entrepreneurial action ratio across the six network structures, consistent with the patterns under the optimism scenario. As reported in Table 5.4, the most number of actors act entrepreneurially when the friction under market imperfection resists the degree of feedback between them. That is, entrepreneurial actions arise from imperfect market process. To visualize this finding, we further plot the interaction effect of the two parameters in the top panel of Figure 5.7. The highest entrepreneurial action ratio is achieved at a low mean and a small standard deviation. And such ratio decreases as either the mean increases (the circle point above the stars and squares), or the standard deviation increases (a downward slope of the circles overlayed by a dashed line), or both. Similar to the optimism scenario, the impacts of initial possessed value parameters (mean, parameter $\mu_{\omega 0}$, and standard deviation, parameter $\sigma_{\omega 0}$) are mixed and marginal. High average value is associated with better entrepreneurial action ratio in most network structures, except from square lattices and scale-free.

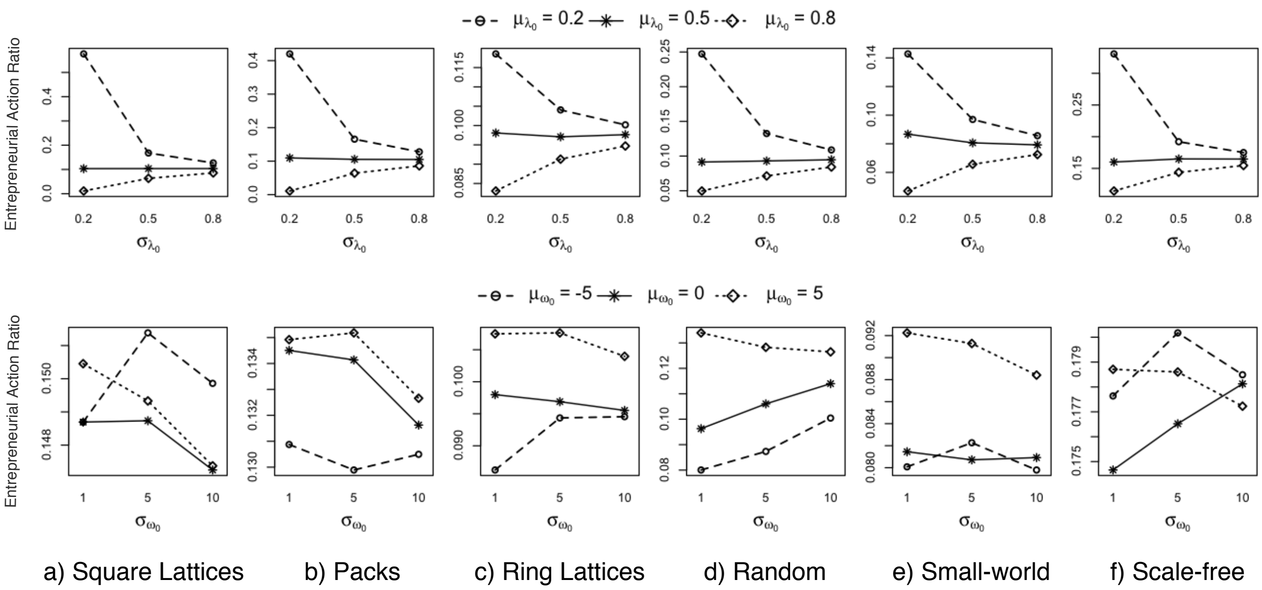


Figure 5.7: Interaction plot of experimental parameters under the martingale scenario

Table 5.4: Entrepreneurial action dynamics under the martingale scenario

	μ_{λ_0}			σ_{λ_0}			μ_{ω_0}			σ_{ω_0}		
	L	M	H	L	M	H	L	M	H	L	M	H
	{0.2}	{0.5}	{0.8}	{0.2}	{0.5}	{0.8}	{−5}	{0}	{5}	{1}	{5}	{10}
$G = 1$	29.04	10.35	5.34	23.03	11.15	10.54	15.00	14.82	14.91	14.93	14.98	14.82
	(0.21)	(0.02)	(0.03)	(0.25)	(0.05)	(0.02)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
$G = 2$	23.78	10.66	5.36	18.02	11.17	10.62	13.04	13.34	13.43	13.34	13.31	13.16
	(0.13)	(0.02)	(0.03)	(0.18)	(0.05)	(0.02)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
$G = 3$	10.76	9.76	8.97	9.99	9.75	9.75	9.17	9.68	10.64	9.72	9.96	9.80
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
$G = 4$	16.29	9.30	6.84	12.94	9.89	9.59	8.93	10.54	12.96	10.34	10.72	11.36
	(0.08)	(0.03)	(0.02)	(0.09)	(0.04)	(0.03)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
$G = 5$	10.85	8.22	6.17	9.22	8.11	7.91	8.07	8.10	9.06	8.46	8.48	8.30
	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$G = 6$	23.26	16.32	13.76	20.17	16.69	16.48	17.88	17.64	17.82	17.70	17.84	17.79
	(0.09)	(0.02)	(0.03)	(0.11)	(0.03)	(0.03)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)

Note. The entrepreneurial action ratio (in percentage value $\delta \times 100$) is based on an average of 100 runs of 81 experiments. Standard deviations are in parentheses.

In summary, under the martingale scenario, square lattice network, pack network, and scale-free network foster entrepreneurial actions for the actors sharing low degree of feedback against friction, and scale-free network and ring lattice network for those sharing high degree of feedback. The entrepreneurial action ratio decreases in the the variation of the degree of feedback among the actors.

5.3.4 Experiment under the pessimism scenario

When actors hold pessimistic opportunity-recognition belief, Figure 5.8 plots the ranking outcomes of the network structures on the entrepreneurial action ratio. Specifically, actors embedded in scale-free ($G = 6$) network are the most likely to act entrepreneurially, followed by those embedded in square lattice ($G = 1$) network, pack ($G = 2$) network. The number of entrepreneurial actions in random ($G = 4$) graph ranks fourth among the six network structures, whereas ring lattice ($G = 3$) network and small-world ($G = 5$) network are tied for the worst ranking outcome.

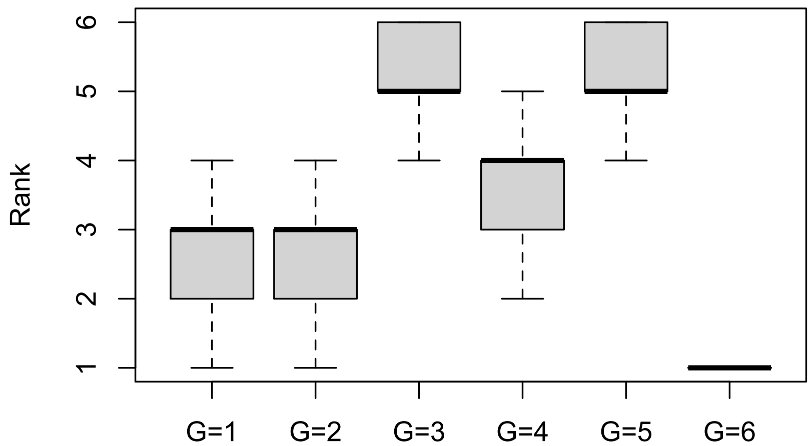


Figure 5.8: Rank of network structures under the pessimism scenario

We summarize the experimental results of entrepreneurial action ratio under the pessimism scenario in Table 5.5. The number of actors acting entrepreneurially are significantly less than that under the martingale scenario; this pattern is consistent across all network structures. Looking down each column of the table, we find that scale-free ($G = 6$) net-

Table 5.5: Entrepreneurial action dynamics under the pessimism scenario

	μ_{λ_0}			σ_{λ_0}			μ_{ω_0}			σ_{ω_0}		
	L	M	H	L	M	H	L	M	H	L	M	H
	{0.2}	{0.5}	{0.8}	{0.2}	{0.5}	{0.8}	{−5}	{0}	{5}	{1}	{5}	{10}
$G = 1$	20.98	9.48	4.45	15.57	9.96	9.38	9.29	11.92	13.69	12.50	11.74	10.67
	(0.12)	(0.02)	(0.03)	(0.16)	(0.05)	(0.03)	(0.07)	(0.11)	(0.12)	(0.11)	(0.10)	(0.09)
$G = 2$	20.81	9.36	4.53	15.22	10.00	9.48	9.54	12.04	13.12	12.60	11.61	10.49
	(0.12)	(0.02)	(0.03)	(0.16)	(0.05)	(0.03)	(0.07)	(0.10)	(0.11)	(0.11)	(0.10)	(0.09)
$G = 3$	4.35	3.71	3.47	3.93	3.78	3.82	3.85	3.78	3.90	4.17	3.75	3.60
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$G = 4$	11.12	7.28	5.57	8.65	7.68	7.64	6.04	6.92	11.02	7.96	7.87	8.14
	(0.05)	(0.04)	(0.03)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
$G = 5$	4.87	3.59	2.87	3.87	3.76	3.70	3.19	3.45	4.69	4.11	3.57	3.66
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
$G = 6$	19.04	14.31	10.79	15.25	14.44	14.46	13.70	16.24	14.20	15.49	14.80	13.85
	(0.06)	(0.03)	(0.04)	(0.08)	(0.04)	(0.03)	(0.04)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)

Note. The entrepreneurial action ratio (in percentage value $\delta \times 100$) is based on an average of 100 runs of 81 experiments. Standard deviations are in parentheses.

work, square lattice ($G = 1$) network, and pack ($G = 2$) network generally facilitate a larger number of entrepreneurial actions than random ($G = 4$) graph, small-world ($G = 5$) network, and ring lattice ($G = 3$) network. When the actors' average degree of feedback against friction is high (i.e., $\mu_{\lambda_0} = 0.8$), however, random graph achieves the second best ranking outcome. In other words, parameter μ_{λ_0} affects the role of network structure in entrepreneurial action dynamics.

Looking across each row of the table, we find that the effects of the experimental parameters in all network structures are consistent under the pessimism scenario. For instance, the networked actors are likely to take entrepreneurial action when their average degree of feedback against friction (parameter μ_{λ_0}) is low and average initial possessed value (parameter μ_{ω_0}) is high. These two mean parameters have more significant effects than the two standard-deviation parameters, σ_{λ_0} and σ_{ω_0}, where low actor variability leads to high entrepreneurial action ratio in both cases. In Figure 5.9 we further plot how the distributions of the actors' degree of feedback and initial values impact the entrepreneurial action dynamics in each network structure. Similar to the optimism and martingale scenarios, the top panel shows that the low average degree of feedback ($\mu_{\lambda_0} = 0.2$, circles overlayed by a dashed line) dominates the medium ($\mu_{\lambda_0} = 0.5$, stars overlayed by a solid line) and high ($\mu_{\lambda_0} = 0.8$, squares overlayed by a dotted line) levels. Yet the advantage diminishes as the standard deviation increases. On the other hand, the bottom panel of Figure 5.9 highlights the favorable return of possessing high initial value ($\mu_{\omega_0} = 5$, squares overlayed by a dotted line), especially for actors embedded in square lattice network, pack network, random network, and small-world network.

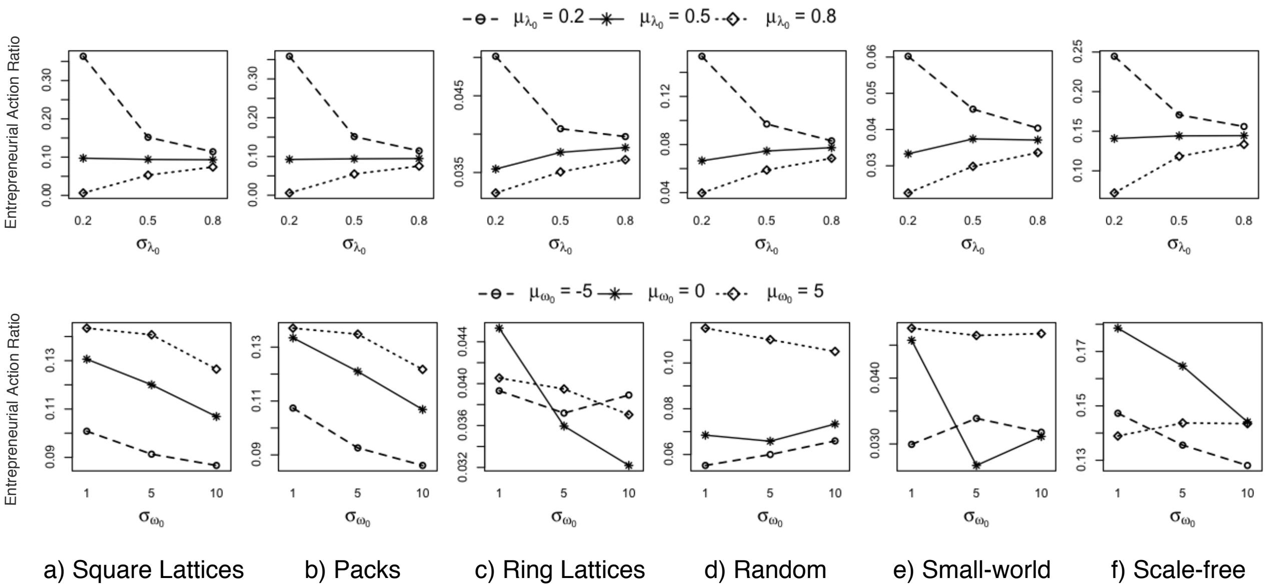


Figure 5.9: Interaction plot of experimental parameters under the pessimism scenario

In summary, under the pessimism scenario, square lattice network, pack network, and scale-free network favor entrepreneurial action for the actors sharing low degree of feedback against friction, and scale-free network and random graph for those sharing high degree of feedback. The number of entrepreneurial action is relatively high when the actors possess high initial value.

5.4 Extension

So far we implicitly assumed compulsory participation in the entrepreneurial process by considering every actors as a potential entrepreneurs. In nature, however, actors often have the possibility and ability to be risk averse and refuse to participate in the entrepreneurial process. Following Hauert and Szebó (2003), we model this by introducing a second character: the loners. Loners act as insulators in the entrepreneurial process; they do not act upon potential opportunities for value creation in despite of neighbors' entrepreneurial feedback.

In this model extension, we refer to both *actors* and *loners* as nodes. The density of actors, denoted as d, in the weighted directed graph is

$$d \equiv \frac{\sum_{i=1}^{n} I_i}{n}, \quad 0 \leq d \leq 1,$$

where $I_i = 1$ indicates an actor i, and $I_j = 0$ a loner j. But there is no feedback between any connected actor and loner, i.e., $\lambda_{ij} = 0$ for $I_i \neq I_j \in \{0, 1\}$ and $i \sim j$. So the number of actors is $[d \times n]$, or $[dn]$, where "$[x]$" is a function which returns the nearest integer to x. We derive the entrepreneurial action ratio as the percentage of actors that act entrepreneurially,

$$\delta = \sum_{i=1}^{[dn]} z_{i,t}/[dn], \quad \text{for } I_i = 1.$$

We examine 81 ($= 3^4$) parameter instances consisting of every combination in Section 5.3 and analyze the impact of parameters to the entrepreneurial action ratio under many actor densities, $d = \{0.2, 0.5, 0.8\}$, and the martingale scenario as illustrated in Table 5.6. (The patterns are similar under the optimistic and pessimistic opportunity-recognition believes; we include the experiment results in the Supplementary Notes). Looking down each column of the table, the entrepreneurial action ratios are not significantly different from each network structure when $d = 0.2$, see panel 1 of Table 5.6. This is intuitive since the low actor density disrupts the designated structure of a graph. The role of network structure in entrepreneurial action dynamics becomes virtual as the density of actors increases. In the panel 3 of Table

Table 5.6: Entrepreneurial action dynamics in the presence of loners under the martingale scenario

	μ_{λ_0}			σ_{λ_0}			μ_{ω_0}			σ_{ω_0}		
	L	M	H	L	M	H	L	M	H	L	M	H
Panel 1: $d = 0.2$												
$G = 1$	47.90	48.20	49.05	49.27	48.09	47.79	**26.91**	**49.18**	**69.06**	47.88	48.24	49.03
	(0.20)	(0.18)	(0.18)	(0.19)	(0.18)	(0.18)	**(0.08)**	**(0.06)**	**(0.07)**	(0.23)	(0.18)	(0.14)
$G = 2$	46.93	46.81	47.25	47.39	46.85	46.74	**26.05**	**47.85**	**67.07**	47.41	47.01	46.56
	(0.19)	(0.18)	(0.17)	(0.18)	(0.18)	(0.18)	**(0.07)**	**(0.06)**	**(0.08)**	(0.23)	(0.18)	(0.13)
$G = 3$	40.23	39.86	39.66	39.95	39.86	39.94	**17.73**	**41.30**	**60.72**	38.03	40.26	41.46
	(0.20)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	**(0.10)**	**(0.05)**	**(0.08)**	(0.26)	(0.18)	(0.11)
$G = 4$	49.80	49.34	48.04	49.27	48.95	48.95	**28.39**	**50.09**	**68.70**	47.64	49.53	50.00
	(0.20)	(0.18)	(0.18)	(0.19)	(0.18)	(0.18)	**(0.11)**	**(0.06)**	**(0.09)**	(0.25)	(0.18)	(0.11)
$G = 5$	43.52	43.02	42.66	43.13	42.99	43.08	**21.67**	**44.94**	**62.59**	41.25	43.28	44.68
	(0.19)	(0.19)	(0.18)	(0.19)	(0.19)	(0.19)	**(0.10)**	**(0.06)**	**(0.08)**	(0.25)	(0.17)	(0.11)
$G = 6$	47.39	45.91	45.13	46.85	45.88	45.71	**24.64**	**46.67**	**67.13**	45.96	46.17	46.31
	(0.21)	(0.19)	(0.19)	(0.20)	(0.19)	(0.19)	**(0.09)**	**(0.07)**	**(0.11)**	(0.25)	(0.19)	(0.13)
Panel 2: $d = 0.5$												
$G = 1$	**43.44**	**40.73**	**33.94**	40.19	39.17	38.75	**33.83**	**39.93**	**44.35**	39.30	39.36	39.45
	(0.08)	**(0.07)**	**(0.07)**	(0.11)	(0.07)	(0.06)	**(0.06)**	**(0.07)**	**(0.08)**	(0.09)	(0.09)	(0.08)
$G = 2$	**40.62**	**38.62**	**34.85**	38.70	37.79	37.60	**30.28**	**39.31**	**44.49**	38.96	38.06	37.07
	(0.09)	**(0.07)**	**(0.06)**	(0.09)	(0.07)	(0.07)	**(0.04)**	**(0.05)**	**(0.06)**	(0.08)	(0.08)	(0.07)
$G = 3$	**27.24**	**26.38**	**25.63**	26.19	26.46	26.61	**17.06**	**28.43**	**33.77**	23.76	26.83	28.66
	(0.09)	**(0.08)**	**(0.08)**	(0.09)	(0.08)	(0.08)	**(0.07)**	**(0.03)**	**(0.03)**	(0.11)	(0.07)	(0.04)
$G = 4$	**40.61**	**35.17**	**28.97**	36.34	34.53	33.89	**27.23**	**34.34**	**43.19**	33.56	35.10	36.09
	(0.11)	**(0.09)**	**(0.09)**	(0.13)	(0.10)	(0.09)	**(0.09)**	**(0.09)**	**(0.09)**	(0.12)	(0.11)	(0.09)
$G = 5$	**31.93**	**30.21**	**28.03**	30.09	30.14	29.94	**25.78**	**30.26**	**34.13**	29.50	30.25	30.42
	(0.06)	**(0.05)**	**(0.05)**	(0.07)	(0.05)	(0.05)	**(0.05)**	**(0.04)**	**(0.04)**	(0.07)	(0.05)	(0.04)
$G = 6$	**41.12**	**32.88**	**29.30**	37.13	33.19	32.98	**27.11**	**34.40**	**41.79**	34.50	34.21	34.59
	(0.13)	**(0.09)**	**(0.08)**	(0.15)	(0.09)	(0.09)	**(0.09)**	**(0.10)**	**(0.11)**	(0.13)	(0.11)	(0.10)
Panel 3: $d = 0.8$												
$G = 1$	**36.86**	**19.74**	**12.02**	29.69	19.93	19.00	22.63	22.95	23.03	22.98	22.83	22.82
	(0.19)	**(0.03)**	**(0.05)**	(0.24)	(0.07)	(0.04)	(0.15)	(0.15)	(0.16)	(0.16)	(0.15)	(0.15)
$G = 2$	**31.15**	**22.24**	**14.81**	25.67	21.63	20.89	21.18	23.11	23.91	23.15	22.65	22.39
	(0.10)	**(0.03)**	**(0.05)**	(0.14)	(0.05)	(0.03)	(0.07)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
$G = 3$	**16.42**	**15.30**	**14.27**	15.31	15.31	15.36	13.34	15.86	16.79	14.53	15.66	15.80
	(0.03)	**(0.02)**	**(0.02)**	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
$G = 4$	**24.80**	**17.15**	**12.18**	20.17	17.20	16.76	14.54	17.53	22.05	17.28	17.99	18.86
	(0.09)	**(0.05)**	**(0.04)**	(0.12)	(0.06)	(0.05)	(0.07)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)
$G = 5$	**17.58**	**14.82**	**12.32**	15.46	14.75	14.52	14.19	14.62	15.92	14.99	14.91	14.83
	(0.04)	**(0.03)**	**(0.03)**	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
$G = 6$	**29.84**	**21.14**	**18.31**	26.20	21.68	21.41	21.98	23.09	24.22	23.05	23.03	23.21
	(0.11)	**(0.03)**	**(0.04)**	(0.13)	(0.04)	(0.04)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)

Note. The experiment settings are identical to those in Table 5.4.

5.6, we highlight that square lattice ($G = 1$) networks, pack ($G = 2$) networks, and scale-free ($G = 3$) networks generally foster a larger number of entrepreneurial actions, consistent with the findings in Section 5.3.

Looking across each row of the table, we observe that the effect of the actors' initial possessed value on entrepreneurial action ratio is significant when the density of actors is relatively low. In contrast, the degree of feedback against friction significantly impacts the number of actors taking entrepreneurial actions when the density of actors is relatively high. In other words, the impact of spatial feedback outweighs the impact of initial endowment as the density of actors increases. This pattern is consistent across all the six network structures.

In summary, the insights we derived from Section 5.3 are preserved in the presence of loners in the model extension.

5.5 Discussion

This chapter formalizes and extends the action-based entrepreneurship framework (McMullen and Shepherd, 2006) into the context of network dynamics. An actor's pursuit of an entrepreneurial opportunity is dependent on the decisions of connected others, who are embedded in the same network with the focal actor. So, network matters since it creates a feedback system where networked actors capture information from a connection's exploitation of an existing opportunity and enhance their identification of subsequent opportunities (Shepherd and Patzelt, 2013). A network depicts whom the actor meets and how they interact with each other, i.e., network structure and the degree of feedback against friction under market imperfection. Herein, we study various well-received types of network structures and how feedback affects each actors' decision of entrepreneurial action, hence influencing the dynamics of entrepreneurship over time and space.

Essentially, entrepreneurial action dynamics vary across alternative networks. The underlying "who-connects-to-whom" structure controls the direction of possible feedback from one actor's opportunity exploitation to opportunity recognition for someone in the same network. Yet the friction often undermines feedback among networked actors under market imperfection, which takes the forms of transactional costs and barriers to trade (Chatain and Zemsky, 2011). Our results support the literature that imperfection in the economy creates entrepreneurial opportunities (e.g., Keyhani et al., 2015): the number of actors acting entrepreneurially increases as their average degree of feedback against friction decreases. In other words, friction gives some actors (the entrepreneurs) advantages to discover opportunities for potential value creation (McMullen and Shepherd, 2006). These findings are consistent across all network structures.

In addition, the impact of network structure in fostering entrepreneurial actions is moderated by actors' beliefs on the presence of a third-person opportunity. According to Shepherd et al. (2007) and Grégoire et al. (2010), entrepreneurs must successfully escape ignorance to form a third-person opportunity-recognition belief and then utilizes the possible feedback to pursue a first-person opportunity for value creation. We observe different entrepreneurial action dynamics across the three opportunity-recognition belief scenarios. For instance, actors holding an optimist belief of receiving feedback from connected neighbors (i.e., the optimism scenario) are most likely to take entrepreneurial actions, especially for those embedded in square lattice network, pack network, and scale-free network. In contrast, actors holding a pessimistic belief of not receiving any feedback from connections (i.e., the pessimism scenario) are relatively less likely to act entrepreneurially among the three scenarios. Finally, structures like random, ring lattice, and small-world facilitate the most number of entrepreneurial actions when actors' opportunity-recognition beliefs follow a martingale.

Note that possessed value is vital to the exploitation of recognized opportunities as entrepreneurial action is inherently a value-based decision (Bradley et al., 2011; Haynie et al., 2009). It determines whether actors will actually engage in entrepreneurial action or not. The higher the possessed value, the more likely the entrepreneurial action will take place. This is supported by our results under the pessimism scenario, where actors tend to ignore third-person opportunities arising from connections' possible feedback. Under the martingale and optimism scenarios, however, a seemly contradicting result in our study is that the initial value does not impose a significant impact on the spatiotemporal dynamics of entrepreneurial actions. Indeed, this finding is in line with McMullen and Dimov's (2013) process view that entrepreneurship is a journey. An actor's possessed value is most likely to change as long as self or any of neighboring actors made an entrepreneurial action. As a result, the effect of the starting value diminishes during a sequence of dynamic interactions among networked actors. In other words, our formulation of entrepreneurial action is truly dynamic over space and time.

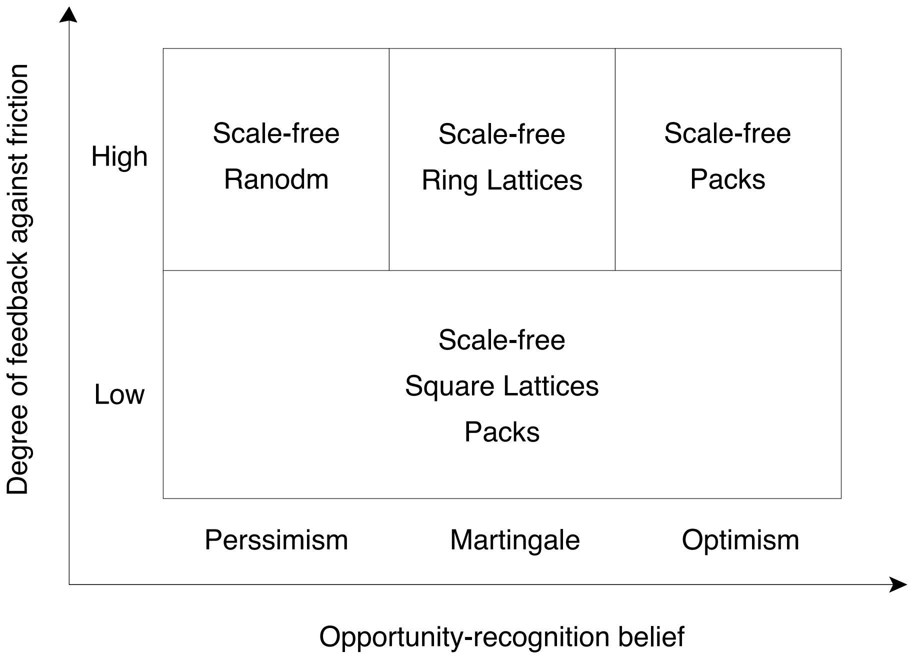


Figure 5.10: The role of network structures on entrepreneurial action dynamics

We conclude that *entrepreneurship is largely influenced by actors' degree of feedback against friction, their opportunity-recognition beliefs, and the embedded network structure.* Figure 5.10 summarizes our insights from the analysis and discussion. This conceptual framework provides managerial insights in the demarcating regions of effective network structures in fostering entrepreneurial actions in space-time. Our introductory case of open government data illustrates this recommendation.Big data brings numerous opportunities to business and public sections so that actors are optimistic about the presence of third-person opportunities. However, the feedback among them are constrained by friction such as limited access to the data, patent, and legislation. For instance, not until the government took the open data initiatives, actors have not been able to utilize the data for entrepreneurial actions. As actors in the big data era are mostly prospective technology-based entrepreneurs, their embedded network often has a scale-free structure where new actors continuously join the network and the pioneers act as hubs. In line with the real-world observation, this scale-free network is effective to facilitate entrepreneurial actions from the ever-increasing number of actors to explore and exploit the value of big data.

5.6 Supplementary Notes

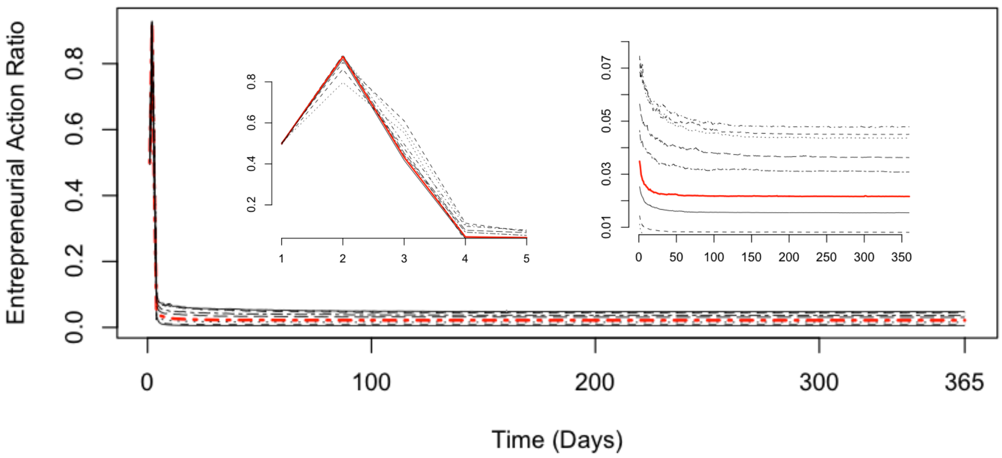
5.6.1 Sensitivity analysis on the rewiring probability in small-world networks

Figure 5.11 depicts the time plot of entrepreneurial action ratio in response to various rewiring probabilities, where $\alpha = 0.1, \cdots, 0.9$ under the optimism, martingale, and pessimism scenarios, respectively.

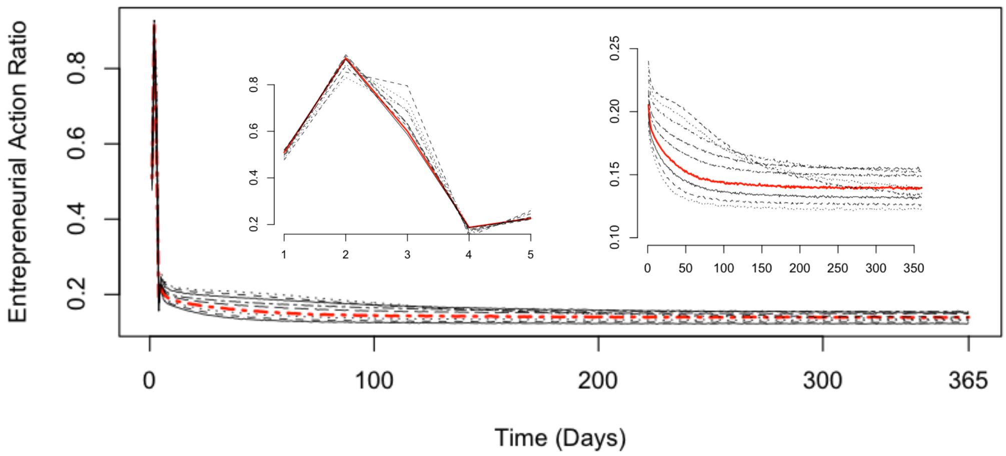
We observe that various rewiring probabilities results in less than 0.05% difference in entrepreneurial action; other than that, the dynamics of entrepreneurial action show the same patterns under each opportunity-recognition scenario. So, the plots suggest that the dynamics of entrepreneurial actions are insensitive to the choice of α.

5.6.2 Extension under the optimism and pessimism scenarios

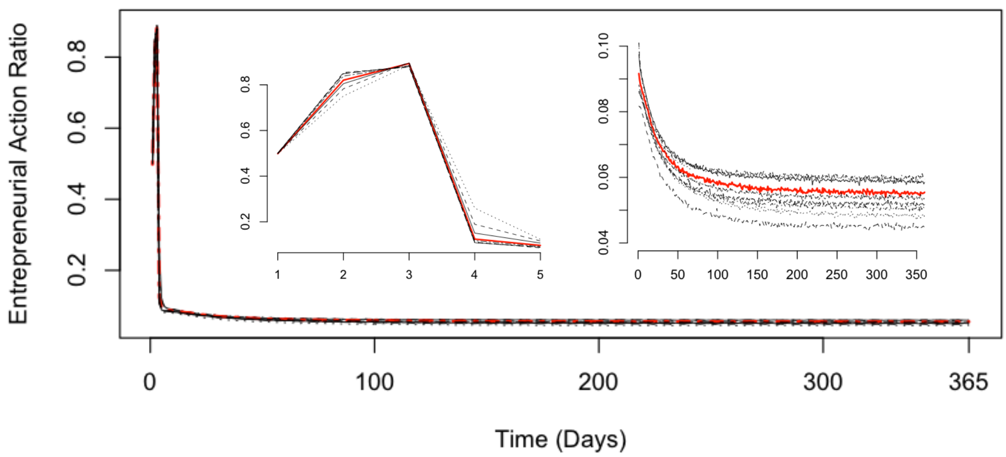
Tables 5.7 and 5.8 summarize the experiment results on the entrepreneurial action dynamics in the presence of loners under the optimism and pessimism scenarios, respectively. The patterns are fairly consistent to those in Table 5.6 (under the martingale scenario) – When the density is relatively low, the initial endowment has a major impact on the number of actors taking entrepreneurial action; and the degree of feedback against friction significantly influence the entrepreneurial action ratio as the density of actors increases. The key findings in Section 5.3 are supported.



a) The optimism scenario



b) The martingale scenario



c) The pessimism scenario

Figure 5.11: Sensitivity analysis on the rewiring probability in small-world networks

Table 5.7: Entrepreneurial action dynamics in the presence of loners under the optimism scenario

	μ_{λ_0}			σ_{λ_0}			μ_{ω_0}			σ_{ω_0}		
	L	M	H	L	M	H	L	M	H	L	M	H
Panel 1: $d = 0.2$												
$G = 1$	49.00	50.28	51.91	50.66	50.18	50.36	**29.61**	**50.61**	**70.98**	50.33	50.24	50.62
	(0.20)	(0.18)	(0.17)	(0.19)	(0.18)	(0.18)	**(0.08)**	**(0.05)**	**(0.07)**	(0.22)	(0.18)	(0.14)
$G = 2$	48.01	48.92	49.81	49.00	48.78	48.95	**28.94**	**49.30**	**68.49**	49.48	49.02	48.24
	(0.19)	(0.17)	(0.16)	(0.18)	(0.17)	(0.17)	**(0.07)**	**(0.05)**	**(0.07)**	(0.21)	(0.17)	(0.13)
$G = 3$	28.67	27.65	27.21	27.48	27.83	28.23	**11.09**	**28.32**	**44.13**	27.54	27.93	28.07
	(0.16)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	**(0.07)**	**(0.05)**	**(0.09)**	(0.20)	(0.14)	(0.10)
$G = 4$	46.09	44.58	43.85	44.75	44.87	44.91	**24.77**	**46.40**	**63.35**	44.72	44.70	45.11
	(0.20)	(0.18)	(0.16)	(0.19)	(0.18)	(0.18)	**(0.10)**	**(0.07)**	**(0.10)**	(0.24)	(0.17)	(0.11)
$G = 5$	34.21	33.01	31.94	32.70	33.13	33.33	**14.50**	**34.16**	**50.50**	32.61	33.16	33.39
	(0.18)	(0.16)	(0.16)	(0.17)	(0.17)	(0.16)	**(0.08)**	**(0.06)**	**0.09()**	(0.22)	(0.16)	(0.11)
$G = 6$	51.26	52.16	52.10	51.68	51.86	51.99	**30.82**	**52.30**	**72.40**	52.00	51.70	51.82
	(0.21)	(0.18)	(0.18)	(0.20)	(0.19)	(0.19)	**(0.10)**	**(0.07)**	**(0.09)**	(0.24)	(0.18)	(0.13)
Panel 2: $d = 0.5$												
$G = 1$	51.98	55.56	52.10	50.00	54.67	54.99	**47.12**	**53.54**	**58.99**	53.50	53.20	52.95
	(0.09)	(0.05)	(0.06)	(0.09)	(0.06)	(0.06)	**(0.07)**	**(0.05)**	**(0.05)**	(0.07)	(0.08)	(0.07)
$G = 2$	49.15	50.90	47.91	47.25	50.22	50.49	**42.71**	**49.75**	**55.50**	49.84	49.53	48.58
	(0.09)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)	**(0.05)**	**(0.04)**	**(0.05)**	(0.07)	(0.07)	(0.07)
$G = 3$	8.68	7.19	6.49	7.31	7.54	7.51	**3.53**	**8.04**	**10.79**	7.15	7.42	7.79
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	**(0.02)**	**(0.02)**	**(0.03)**	(0.05)	(0.04)	(0.03)
$G = 4$	**28.12**	**23.17**	**17.95**	23.19	23.04	23.02	**19.46**	**23.95**	**25.84**	23.60	23.42	22.23
	(0.07)	**(0.05)**	**(0.06)**	(0.10)	(0.06)	(0.06)	**(0.07)**	**(0.07)**	**(0.07)**	(0.08)	(0.07)	(0.07)
$G = 5$	13.88	11.48	9.81	11.35	11.84	11.99	**8.81**	**12.23**	**14.13**	11.40	11.98	11.79
	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	**(0.04)**	**(0.03)**	**(0.04)**	(0.05)	(0.04)	(0.03)
$G = 6$	**50.60**	**45.10**	**37.07**	43.32	44.36	45.10	**38.67**	**45.00**	**49.10**	44.92	44.19	43.67
	(0.10)	**(0.09)**	**(0.11)**	(0.14)	(0.10)	(0.09)	**(0.10)**	**(0.11)**	**(0.11)**	(0.12)	(0.11)	(0.11)
Panel 3: $d = 0.8$												
$G = 1$	**53.44**	**46.93**	**25.14**	38.69	43.64	43.18	40.96	41.90	42.65	41.86	41.82	41.82
	(0.06)	**(0.06)**	**(0.12)**	(0.21)	(0.12)	(0.07)	(0.14)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
$G = 2$	**53.10**	**48.60**	**31.94**	40.61	46.42	46.60	43.08	44.57	45.98	44.70	44.67	44.26
	(0.05)	**(0.04)**	**(0.11)**	(0.17)	(0.09)	(0.05)	(0.11)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)
$G = 3$	**1.79**	**1.16**	**0.87**	1.31	1.27	1.25	0.78	1.53	1.51	1.07	1.30	1.45
	(0.01)	**(0.01)**	**(0.01)**	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$G = 4$	**13.36**	**6.66**	**5.29**	11.01	7.41	6.89	7.83	8.73	8.74	8.84	8.47	8.00
	(0.07)	**(0.02)**	**(0.02)**	(0.09)	(0.03)	(0.02)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
$G = 5$	**3.68**	**2.26**	**1.54**	2.55	2.49	2.44	2.30	2.41	2.77	2.22	2.58	2.67
	(0.02)	**(0.01)**	**(0.01)**	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
$G = 6$	**43.45**	**31.56**	**18.96**	33.37	30.85	29.74	31.05	31.66	31.26	31.95	31.20	30.82
	(0.11)	**(0.08)**	**(0.09)**	(0.19)	(0.11)	(0.09)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)

Note. The experiment settings are identical to those in Table 5.4.

Table 5.8: Entrepreneurial action dynamics in the presence of loners under the pessimism scenario

	μ_{λ_0}			σ_{λ_0}			μ_{ω_0}			σ_{ω_0}		
	L	M	H	L	M	H	L	M	H	L	M	H
Panel 1: $d = 0.2$												
$G = 1$	46.30	45.87	45.36	46.54	45.57	45.43	**23.48**	**46.78**	**67.27**	46.78	45.90	44.85
	(0.20)	(0.19)	(0.19)	(0.20)	(0.19)	(0.19)	**(0.07)**	**(0.06)**	**(0.08)**	(0.23)	(0.19)	(0.14)
$G = 2$	45.85	45.51	45.40	45.86	45.29	45.25	**23.84**	**46.50**	**66.06**	46.80	45.56	44.05
	(0.19)	(0.18)	(0.18)	(0.19)	(0.18)	(0.19)	**(0.06)**	**(0.06)**	**(0.08)**	(0.23)	(0.18)	(0.13)
$G = 3$	36.66	34.89	34.29	34.73	35.46	35.65	**15.48**	**36.49**	**53.87**	34.07	35.51	36.26
	(0.18)	(0.17)	(0.17)	(0.17)	(0.18)	(0.17)	**(0.09)**	**(0.05)**	**(0.08)**	(0.23)	(0.16)	(0.10)
$G = 4$	48.18	46.49	45.05	46.87	46.46	46.40	**24.44**	**47.97**	**67.32**	45.38	46.68	47.66
	(0.21)	(0.20)	(0.19)	(0.20)	(0.20)	(0.20)	**(0.11)**	**(0.07)**	**(0.09)**	(0.26)	(0.19)	(0.12)
$G = 5$	42.03	39.36	37.24	39.53	39.55	39.55	**39.66**	**39.52**	**39.46**	39.51	39.35	39.77
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	**(0.06)**	**(0.06)**	**(0.06)**	(0.06)	(0.06)	(0.06)
$G = 6$	45.45	43.82	43.09	44.71	43.98	43.68	**21.34**	**45.04**	**65.99**	44.85	44.20	43.33
	(0.21)	(0.20)	(0.19)	(0.21)	(0.20)	(0.20)	**(0.08)**	**(0.07)**	**(0.11)**	(0.26)	(0.19)	(0.14)
Panel 2: $d = 0.5$												
$G = 1$	**37.90**	**34.93**	**30.15**	35.69	33.83	33.46	**24.22**	**32.26**	**42.51**	37.17	34.36	31.44
	(0.11)	**(0.09)**	**(0.08)**	(0.12)	(0.09)	(0.09)	**(0.04)**	**(0.07)**	**(0.07)**	(0.10)	(0.10)	(0.09)
$G = 2$	**37.93**	**35.08**	**30.81**	35.38	34.31	34.12	**24.47**	**36.79**	**42.56**	37.52	34.71	31.58
	(0.11)	**(0.09)**	**(0.08)**	(0.11)	(0.09)	(0.09)	**(0.04)**	**(0.07)**	**(0.07)**	(0.10)	(0.10)	(0.08)
$G = 3$	**19.58**	**17.79**	**16.59**	17.62	18.10	18.23	**11.93**	**19.18**	**22.85**	16.53	18.24	19.17
	(0.06)	**(0.06)**	**(0.05)**	(0.06)	(0.06)	(0.06)	**(0.05)**	**(0.03)**	**(0.04)**	(0.08)	(0.05)	(0.04)
$G = 4$	**36.13**	**30.77**	**25.48**	31.47	30.62	30.29	**21.78**	**30.30**	**40.30**	28.98	31.08	32.33
	(0.12)	**(0.10)**	**(0.10)**	(0.14)	(0.11)	(0.10)	**(0.09)**	**(0.09)**	**(0.09)**	(0.13)	(0.11)	(0.09)
$G = 5$	**27.04**	**20.80**	**16.89**	21.56	21.62	21.55	**21.61**	**21.55**	**21.57**	21.58	21.57	21.57
	(0.04)	**(0.03)**	**(0.03)**	(0.05)	(0.05)	(0.05)	**(0.05)**	**(0.05)**	**(0.05)**	(0.05)	(0.05)	(0.05)
$G = 6$	**37.35**	**30.73**	**27.49**	33.76	31.11	30.71	**21.56**	**33.03**	**40.99**	32.67	31.80	31.10
	(0.15)	**(0.10)**	**(0.09)**	(0.16)	(0.10)	(0.10)	**(0.07)**	**(0.09)**	**(0.12)**	(0.13)	(0.12)	(0.11)
Panel 3: $d = 0.8$												
$G = 1$	**27.64**	**19.13**	**11.47**	22.43	18.26	17.54	15.29	20.32	22.62	21.25	19.59	17.39
	(0.11)	**(0.05)**	**(0.05)**	(0.15)	(0.06)	(0.04)	(0.07)	(0.10)	(0.11)	(0.10)	(0.10)	(0.09)
$G = 2$	**27.90**	**19.66**	**12.67**	22.63	19.15	18.45	16.13	21.16	22.95	22.18	20.21	17.85
	(0.10)	**(0.04)**	**(0.05)**	(0.14)	(0.06)	(0.04)	(0.06)	(0.09)	(0.10)	(0.10)	(0.09)	(0.09)
$G = 3$	**8.41**	**7.31**	**6.64**	7.38	7.43	7.55	6.55	7.88	7.92	7.12	7.62	7.62
	(0.02)	**(0.02)**	**(0.02)**	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$G = 4$	**19.17**	**13.20**	**10.17**	15.23	13.70	13.61	10.34	13.56	18.64	13.61	14.35	14.58
	(0.08)	**(0.05)**	**(0.05)**	(0.10)	(0.06)	(0.05)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$G = 5$	**12.69**	**8.76**	**5.59**	9.02	9.03	9.00	9.03	8.98	9.03	9.01	9.04	9.00
	(0.02)	**(0.02)**	**(0.02)**	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$G = 6$	**25.77**	**18.92**	**15.61**	21.79	19.44	19.06	17.16	21.30	21.83	21.23	19.96	19.10
	(0.10)	**(0.04)**	**(0.04)**	(0.12)	(0.05)	(0.04)	(0.06)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)

Note. The experiment settings are identical to those in Table 5.4.

Chapter 6

A synthesized model of entrepreneurial action under uncertainty

6.1 The role of uncertainty in entrepreneurial action process

Entrepreneurial action is inherently uncertain. To be an entrepreneur is to explore a new, untried opportunity in the dynamic, complex market, and then exploit it before the associated economic, social, and environmental value is known (Phan and Chambers, 2013; Schumpeter, 1934; Shane and Venkataraman, 2000). So a key question for scholars and prospective entrepreneurs lies in the reduction of uncertainty that prevents both recognizing and acting on a possible opportunity for value creation. Uncertainty in times of disasters is extremely strong to impede actions by obfuscating the identification of an entrepreneurial opportunity, as well as the evaluation of this opportunity worth pursing (McMullen and Shepherd, 2006). However, uncertainty taking the form of good luck and jackpot may encourage actors to discover and pursue entrepreneurial opportunity, which is largely overlooked by the literature. For instance, as mentioned in the early chapters, the era of big data brings numerous opportunities to business and public sectors. Therefore, this chapter, building upon the formal spatiotemporal model in Chapter 5, is to investigate different types of uncertainty and how they informs the decisions of entrepreneurs to pursue an opportunity for value creation.

Following the proposed formal model in Chapter 5, actor i's entrepreneurial action at time t is

$$z_{i,t} = \mathbf{1}(p_{i,t} - \underbrace{\varepsilon_{i,t}}_{response\ uncertainty} \geq 0) \quad \text{for } t = 1, 2, \cdots, T \text{ and } i = 1, 2, \cdots, n,$$

where $z_{i,t} = 1$ indicates an action and $z_{i,t} = 0$ otherwise. We model actor i's likelihood of taking entrepreneurial action at time t as an expected utility function being, which is further influenced by value-changing uncertainty $\zeta_{i,t}$,

$$\begin{aligned} \text{logit}(p_{i,t}) &= \log(\frac{p_{i,t}}{1 - p_{i,t}}) \\ &= \omega_{i,t-1} + \sum_{j \sim i} \lambda_{ji,t-1} \omega_{j,t-1} - \sum_{i \sim j} \lambda_{ij,t-1} \omega_{i,t-1} + \underbrace{\zeta_{i,t}}_{value\text{-}changing\ uncertainty} \end{aligned} \tag{6.1}$$

where $\omega_{i,t-1}$ is the value that the actor i possessed at time $t-1$, $i \sim j$ is a set of actors j whom actor i connects to, and $\lambda_{ij,t-1}$ is the degree of feedback against friction between a neighbor j and actor i at time $t-1$. Parameter $\zeta_{i,t}$ represents the effect of value-changing uncertainty, either value-destroying or value-adding, at time t: an exogenous state uncertainty impacting actor i's expected value at time t. Therefore, our formulation is in line with the work of Milliken (1987) and McMullen and Shepherd (2006) that response uncertainty is frequently stimulated by state uncertainty.

While such state uncertainty may not occur every period, we denote the frequency as $0 < \tau < 1$. In addition, parameter $m \in [0, 1]$ describes the extent of the uncertainty: The greater extend a value-changing uncertainty is, the larger proportion of the networked actors will be affected. Once the value-changing uncertainty hits the networked system, we model it following a Gumbel (or Type I extreme value) distribution

$$\zeta_{i,t} \sim \text{Gumbel } (a, b).$$

Extreme value distributions, in particular for Gumbel, have long be applied in environmental science (Krishnamoorthy, 2006; Sharma et al., 1999), supply chain disruption and emergency management (Craighead et al., 2007; Sheffi, 2007), new produce development (Dahan and Mendelson, 2001; Girotra et al., 2010), and financial risk management (Diebold et al., 2000; Grossi and Kunreuther, 2005). We model the effect of state uncertainty either in a direction of value adding (i.e., good luck, such as hitting the jackpot), shortly *value-adding uncertainty*, or in a direction of value destroying (i.e., bad luck, such as natural disaster and terrorist attacks), shortly *value-destroying uncertainty*, to the network actors, indicated by parameter a: $a \geq 0$ for value-adding and $a < 0$ for value-destroying. In addition, $b > 0$ is the scale parameter for the distribution. This Gumbel process in our setting enables us to examine the impact of uncertainty that is crucial for better understanding entrepreneurial-action dynamics (McMullen and Shepherd, 2006; Milliken, 1987). [The other model settings are identical to those in Section 5.2.]

6.2 Analysis

We examine the dynamics of entrepreneurship under two scenarios – value-adding uncertainty and value-destroying uncertainty. First a base case analysis is conducted to understand actors' entrepreneurial decision-making process under uncertainty. We next carefully develop a experimental design to understand the sensitivity of model parameters on entrepreneurial action in space-time. In all cases, the reported results are averages based on 100 runs of each parameter instance.

6.2.1 Base case

Based on recent reports on emergency management and supply chain disruption (Glendon and Bird, 2013; Marchese and Paramasivam, 2013), around 80 percent of firms involved in supply chains had experienced disruptive events ranging from one to five times in the previous 12 months and consistently over four years. In the base model, therefore, exogenous state uncertainty is introduced four times within one-year time ($\tau = 4/365$) and can impact 80 percent of actors in a networked system ($m = 0.8$). Such state uncertainty may generate either a value-adding or value-destroying effect. In terms of value-destroying uncertainty we set the location parameter $a = -5$ and the scale parameter $b = 1.36$, at which an actor's possessed value is negatively affected at a probability of 97.5%. Likewise, value-adding uncertainty is assumed to have $a = 5$ and $b = 3.825$ so that an actor has a probability of

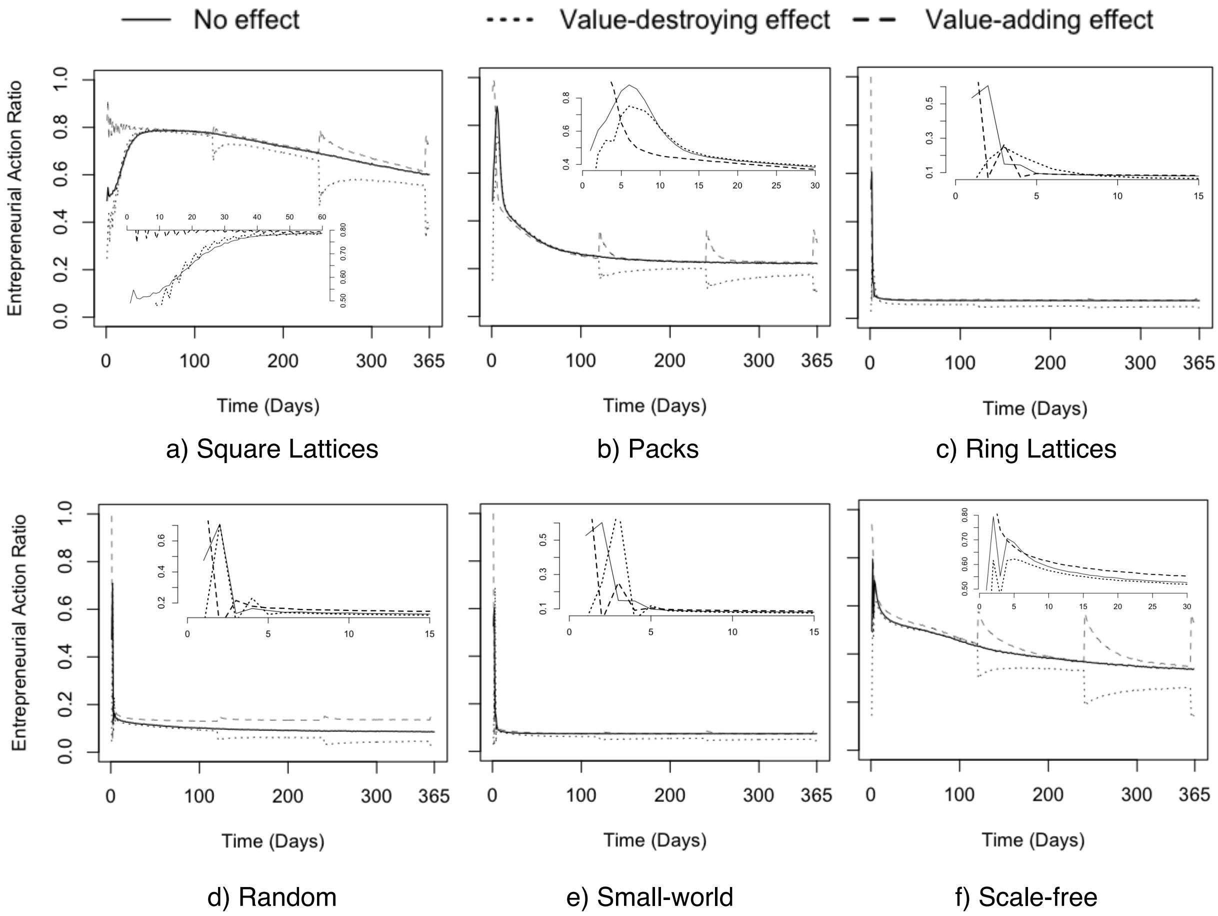
97.5% of experiencing an increase in possessed value. Table 6.1 summarizes the parameters used in the base case.

Table 6.1: Parameter values in base case setting

Parameter	Values	Meaning
G	{1, 2, 3, 4, 5, 6}	Six network structures
α	0.4	Rewiring probability in small-world networks
n	960	Total number of actors (economic size) on the network
ω_{i_0}	$N(0,1)$	Value possess at time 0
λ_{ij_0}	$TN(0.2, 0.2)$	Degree of feedback between actor pairs ($0 \leq \lambda_{ij} \leq 1$)
m	0.8	Extent of uncertainty
τ	4/365	Frequency of uncertainty
ζ_i	Gumbel (-5, 1.36)	Value-destroying uncertainty
	Gumbel (5, 3.825)	Value-adding uncertainty

We would expect that value-destroying uncertainty decreases the entrepreneurial action ratio, whereas value-adding uncertainty increases it for all six network structures, at least in the short term. This intuition is confirmed in Figure 6.1 by a big drop (rise) of entrepreneurial action ratio in dotted-line (dashed-line) every time value-destroying (value-adding) uncertainty is introduced into the system. Yet the actors will quickly adjust their subsequent entrepreneurial actions to cope with such uncertainty over time. For instance, an increased number of actors immediately take entrepreneurial action to recover from the disruptive value-destroying uncertainty, whereas a large value increment arising from value-adding uncertainty may reduce the actors' perceived need to act, resulting in a decreased entrepreneurial action ratio. In the long run, the number of actors acting entrepreneurially under either uncertainty scenario will converge to that under no exogenous uncertainty scenario (straight-line). That is, the effect of state uncertainty, either value-destroying or value-adding, is fully absorbed by the networked actors if the reaction time is sufficiently long. Therefore, our model successfully captures the dynamics of entrepreneurial action under uncertainty.

Figure 6.1 also shows that network structures generate heterogeneous impacts on the



Note. For each network, the main figure illustrates the time plots of entrepreneurial action ratio over one-year time (365 days). To take a close look at the changes at the early days, we include a small figure at the corner, showing the time plot over a short starting period. Note that entrepreneurial action ratio mostly starts from 0.5 across all networks due to our setting of initial possessed value.

Figure 6.1: Base case of entrepreneurial action ratio under uncertainty

dynamics of entrepreneurial action. The results are consistent among the two uncertainty scenarios. In general, we can observe a larger number of entrepreneurial actions from actors embedded in square lattice ($G = 1$) networks, pack ($G = 2$) networks, and scale-free ($G = 6$) networks. For instance, in a scale-free network, over 30-percent of actors act entrepreneurial in each time period. On the contrary, only a small number of actors (around 10-percent) are motivated to take entrepreneurial actions when they are embedded in ring lattice ($G = 3$) networks, random ($G = 4$) graphs, and small-world ($G = 5$) networks.

A closer look at Figure 6.1 illustrates that most entrepreneurial action dynamics occur at the starting time period across all networks. As highlighted by the corner subfigures, the number of entrepreneurs (i.e., actors take entrepreneurial action) reaches the peak soon after several times of interactions in the beginning. For instance, in the square lattices, packs, and scale-free networks, up to 80-percent of actors take entrepreneurial action at the peak time. These observations, in general, suggest that networked actors' discovery of entrepreneurial opportunities are regulated in a short run no matter which network structure the actors are embedded in and the entrepreneurial behavior among the actors is steady in the long run.

Overall, the above observations clearly show that network structures play a significant role in each networked actor's decision on entrepreneurial action in the presence of uncertainty.

6.2.2 Experimentation

We develop a factorial design to examine the effect of key model parameters and to check the robustness of results from the base case. The parameter values used in our experiment are listed in Table 6.2. We set the degree of feedback parameters (μ_{λ_0} and σ_{λ_0}) and initial possessed value parameters (μ_{ω_0} and σ_{ω_0}) to be levels that can be practically distributed among actors in a networked system. In addition to a low-frequent state uncertainty setting in the base case, we model high-frequent state uncertainty occurring every 22 days, or 17 times ($\tau = 17/365$) over one-year time period based on Sheffi's (2007) study on statistics of annual earthquake around the world. In total, we examine 576 parameter instances consisting of a wide range of possible scenarios. We run each parameter instance 100 times to achieve statistical reliability (giving a total of 57600 experiments for each of the six network structures) for inference.

Table 6.2: Parameter values in experiments

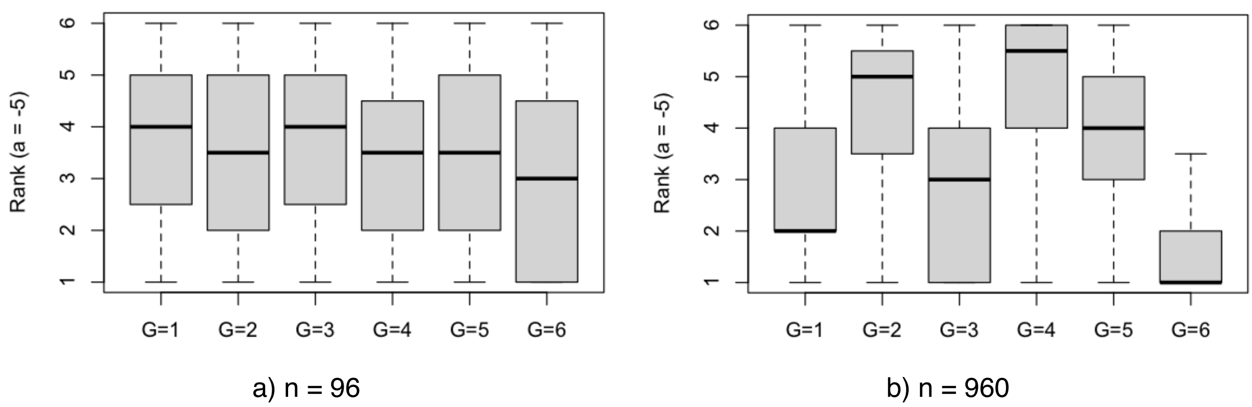
Parameter	Values	Meaning
μ_{λ_0}	{0.2, 0.5, 0.8}	Actors' average degree of feedback
σ_{λ_0}	{0.2, 0.5, 0.8}	Actors' variability in degree of feedback
μ_{ω_0}	{-5, 5}	Actors' average possessed value at time 0
σ_{ω_0}	{1, 10}	Actors' variability in initial possessed value
τ	{4/365, 17/365}	Frequency of value-destroying/-adding uncertainty
m	{0.2, 0.8}	Extent of value-destroying/-adding uncertainty
a	{-5, 5}	Average effect of value-destroying and value-adding uncertainty
b	{1.36, 3.825}	The scale of value-destroying/-adding uncertainty

We investigate the dynamics of entrepreneurial actions under value-destroying uncertainty scenario ($a = -5$) and value-adding uncertainty scenario ($a = 5$), respectively. This gives each scenario 28800 experiments for analysis and inference. Under each scenario, we explain how differences in economic size, the frequency and extend of uncertainty, actors' initial possessed value, and their degree of feedback against friction change the number of actors taking entrepreneurial action.

6.2.3 Value-destroying uncertainty scenario

Under the value-destroying uncertainty scenario, there are distinctive dynamics of entrepreneurial actions among the six network structures. In Figure 6.2, we show the ranking on the entrepreneurial action ratio, among the network structures, at the end of the simulation time. Rank 1 indicates the highest entrepreneurial action ratio and rank 6 indicates the lowest. Comparing Figures 6.2a to 6.2b it is obvious that the entrepreneurial action dynamics are quite sensitive to the economic size. Furthermore, we do not observe a significant ranking difference among the six network structures when the economic size is small (i.e., $n = 96$). In other words, no particular network structure is superior in promoting entrepreneurial action.

As the economic size grows, however, the impact of network structure is substantial. Under a large economic size where $n = 960$, the actors embedded in scale-free ($G = 6$) networks, square lattice ($G = 1$) networks, and ring lattice ($G = 3$) networks are more likely to act entrepreneurially than those embedded in the other three networks, among which random ($G = 4$) graphs facilitate the least number of entrepreneurial action. Therefore, networks structure can influence entrepreneurial action dynamics under value-destroying uncertainty for a sufficiently large economic size.



Note. Network structures with smaller numbers rank higher in entrepreneurial action ratio, where 1 is the best possible ranking. Each boxplot is based on 28800 experiments under the value-destroying uncertainty scenario.

Figure 6.2: Ranking of network structures under value-destroying uncertainty

Besides the effect of the economic size, in Table 6.3 we summarize the impact of key model parameters on the entrepreneurial action dynamics. Holding fixed the network structure and economic size, we find that the parameters impact the entrepreneurial action dynamics in a consistent way under the value-destroying uncertainty scenario. In the table, the parameter levels (at column 2) shadowed in grey are associated with higher entrepreneurial action ratio, with some exceptions highlighted separately in the cells. Specifically, the extent (parameter m) and frequency (parameter τ) of value-destroying uncertainty, as well as the degree of feedback (both mean, parameter μ_{λ_0}, and standard deviation, parameter σ_{λ_0}) have the most significant adverse impact on entrepreneurial action ratio. On the other hand, the number of actors acting entrepreneurially increases in the scale of value-destroying uncertainty (parameter b) and the actors' average initial possessed value (parameter μ_{ω_0}). We explain the details in the following.

Looking down each column of the table, we see a nonlinear negative impact of the degree of feedback on the entrepreneurial action dynamics across all network structures. The number of actors acting entrepreneurially decreases at an accelerate rate as the mean and the standard deviation increase. The most number of entrepreneurial actions are likely to occur when the degree of feedback between most actor pairs is low, i.e., $\mu_{\lambda_0} = 0.2$, and the variability is not widely dispersed, i.e., σ_{λ_0}. Likewise, examining each row, i.e., holding parameters μ_{λ_0} (σ_{λ_0}) fixed, we highlight the differences among network structures. For a large economic size ($n = 960$), the actors embedded in the scale-free networks, square lattice networks, and ring lattice networks are likely to have high entrepreneurial action ratio. For a small economic size ($n = 96$), square lattice networks, small-world networks and ring lattice networks are associated with high entrepreneurial action ratio for the low level of parameter μ_{λ_0} (σ_{λ_0}); whereas scale-free networks, pack networks, and random graphs are associated with high entrepreneurial action ratio for the medium or high level of parameter μ_{λ_0} (σ_{λ_0}).

The impacts of the actors' possessed value at the beginning are mixed. For most network structures, the entrepreneurial action ratio increases in the mean but decreases in the standard deviation. So the number of entrepreneurial action is relatively high when most actors initially have high value (large μ_{ω_0}) and small inter-individual variability (small σ_{ω_0}). Yet in the scale- free networks, we observe a reversed relationship – large variability in initial possessed value leads to higher entrepreneurial action ratio. Nonetheless, the changes in entrepreneurial action dynamics stemming from initial possessed value are rather marginal in comparison to those resulting from the degree of feedback. (In the supplementry note, this finding is confirmed via a regression analysis that the effects of initial possessed value parameters, μ_{ω_0} and σ_{ω_0}, are insignificant, i.e., $p > .05$, for many network structures.) A plausible explanation is that repeated interaction makes the impact of the actors' initial possessed value weak or negligible. When we hold parameters μ_{ω_0} and σ_{ω_0} fixed, actors

Table 6.3: Entrepreneurial action dynamics under the value-destroying uncertainty scenario

		$G=1$		$G=2$		$G=3$		$G=4$		$G=5$		$G=6$	
		n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960
μ_{λ_0}	L (0.2)	**18.30**	**19.88**	11.20	6.94	**15.11**	5.33	13.05	3.73	**15.59**	4.31	9.65	**12.26**
		(.208)	**(.192)**	(.091)	(.054)	**(.151)**	(.019)	(.134)	(.031)	**(.168)**	(.017)	(.081)	**(.087)**
	M (0.5)	5.51	**5.48**	**7.04**	3.13	5.52	5.01	6.32	2.35	6.00	3.39	**7.44**	**7.64**
		(.039)	**(.028)**	**(.049)**	(.018)	(.040)	(.019)	(.046)	(.018)	(.043)	(.013)	**(.055)**	**(.045)**
	H (0.8)	2.60	2.61	3.35	1.47	2.64	**4.88**	**4.63**	1.79	3.25	2.68	**6.46**	**5.86**
		(.029)	(.023)	(.035)	(.-14)	(.029)	**(.018)**	**(.038)**	(.014)	(.032)	(.011)	**(.048)**	**(.035)**
σ_{λ_0}	L (0.2)	**15.36**	**16.94**	8.65	5.26	**12.26**	5.12	10.96	3.00	**12.88**	3.75	8.46	**10.08**
		(.221)	**(.210)**	(.098)	(.061)	**(.163)**	(.021)	(.138)	(.031)	**(.177)**	(.019)	(.077)	**(.090)**
	M (0.5)	5.78	**5.81**	**6.65**	3.27	5.73	5.05	**6.63**	2.46	6.35	3.35	**7.59**	**8.06**
		(.051)	**(.040)**	**(.053)**	(.025)	(.049)	(.018)	**(.053)**	(.020)	(.052)	(.014)	**(.057)**	**(.051)**
	H (0.8)	5.28	**5.23**	**6.29**	3.01	5.28	5.05	**6.41**	2.40	5.88	3.28	**7.49**	**7.63**
		(.041)	**(.030)**	**(.047)**	(.019)	(.041)	(.018)	**(.049)**	(.018)	(.044)	(.013)	**(.056)**	**(.044)**
μ_{ω_0}	L (-5)	**8.75**	**9.28**	6.86	3.85	7.64	3.67	7.72	1.96	**8.28**	3.02	7.89	**8.63**
		(.129)	**(.135)**	(.065)	(.041)	(.104)	(.014)	(.090)	(.018)	**(.113)**	(.015)	(.063)	**(.067)**
	H (5)	**8.86**	**9.37**	7.53	3.85	7.87	**6.48**	**8.27**	3.28	**8.46**	3.90	7.81	**8.55**
		(.223)	**(.210)**	(.106)	(.062)	(.167)	**(.010)**	**(.141)**	(.035)	**(.179)**	(.018)	(.080)	**(.087)**
σ_{ω_0}	L (1)	**8.84**	**9.36**	7.26	3.85	7.79	4.81	7.91	2.30	**8.41**	3.49	7.79	**8.39**
		(.142)	**(.136)**	(.072)	(.041)	(.107)	(.023)	(.091)	(.023)	**(.115)**]	(.015)	(.063)	**(.066)**
	H (10)	**8.77**	**9.29**	7.13	3.85	7.72	5.34	8.08	2.95	**8.33**	3.44	7.91	**8.79**
		(.164)	**.159**	(.073)	(.048)	(.120)	(.011)	(.108)	(.021)	**(.133)**	(.017)	(.069)	**(.074)**
τ	L (120)	**10.67**	**11.17**	9.91	5.15	9.94	5.26	**10.54**	3.50	**10.49**	3.83	**10.88**	**11.44**
		.155	**(.160)**	(.090)	(.054)	(.133)	(.021)	**(.099)**	(.025)	**(.127)**	(.015)	**(.062)**	**(.066)**
	H (22)	**6.94**	**7.48**	4.48	2.55	5.57	4.89	5.46	1.74	**6.25**	3.09	4.82	**5.73**
		(.135)	**(.126)**	(.050)	(.031)	(.091)	(.019)	(.084)	(.020)	**(.109)**	(.015)	(.051)	**(.055)**
m	L (0.2)	**11.17**	**11.77**	10.15	5.31	10.43	5.45	**11.03**	3.61	**11.07**	3.96	**11.26**	**11.84**
		(.148)	**(.149)**	(.078)	(.046)	(.119)	(.019)	**(.095)**	(.024)	**(.121)**	(.145)	**(.062)**	**(.064)**
	H (0.8)	**6.44**	**6.88**	4.24	2.39	5.09	4.70	4.96	1.64	**5.67**	2.96	4.44	**5.34**
		(.157)	**(.138)**	(.051)	(.034)	(.101)	(.021)	(.089)	(.018)	**(.120)**	(.015)	(.047)	**(.057)**
b	L (1.36)	**8.22**	**8.64**	6.47	3.51	7.08	4.80	7.22	2.19	**8.77**	3.32	7.08	**7.75**
		(.140)	**(.130)**	(.068)	(.039)	(.102)	(.021)	(.091)	(.023)	**(.112)**	(.016)	(.063)	**(.064)**
	H (3.825)	**9.39**	**10.01**	7.92	4.19	8.43	5.35	7.68	3.05	**9.06**	3.60	8.62	**9.43**
		(.150)	**(.145)**	(.058)	(.036)	(.106)	(.018)	(.090)	(.022)	**(.119)**	(.015)	(.054)	**(.058)**

Note. The entrepreneurial action ratio (percentage value $\delta \times 100$) is based on an average of 100 runs of 288 experiments. Standard deviations are in parentheses.

embedded in square lattice networks are the most likely to take entrepreneurial actions, in despite of the economic size. In addition, small-world networks and scale-free networks promote a large number of entrepreneurial action for a small and large network of actors, respectively.

Table 6.3 supports our expectation that the number of actors taking entrepreneurial action is reduced when the value-destroying uncertainty is destructive, large extent, and frequent. Specifically speaking, we observe a negative impact of extent and frequency and a positive impact of scale on the entrepreneurial action ratio. Note that the scale (b) determines the average disruptive effect of value-destroying uncertainty, $a - b\Gamma^{'}(1)$, where $\Gamma^{'}(1) = -0.57722$ is the first derivative of the gamma function $\Gamma(n)$ with respect to n at $n = 1$. Hence, an increase in $b > 0$ makes the value-destroying uncertainty less destructive, leading to an increase in the number of entrepreneurial actions in the networked system. Only a small number of actors embedded in square lattice networks and small-world networks can cope well with such value-destroying uncertainty. As for a large economic size ($n = 960$), square lattice networks and scale-free networks foster more entrepreneurial actions than the other four networks.

Table 6.4 further examines the entrepreneurial action dynamics under four types of value-destroying uncertainty. We categorize the types by a collective measure of extent and frequency. The resulting entrepreneurial action ratios are displayed in respective panels of Table 6.4. For a small economic size ($n = 96$), random graphs and scale-free networks are slightly better in fostering entrepreneurial actions while the value-destroying uncertainty is light and infrequent, see Panel 1. Under the other three types of value-destroying uncertainty, square lattice networks and small-world networks are better in terms of entrepreneurial action ratio for a small economic size, as illustrated in Panels 2 to 4. On the other hand, when the number of actors in the network is large (a large economic size), the scale-free networks and square lattice networks are in favor of entrepreneurial action across Panels 1 to 3. Finally, square lattice networks and small-world networks encourage entrepreneurial action under frequent and large extent value-destroying uncertainty (see

Table 6.4: Entrepreneurial action dynamics under four types of value-destroying uncertainty

$G=1$		$G=2$		$G=3$		$G=4$		$G=5$		$G=6$	
n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960
Panel 1: m (L = 0.2) and τ (L = 4/365)											
12.73	**13.29**	12.83	6.54	12.37	5.64	**13.64**	4.47	12.98	4.33	**14.38**	**14.64**
(.149)	**(.152)**	(.088)	(.051)	(.128)	(.019)	**(.096)**	(.024)	(.122)	(.014)	**(.060)**	**(.063)**
Panel 2: m (L = 0.2) and τ (H = 17/365)											
9.61	**10.25**	7.48	4.08	8.48	5.25	8.43	2.75	**9.16**	3.60	8.15	**9.04**
(.145)	**(.144)**	(.053)	(.035)	(.)107	(.019)	(.086)	(.020)	**(.116)**	(.015)	(.047)	**(.050)**
Panel 3: m (H = 0.8) and τ (L = 4/365)											
8.60	**9.04**	6.99	3.76	7.52	4.88	7.44	2.54	**8.00**	3.33	7.38	**8.25**
(.137)	**(.128)**	(.051)	(.034)	(.096)	(.017)	(.079)	(.020)	**(.104)**	(.014)	(.042)	**(.045)**
Panel 4: m (H = 0.8) and τ (H = 17/365)											
4.28	**4.71**	1.49	1.01	2.66	**4.53**	2.48	0.73	**3.34**	2.58	1.50	2.42
(.118)	**(.098)**	(.018)	(.013)	(.058)	**(.018)**	(.069)	(.012)	**(.091)**	(.014)	(.027)	(.038)

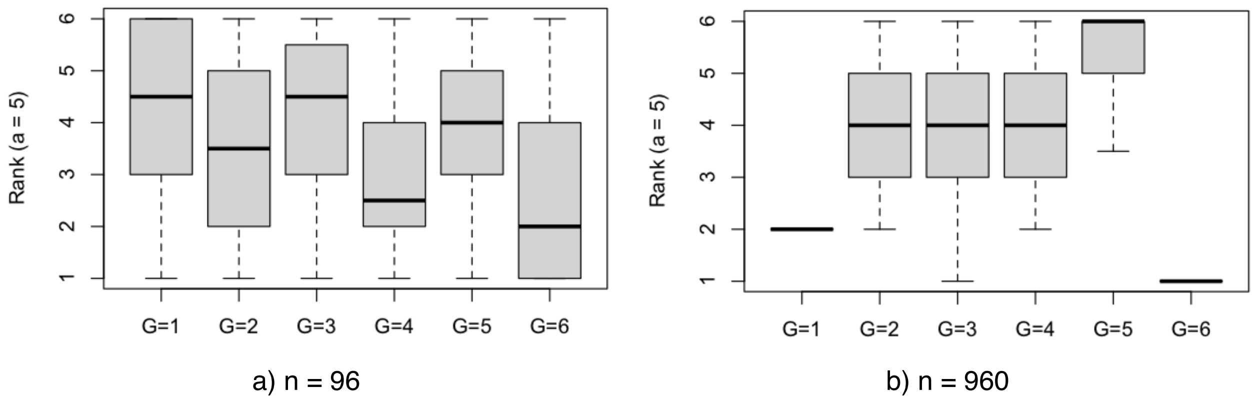
Note. The experiment setting is the same as that in Table 6.3.

Panel 4). The patterns above confirm and extend the findings in Table 6.3.

In summary, under the value-destroying scenario, scale-free networks and square lattice networks mainly favor entrepreneurial action for the actors of a large economic size, and square lattice networks and small-world networks for the actors of a small economic size. Actors are more likely to act entrepreneurially if most of them initially possess high value and low degree of feedback and the value-destroying uncertainty is light and infrequent.

6.2.4 Value-adding uncertainty scenario

Figure 6.3 plots the ranks of the six network structures regarding the entrepreneurial action ratio under the value-adding scenario. Similar to the value-destroying uncertainty scenario, the dynamics are rather different between a small economic size ($n = 96$) and a large economic size ($n = 960$). For a small economic size, scale-free ($G = 6$) networks, random ($G = 4$) graphs, and pack ($G = 2$) networks foster a greater number of entrepreneurial action than square lattice ($G = 1$) networks, ring lattice ($G = 3$) networks, and small-world



Note. Network structures with smaller numbers rank higher in entrepreneurial action ratio, where 1 is the best possible ranking. Each boxplot is based on 28800 experiments under the value-adding uncertainty scenario.

Figure 6.3: Ranking of network structures under value-adding uncertainty

($G = 5$) networks. As to the actors of a large economic size, the number of entrepreneurial actions is likely to be greater when they are embedded in scale-free networks (rank 1) and square lattice networks (rank 2) than in small-world networks (rank 6), whereas the other three network structures rank in the middle. In sum, when experiencing value-adding uncertainty, the actors are consistently more positive to take entrepreneurial action when they are embedded in scale-free networks than in other networks.

In addition to the structural properties of networks, the impact of other model parameters on entrepreneurial action dynamics are summarized in Table 6.5. Apart from some inconsistencies in actors' initial possessed value, the parameters impact the number of actors taking entrepreneurial action in the same direction across all network structures. We highlight the effects in grey. In general, the parameter effects here are very similar to those under the value-destroying uncertainty scenario, with the only exception of parameter m (the extent of uncertainty). Specifically, the degree of feedback (both mean, parameter μ_{λ_0}, and standard deviation, parameter σ_{λ_0}), the standard deviation of initial possessed value (parameter σ_{ω_0}), as well as the frequency (parameter τ) of value-adding uncertainty have adverse impact on the entrepreneurial action ratio. And the mean of the actors' initial possessed value, parameter μ_{ω_0}, and the extent (parameter m) and scale (parameter b) of value-adding uncertainty have positive impact on the dynamics of entrepreneurial action.

Holding fixed the network structure and economic size, we find that the impact of the degree of feedback between actor pairs is convex with respect to the mean and standard deviation. The entrepreneurial action ratio decreases sharply when parameter μ_{λ_0} and parameter σ_{λ_0} increase from a low level (0.2) to a medium level (0.5). Yet the reductions are marginal when the two parameters increase from a medium level (0.5) to a high level (0.8). The changes in parameter μ_{λ_0} result in a more significant effect on entrepreneurial action dynamics than the changes in parameter σ_{λ_0}. The findings are consistent across all network structures. So the networked actors can achieve more entrepreneurial actions when their degree of feedback is relatively low (small mean) and the individual variability is not large (small variance). Likewise, we examine the role of network structure by holding fixed the degree of feedback parameters. When the economic size is large ($n = 960$), square lattice networks and scale-free networks are the most effective network structures to foster entrepreneurial actions. In comparison, there are multiple choices for the actors of a small economic size to facilitate the number of entrepreneurial actions. For instance, square lattice networks and ring lattice networks are more effective than the other four networks when parameters μ_{λ_0} and σ_{λ_0} are low, whereas random graphs, scale-free networks, and pack networks work better when parameters μ_{λ_0} and σ_{λ_0} are increased to a medium or high level.

In terms of initial possessed value, the impacts of parameter μ_{ω_0} and parameter σ_{ω_0} on entrepreneurial action dynamics are marginal. The differences of the entrepreneurial action ratio resulting from changes in the initial possessed value distribution are mostly within 0.1%. Similar to the value-destroying uncertainty scenario, the number of actors taking entrepreneurial action at the end of the simulation time is largely determined by the dynamic interaction process, rather than the starting possessed value. (The regression analysis in the supplementary note confirms that the effect of parameter μ_{ω_0} and parameter σ_{ω_0} are not significant, i.e., $p > .05$, for most network structures.) When examining the rows, we find that scale-free networks and random graphs are most effective to generate

Table 6.5: Entrepreneurial action dynamics under the value-adding uncertainty scenario

		$G=1$		$G=2$		$G=3$		$G=4$		$G=5$		$G=6$	
		n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960
μ_{λ_0}	L (0.2)	**33.66**	**34.69**	31.29	15.80	**34.00**	6.97	30.65	9.67	31.87	6.03	26.70	**30.42**
		(.251)	**(.250)**	(.156)	(.078)	**(.243)**	(.011)	(.163)	(.033)	(.209)	(.014)	(.106)	**(.116)**
	M (0.5)	11.94	**11.92**	15.97	7.33	12.49	6.68	**16.82**	6.80	13.68	4.94	**18.72**	**18.37**
		(.041)	**(.016)**	(.048)	(.012)	(.044)	(.013)	**(.046)**	(.017)	(.044)	(.010)	**(.053)**	**(.030)**
	H (0.8)	6.08	6.10	7.85	3.57	6.21	6.41	**12.44**	5.47	8.24	4.02	**15.42**	**13.81**
		(.046)	(.037)	(.056)	(.023)	(.047)	(.015)	**(.048)**	(.016)	(.047)	(.010)	**(.052)**	**(.031)**
σ_{λ_0}	L (0.2)	**26.43**	**27.41**	23.18	11.40	**26.48**	6.74	24.73	8.10	24.91	5.23	22.02	**24.88**
		(.299)	**(.302)**	(.213)	(.110)	**(.293)**	(.014)	(.197)	(.042)	(.252)	(.019)	(.126)	**(.152)**
	M (0.5)	13.01	**13.02**	**16.33**	7.89	13.52	6.67	**17.68**	6.99	14.69	4.91	**19.51**	**19.40**
		(.070)	**(.055)**	**(.078)**	(.035)	(.073)	(.013)	**(.064)**	(.020)	(.069)	(.011)	**(.063)**	**(.057)**
	H (0.8)	12.24	**12.27**	**15.59**	7.41	12.71	6.66	**17.50**	6.86	14.20	4.85	**19.31**	**18.34**
		(.048)	**(.027)**	**(.055)**	(.018)	(.051)	(.013)	**(.051)**	(.017)	(.051)	(.010)	**(.056)**	**(.034)**
μ_{ω_0}	L (−5)	17.26	**17.56**	18.31	8.89	17.55	5.64	**19.78**	7.49	17.88	4.59	**20.26**	**21.07**
		(.191)	**(.191)**	(.138)	(.070)	(.187)	(.009)	**(.128)**	(.031)	(.161)	(.013)	**(.087)**	**(.098)**
	H (5)	17.19	**17.57**	18.42	8.91	17.59	7.74	**20.16**	7.14	17.98	5.40	**20.30**	**20.67**
		(.298)	**(.302)**	(.215)	(.111)	(.293)	(.006)	**(.198)**	(.041)	(.254)	(.020)	**(.128)**	**(.156)**
σ_{ω_0}	L (1)	17.18	**17.56**	18.47	8.91	17.59	6.75	**19.98**	7.13	17.90	5.04	**20.37**	**20.55**
		(.190)	**(.192)**	(.140)	(.070)	(.188)	(.013)	**(.128)**	(.029)	(.161)	(.014)	**(.088)**	**(.100)**
	H (10)	17.28	**17.57**	18.26	8.89	17.55	6.63	**19.96**	7.51	17.96	4.95	**20.19**	**21.19**
		(.228)	**(.228)**	(.160)	(.083)	(.222)	(.010)	**(.152)**	(.034)	(.191)	(.015)	**(.099)**	**(.114)**
τ	L (120)	17.45	**17.62**	**19.05**	9.25	17.64	6.81	**20.09**	7.17	18.15	5.12	**20.68**	**21.43**
		(.185)	**(.183)**	**(.131)**	(.069)	(.169)	(.015)	**(.116)**	(.026)	(.153)	(.014)	**(.079)**	**(.090)**
	H (22)	17.01	**17.52**	17.68	8.55	17.50	6.56	**19.85**	7.46	17.71	4.87	**19.88**	**20.31**
		(.192)	**(.195)**	(.131)	(.065)	(.193)	(.012)	**(.129)**	(.028)	(.162)	(.014)	**(.087)**	**(.098)**
m	L (0.2)	15.88	**16.28**	17.03	8.25	15.98	6.56	**18.24**	6.65	16.42	4.86	**18.85**	**19.24**
		(.174)	**(.176)**	(.126)	(.063)	(.164)	(.014)	**(.114)**	(.026)	(.145)	(.014)	**(.077)**	**(.086)**
	H (0.8)	18.58	**18.85**	19.70	9.55	19.16	6.82	**21.70**	7.99	19.44	5.14	**21.71**	**22.50**
		(.242)	**(.244)**	(.175)	(.089)	(.245)	(.011)	**(.161**	(.033)	(.206)	(.015)	**(.109)**	**(.128)**
b	L (1.36)	17.07	**17.45**	18.30	8.85	17.42	6.68	**19.84**	7.26	17.81	5.00	**20.11**	**20.64**
		(.189)	**(.190)**	(.138)	(.069)	(.185)	(.013)	**(.125)**	(.029)	(.160)	(.014)	**(.087)**	**(.098)**
	H (3.825)	17.38	**17.69**	18.43	8.95	17.72	6.69	**20.11**	7.37	18.05	5.00	**20.45**	**21.10**
		(.197)	**(.202)**	(.135)	(.068)	(.195)	(.012)	**(.134)**	(.028)	(.167)	(.014)	**(.088)**	**(.100)**

Note. The entrepreneurial action ratio (percentage value $\delta \times 100$) is based on an average of 100 runs of 288 experiments. Standard deviations are in parentheses.

entrepreneurial action for a small-sized network ($n = 96$), and scale-free networks and square lattice networks for a large-sized network ($n = 960$). In particular, scale-free networks are always associated with the most entrepreneurial actions among the six networks.

Finally, Table 6.5 shows that more entrepreneurial actions are attained when a large number of actors experience value-adding uncertainty. That is, the entrepreneurial action ratio increases in parameters m and b. However, such intensive value-adding uncertainty, if occurring frequently within the simulation time period, will be detrimental to the dynamics of entrepreneurial action. This is in line with the findings in the base case where the value gained from such uncertainty may discourage the actors from identifying subsequent entrepreneurial opportunities. Holding the uncertainty-related parameters fixed, we find that a small economic size of actors embedded in the scale-free networks and random graphs can best cope with value-adding uncertainty. As for a large economic size of actors ($n = 960$), square lattice networks and scale-free networks foster a larger number of entrepreneurial actions than the other four networks. A further inspection on the network effect under four types of value-adding uncertainty confirm the above patterns, as illustrated in Table 6.6.

In summary, under the value-adding uncertainty scenario, scale-free networks favor entrepreneurial actions regardless of the economic size. Furthermore, square lattice networks foster entrepreneurial actions for a large economic size of actors and the random graphs for a small economic size of actors. We conclude that the large number of entrepreneurial actions can be achieved in an effective manner when most actors initially possess high value and low degree of feedback and the value-adding uncertainty is large extent (high m) yet infrequent (low τ).

6.3 Discussion

This work provides a synthesized formal model of entrepreneurial dynamics over space and time with the presence of uncertainty. Essentially, entrepreneurial action dynamics vary across alternative network structures; and the effects are moderated by some contextual factors such as the economic size and the state uncertainty scenarios. Intuitively, value-

Table 6.6: Entrepreneurial action dynamics under four types of value-adding uncertainty

$G=1$		$G=2$		$G=3$		$G=4$		$G=5$		$G=6$	
n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960	n=96	n=960
Panel 1: m ($L=0.2$) and τ ($L=4/365$)											
16.01	**16.25**	17.15	8.40	15.99	6.54	**18.01**	6.22	16.49	4.90	**18.94**	**19.43**
(.176)	**(.174)**	(.126)	(.065)	(.161)	(.015)	**(.112)**	(.026)	(.145)	(.014)	**(.077)**	**(.087)**
Panel 2: m ($L=0.2$) and τ ($H=17/365$)											
15.74	**16.32**	16.90	8.10	15.98	6.58	**18.47**	7.07	16.35	4.82	**18.76**	**19.05**
(.172)	**(.178)**	(.125)	(.061)	(.167)	(.013)	**(.117)**	(.025)	(.145)	(.014)	**(.077)**	**(.086)**
Panel 3: m ($H=0.8$) and τ ($L=4/365$)											
18.88	**18.99**	20.95	10.10	19.29	7.08	**22.18**	8.12	19.82	5.34	**22.42**	**23.42**
(.201)	**(.199)**	(.161)	(.081)	(.199)	(.012)	**(.136)**	(.031)	(.173)	(.014)	**(.097)**	**(.111)**
Panel 4: m ($H=0.8$) and τ ($H=17/365$)											
18.28	**18.71**	18.45	9.00	19.02	6.55	**21.33**	7.85	19.07	4.93	**21.00**	**21.58**
(.209)	**(.210)**	(.137)	(.069)	(.215)	(.011)	**(.140)**	(.030)	(.177)	(.013)	**(.095)**	**(.108)**

Note. The experiment setting is the same as that in Table 6.5.

adding uncertainty leads to more entrepreneurial actions than value-destroying uncertainty. In the square lattices and scale-free networks, most actors are likely to act entrepreneurially when the economic size is large. On the contrary, in the packs, ring lattices, random graphs, and small-world networks, entrepreneurial action ratio is high in a network of small economic size. Table 6.7 summarizes our findings contingent on the economic size and the type of state uncertainty. The table shows under which condition the network structures are beneficial to entrepreneurial action ratio (the light grey cells including a plus sign), and those conditions in which the network structures are detrimental to foster entrepreneurial actions (the dark grey cells including a minus sign).

Square lattice ($G=1$) network facilitate most number of entrepreneurial actions among the three regular networks. Although the packs ($G=2$) and ring lattices ($G=3$) both have the same uniform degree distribution as the square lattices, according to Miller and Page (2007), they are different in the patterns of "shared" connections, defined as the average

Table 6.7: Entrepreneurial action dynamics under uncertainty

			Small economic size						Large economic size					
			$G=1$	$G=2$	$G=3$	$G=4$	$G=5$	$G=6$	$G=1$	$G=2$	$G=3$	$G=4$	$G=5$	$G=6$
Value-destroying	High τ	Low m	+	−	0	0	+	0	+	0	0	−	−	+
		High m	+	−	0	0	+	−	+	−	+	−	0	0
	Low τ	Low m	0	0	0	+	0	+	+	0	0	−	−	+
		High m	+	−	0	0	+	0	+	0	0	−	−	+
Value-adding	High τ	Low m	−	0	−	+	0	+	+	0	0	0	−	+
		High m	−	−	0	+	0	+	+	0	−	0	−	+
	Low τ	Low m	−	0	−	+	0	+	+	0	0	0	−	+
		High m	−	0	0	+	0	+	+	0	−	0	−	+

Note. A plus sign denotes that the network structure has a top rank associated with high entrepreneurial action ratio. A negative sign denotes that the network structure fosters a small number of entrepreneurial actions, i.e., low rank. A zero denotes that the entrepreneurial action ratio rank of the network structure is in the middle. Each result is on average of 7200 experiments.

number of overlap between an actor's connections (including oneself) to the connections of her/his connections. For instance, consider an actor in a ring lattices. S/he shares 4 connections with the nearest neighbor; the next nearest neighbor has 3 connections in common. So the overlap of ring lattices is 3.5. Similarly, the overlaps of packs and square lattices equal to 3 and 2, respectively. In this sense, given the same number of connections, actors embedded in square lattices are more likely to access diverse possessed values for the discovery of entrepreneurial opportunity (Smilor, 1997).

Besides, scholars verify that scale-free networks has exceptional robustness to random node failures than random graphs and small-world networks (Albert et al., 2000; Motter, 2004). That is, the information and resource flows among networked actors are not disrupted under random actor's non-action decision. Unless the rare condition occurs that the hub actors are attacked by extreme value-destroying uncertainty, then we grossly overestimate the potential entrepreneurial action ratio, as verified by the minus sign under the severe and frequent value-destroying uncertainty scenario in Table 6.7.

Overall, square lattices and scale-free networks are better at fostering actors acting

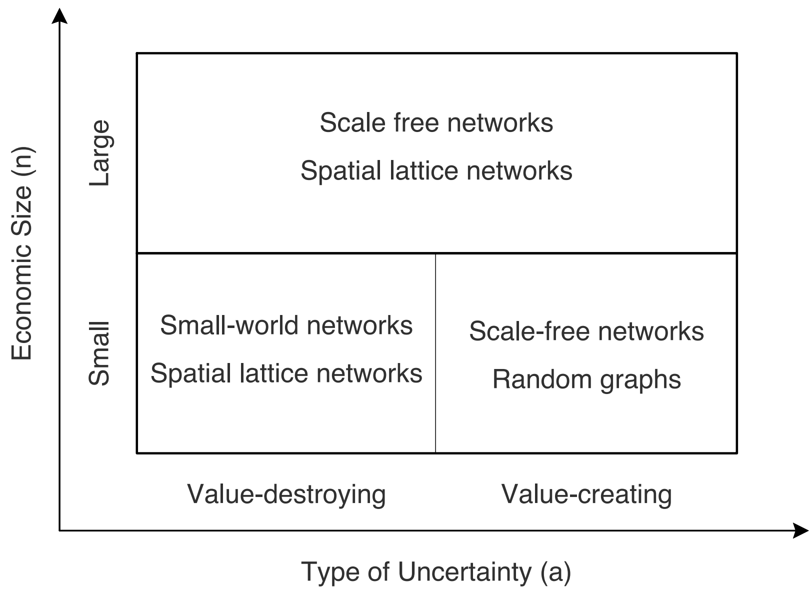


Figure 6.4: Entrepreneurial action dynamics on graphs

entrepreneurially than the other four network structures in most scenarios. They are more robust against value-change uncertainty than loop-based structures including packs, ring lattices, and small-world networks, especially when the economic size is large. (Note that packs have a small-world-alike structure that each actor has a group of localized connections together with one connection outside of the local group (Miller and Page, 2007).)

The insights from the analysis and discussion are distilled into a conceptual framework in Figure 6.4, which provides managerial insights in the demarcating regions of effective network structures in fostering entrepreneurial action under uncertainty. Specifically, the actors embedded the scale-free networks and spatial lattices are beneficial to grow a large economic size. These two network structures favor entrepreneurial action under both value-creating uncertainty and value-destroying uncertainty scenarios. When the economic size is small, small-world networks and packs facilitate a great amount of entrepreneurial action under value-destroying uncertainty, whereas the actors embedded in scale-free networks and random graphs are more likely to act entrepreneurially under the value-adding uncertainty. This recommendation is applicable to the era of big data, which is considered value-adding uncertainty that brings numerous opportunities to business actors. A small number of big-data pioneers, who were randomly connected, were alerted to the opportunities for potential value creation (located in the right bottom cell of Figure 6.4). Later, an increasing number of actors joined the network, which grows to be a scale-free network with the pioneers as the hubs (moved to the right top bell). Then, this scale free network has continuously encouraged entrepreneurial actions from the ever-increasing number of actors to explore and exploit the value of big data.

Chapter 7

Conclusion

This thesis responds Shepherd's (2015) call for a more interaction- and community-based perspective of entrepreneurial action to alleviate human suffering following uncertain value-destroying events such as nature- and man-made disasters. We extend recent literature and develop the idea that the connection structure and feedback pattern between community members can foster different forms and levels of entrepreneurial action to bring about relief and well being for the community in response to a disaster. Our extension is realized through three graph-theoretic models to study how different levels of prosocial motivation (i.e., the desire to benefit others) affect the community's collective value resulting from entrepreneurial action upon uncertain value destruction. We operationalize the models using the computational techniques, CA and ABM, to explore the entrepreneurial dynamics over space and time.

In our models, we incorporate feedback from the connected community members into an actor's entrepreneurial-action decision process (e.g., Keyhani et al., 2015; Shepherd and Patzelt, 2013), as a central element in an interaction-based entrepreneurial action in response to random value-destroying events. That is, the actor makes sense of other members' pains and losses following a disaster to discover, evaluate and exploit a potential opportunity in pursuit of value creation for one self and the entire community (McMullen and Shepherd, 2006; Patzelt and Shepherd, 2011; Shepherd, 2015; Shepherd et al., 2007).

We show that under a chain structure (i.e., supply chains in Chapter 3), actors that are strive to help neighboring members through benchmarking are likely to create high collective values in the aftermath of disasters, in particular for a small-size community. Under the grid structure in Chapter 4, we observe better community value creation when members are more likely to help each other through exchanging reciprocal benefits over time. This finding is robust in large communities. When further comparing grid structure with other network structures in Chapters 5 and 6, we find that actors embedded in a scale-free network are even more likely to engage in pro-social entrepreneurial actions in face of adversity. Our result implies a new framework of entrepreneurship as a spatiotemporal process to develop suffering venturing for collective value creation.

Our work offers several important implications to theory and practice of entrepreneurial action in the aftermath of disasters. Entrepreneurial action is the emergence resulted from the dynamic interactions among community members who have potential to act entrepreneurially (Parker, 2008; Phan and Chambers, 2013). This implies that network structure in which the members are embedded has such a nonignorant impact on entrepreneurial action dynamics. No much development in entrepreneurship theory can be achieved unless we exploit the network structure. To the best our knowledge, this work is the first attempt to extend the action-based entrepreneurship framework into the context of network dynamics and disasters. Specifically, we clarify the importance of the joint effect of network structure, feedback, reciprocity, resourcefulness, and uncertainty type on the identification of third person and evaluation of first person opportunities, entrepreneurial action process and collective value creation. Importantly, we find support for the impact of network structure on the spatiotemporal dynamics of entrepreneurial action in times of disasters. We claim that this is the first attempt to link the entrepreneurial action theory and graph theory to formalize and explain pro-social entrepreneurial action processes and outcomes over time and space.

7.1 Limitation and future research

In this thesis, we employ the best practice for developing management theory through computer simulations and deriving insights for prospective entrepreneurs to identify, evaluate and exploit possible opportunities for value creation. As noted by Davis et al. (2007); Harrison et al. (2007), and Miller and Page (2007), when a study does not aim to predict the outcome of a particular set of equations, as in our study, a computational model using a set of parameter values is a valid experimental process if it satisfies the problem's general conditions and shows a property of general interest.

In practice, community members' entrepreneurial activities for disaster recovery must satisfy two prerequisites: 1) desirability (i.e., the motivation to help others alleviate their sufferings), and 2) feasibility (i.e., the ability to meet the resource consumption requirements for taking actions). The three models in the thesis all consider both desirability and feasibility of pro-social entrepreneurial actions in the aftermath of disasters. Our model settings thus mimic the behavioral aspects of entrepreneurship and emergency management by considering the motivation behind actions and the limits of resource consumption (e.g., Sheu, 2007; 007b; 2010). However, in addition to the selected decision rules – recovery strategies in Chapter 3, altruistic entrepreneurial opportunity beliefs in Chapter 4, and the expected utility function of entrepreneurial action in Chapters 5 and 6 – future studies can explore and examine other novel rules that could effectively improve the collective community value creation in times of disasters.

Second, our formal models in chapters 3 to 6 all have fixed community size, following the lead of Rivkin and Siggelkow (2007) and Szabó and Fáth (2007). So the total number of community members is constant. Future research can extend to consider the community as an evolving system so that it can respond disasters by adding and/or removing a member (i.e., flexible community size) over time.

Finally, further empirical research could test our findings in different industries (i.e., logistic, semiconductor, service) with real disaster dataset (e.g., www.emdat.be; www.airdisaster.com). We believe that the analytical observations and managerial framework derived from our results provide rich insights into pro-social entrepreneurial-action decisions facing disastrous events and lay the groundwork for future analytical and empirical studies in this increasingly important field.

7.2 Conclusion

This thesis begins with the grand idea that pro-social entrepreneurship spreads over space and time in the aftermath of disasters (Shepherd, 2010; Shepherd and Williams, 2014; Shepherd, 2015), and, from this starting point, we formalize the action-based entrepreneurship framework (McMullen and Shepherd, 2006) from an interaction- and community-based perspective and extend it to the context of disasters. An actor's pursuit of an entrepreneurial opportunity to alleviate others' pains and losses is dependent on the decisions of other community members. So, connection structure of the community (i.e., network structure) matters since it depicts whom the actor meets and how they interact with each other. We study various well-received types of network structures and how their (reciprocal) interactions affect each actor's decision of entrepreneurial action in face of adversity, hence influencing the dynamics of entrepreneurship at both time and space dimensions.

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Chapter 8

Appendix

8.1 MATLAB code for Chapter 3

8.1.1 Base model

The following MATLAB code is applied in Section 3.3 for both the base case analysis and the experimental design analysis. The statement following % is a comment. Herein, we use DR10 as an example. Different recovery strategies are provided separately afterwards and can be implemented by substituting the relevant part of the sample code (see the comment).

function [average_performance_per_period] = ca_DR10_RC1_ran(N, T, Delta, g, f, RC1)

```
%% Initial setting %%
for i = 1 : 1 : N
        R(i, 1) = 3;        % set the initial resource level
    x = rand;                  % firms have random states – Random setting
        if x <= 0.33
            s(i, 1) = 0;
        elseif 0.33 < x <= 0.67
            s(i, 1) = 1;
        else
            s(i, 1) = 2;
        end
    % s_{i,1} = 2;             % firms have good state – Good setting
end
```

```
for t = 1 : 1 : T
    performance(t)= 0;

    %% Disaster strikes %%
    for i = 1 : 1 : N
        x = rand;
            if (x < f)
                s(i, t) = 0;                      % hit by a severe disaster
            elseif (f < x) & (x < f + g)
                s(i, t) = max(s(i, t) − 1, 0);    % hit by a mild disaster
            else
                s(i, t) = s(i, t);
            end
        end

    %% Recovery activities %%
    for i = 1 : 1 : N
        % Apply recovery strategy here (use DR10 as an example) %
        if (i == 1);        % Firm 1
            if (s(i, t)  = max(2, s(i + 1, t)))
                (s(i, t + 1) = max(2, s(i + 1, t)));
            else
                s(i, t + 1) = min(s(i, t) + 1, 2);
            end
        elseif (i == N);    % Firm N
            if (s(i, t)  = max(s(i − 1, t), 2))
                (s(i, t + 1) = max(s(i − 1, t), 2));
            else
                s(i, t + 1) = min(s(i, t) + 1, 2);
            end
        else                % Firm 2, 3, · · · , N − 1
            if (s(i, t)  = max(s(i − 1, t), s(i + 1, t)))
                (s(i, t + 1) = max(s(i − 1, t), s(i + 1, t)));
            else
                s(i, t + 1) = min(s(i, t) + 1, 2);
            end
```

```
            end
            % The recovery strategy ends here %

            % Apply resource consumption function C %
            if (s(i,t) == 0) & (s(i,t+1) == 1)
                R(i,t+1) = R(i,t) + Delta − RC1(1);   % apply c_1 (0 → 1)
            elseif (s(i,t) == 1) & (s(i,t+1) == 2)
                R(i,t+1) = R(i,t) + Delta − RC1(2);   % apply c_2 (1 → 2)
            elseif (s(i,t) == 0) & (s(i,t+1) == 2)
                R(i,t+1) = R(i,t) + Delta − RC1(3);   % apply c_3 (0 → 2)
            else
                R(i,t+1) = R(i,t) + Delta;
            end

            if R(i,t+1) < 0        % lack of resources to execute the strategy
                s(i,t+1) = s(i,t);
                R(i,t+1) = R(i,t) + Delta;
            end
            performance(t)=performance(t)+s(i,t+1);
        end
end

performance;
x = 0;
for t = 1 : 1 : T
        x = x + performance(t);
end
average_performance_per_period=x/T;
end
```

function[] = main()

```
        N = 5;       % for base case, later vary for experimental design {3,5,10}
        T = 365;     % for base case, later vary for experimental design {365, 3650}
        Delta = 1; % for base case, later vary for experimental design {1,10}
        g = 134/365;
```

```
f = 17/365;
RC(1, :) = [1, 2, 10];
RC(2, :) = [2, 1, 10];
RC(3, :) = [1, 10, 2];
RC(4, :) = [2, 10, 1];
RC(5, :) = [10, 1, 2];
RC(6, :) = [10, 2, 1];
sumulation_num = 200;        %200 runs
total_performance = 0;

for j = 1 : 1 : 6
    for i = 1 : 1 : simulation_num
    [performance_DR10_RC(i, j)] = ca_DR10_RC1_ran(N, T, Delta, g, f, RC(j, :))
    end
end

for j = 1 : 1 : 6
    mu_DR10(j)_ran = mean(performance_DR10_RC(:, j));   % mean performance
    sd_DR10(j)_ran = std(performance_DR10_RC(:, j));       % standard deviation
    per25_DR10(j)_ran = prctile(performance_DR10_RC(:, j), 25);   % 25% percentile
    per5_DR10(j)_ran = prctile(performance_DR10_RC(:, j), 5);      % 5% percentile
    per1_DR10(j)_ran = prctile(performance_DR10_RC(:, j), 1);      % 1% percentile
end

mu_DR10(j)_ran
sd_DR10(j)_ran
per25_DR10(j)_ran
per5_DR10(j)_ran
per1_DR10(j)_ran
end
%%%%%%%%%%%%%%%%%% The end of sample code %%%%%%%%%%%%%%%%%%
```

The codes for DR1 to DR9 are specified in the following:

```
% DR1 %
    s(i, t + 1) = 2;
```

% DR2 %

```
if (i == 1);        % Firm 1
    s(i,t+1) = 2
elseif (i == N);    % Firm N
    s(i,t+1) = 2
else                % Firm 2,3,...,N-1
    if (max(s(i-1,t),max((s(i,t),s(i+1,t))) == 2
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
end
```

% DR3 %

```
if (i == 1);        % Firm 1
    if (s(i,t) == 2 | s(i+1,t) == 2)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
elseif (i == N);    % Firm N
    if (s(i-1,t) == 2 | s(i,t) == 2)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
else                % Firm 2,3,...,N-1
    if (s(i-1,t) == 2 & s(i,t) == 2) | (s(i-1,t) == 2 & s(i+1,t) == 2) |
    (s(i,t) == 2 & s(i+1,t) == 2)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
end
```

% DR4 %

```
if (i == 1);        % Firm 1
    if (s(i,t) + s(i+1,t) == 4)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
elseif (i == N);    % Firm N
    if (s(i-1,t) + s(i,t) == 4)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
else                % Firm 2,3,...,N-1
    if (s(i-1,t) + s(i,t) + s(i+1,t) == 6)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
end
```

% DR5 %

```
if (i == 1);        % Firm 1
    if (s(i,t) + s(i+1,t) < 4)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
elseif (i == N);    % Firm N
    if (s(i-1,t) + s(i,t) < 4)
        s(i,t+1) = 2;
    else
        s(i,t+1) = 1;
    end
else                % Firm 2,3,...,N-1
```

```
        if (s(i − 1, t) + s(i, t) + s(i + 1, t) < 6)
            s(i, t + 1) = 2;
        else
            s(i, t + 1) = 1;
        end
    end

% DR6 %
    if (i == 1);        % Firm 1
        s(i, t + 1) = max(2, max(s(i, t), s(i + 1, t)));
    elseif (i == N);    % Firm N
        s(i, t + 1) = max(s(i − 1, t), s(i, t), 2);
    else                % Firm 2, 3, ··· , N − 1
        s(i, t + 1) = max(s(i − 1, t), max(s(i, t), s(i + 1, t)));
    end

% DR7 %
    s(i, t + 1) = min(s(i, t) + 1, 2);

% DR8 %
    if (i == 1);        % Firm 1
        if (s(i, t)  = 2)
            (s(i, t + 1) = 2);
        else
            s(i, t + 1) = min(s(i, t) + 1, 2);
        end
    else                % Firm 2, 3, ··· , N
        if (s(i, t)  = s(i − 1, t))
            (s(i, t + 1) = s(i − 1, t));
        else
            s(i, t + 1) = min(s(i, t) + 1, 2);
        end
    end

% DR9 %
```

```
if (i == N);        % Firm N
    if (s(i,t)  = 2)
        (s(i,t+1) = 2);
    else
        s(i,t+1) = min(s(i,t)+1,2);
    end
else                % Firm 1,2,3,··· ,N−1
    if (s(i,t)  = s(i+1,t))
        (s(i,t+1) = s(i+1,t));
    else
        s(i,t+1) = min(s(i,t)+1,2);
    end
end
```

8.1.2 Stochastic decision rule

The following MATLAB code is for DR11 in Section 3.4. We first assign the initial probabilities for each of the ten recovery strategy at time 0:

```
for k = 1 : 1 : 10
    prob(k) = 0.1;
end
thres(1) = prob(1);
for k = 2 : 1 : 10
    thres(k) = thres(k − 1) + prob(k);
end
```

Then, the rest of the code can be applied by substitute the relevant part of the sample code in the previous section, as other recovery strategies.

```
x = rand;
    if x < thres(1)        % DR1 is selected
        for i = 1 : 1 : N
            s(i,t+1) = 2;
            performance(t) = performance(t) + s(i,t+1);
        end
```

% Compare performance t with average performance per period till $t-1$

old_performance $= 0$;

for $tt = 1:1:t$

    old_performance = old_performance + performance(t);

end

if performance(t) > old_performance + performance(t);

    prob(2) $= \max(\text{prob}(2) - 0.001, 0)$;

    prob(3) $= \max(\text{prob}(3) - 0.001, 0)$;

    prob(4) $= \max(\text{prob}(4) - 0.001, 0)$;

    prob(5) $= \max(\text{prob}(5) - 0.001, 0)$;

    prob(6) $= \max(\text{prob}(6) - 0.001, 0)$;

    prob(7) $= \max(\text{prob}(7) - 0.001, 0)$;

    prob(8) $= \max(\text{prob}(8) - 0.001, 0)$;

    prob(9) $= \max(\text{prob}(9) - 0.001, 0)$;

    prob(10) $= \max(\text{prob}(10) - 0.001, 0)$;

    prob(1) = 1− prob(2)− prob(3)− prob(4)− prob(5)− prob(6)− prob(7)− prob(8)− prob(9)− prob(10);

    thres(1)=prob(1);

    for $k = 2:1:10$

        thres(k) = thres($k-1$) + prob(k);

    end

end

elseif thres(1) $< x <$thres(2)

for $i = 1:1:N$

if $i == 1$;

    %%% *** %%%

    if $\max(2, \max(s(i,t), s(i+1,t))) == 2$

        $s(i,t+1) = 2$;

    if $(s(i,t) == 1)$ & $(s(i,t+1) == 2)$

        $R(i,t+1) = R(i,t)+$Delta − RC1(2);

    elseif $(s(i,t) == 0)$ & $(s(i,t+1) == 2)$

        $R(i,t+1) = R(i,t)+$Delta − RC1(3);

    else

        $R(i,t+1) = R(i,t)+$Delta;

```
        end
        else
            s(i,t+1) = 1;
        if (s(i,t) == 0) & (s(i,t+1) == 1)
            R(i,t+1) = R(i,t)+Delta - RC1(1);
        else
            R(i,t+1) = R(i,t)+Delta;
        end
        end
        %%% *** %%%
    elseif i == N
        repeat the *** section
    else
        repeat the *** section
    end

    % Compare performance t with average performance per period till t - 1
    ...
    end

elseif thres(2) < x <thres(3)
    ...
elseif thres(3) < x <thres(4)
    ...
elseif thres(4) < x <thres(5)
    ...
elseif thres(5) < x <thres(6)
    ...
elseif thres(6) < x <thres(7)
    ...
elseif thres(7) < x <thres(8)
    ...
elseif thres(8) < x <thres(9)
    ...
else thres(9) < x <thres(10)
```

```
        ...
prob;
performance;
x = 0;
for t = 2 : 1 : T + 1
    x = x + performance(t);
end

average_performance_per_period=x/T;
end
```

8.2 MATLAB code for Chapter 4

The following MATLAB code is applied in Section 4.4 for both the base case analysis and experimental design analysis. The statement following % is a comment. Herein, we use O5 as an example. The codes for other opportunity beliefs are consistent with the illustrations in Table 4.1.

function [average_value] = ca_O1_Y1_ran(N, K, T, Delta, g, f, Y1)

```
% Initial setting at t = 0, n is the column of the network, k indicate the row number
for n = 1 : 1 : N
        for k = 1 : 1 : K
        U(n, k, 1) = 3;        % set the initial resource level
    x = rand;                  % firms have random states – Random setting
        if x <= 0.33
            s(n, k, 1) = 0;
        elseif 0.33 < x <= 0.67
            s(n, k, 1, ) = 1;
        else
            s(n, k, 1) = 2;
        end
end

for t = 1 : 1 : T
```

```
% Row 1 (k = 1)
for k = 1 : 1 : K
    value(k, t)= 0;

% Disaster strikes
for n = 1 : 1 : N
    x = rand
        if (x < f)
            s(n, k, t) = 0;                          % hit by a major disaster
        elseif (f < x) & (x < f + g)
            s(n, k, t) = max(s(n, k, t) - 1, 0);   % hit by a minor disaster
        else
            s(n, k, t) = s(n, k, t);
        end
end
end

% Actions
for n = 1 : 1 : N
if n == 1
    h(n, k, t + 1) = max(2, max(s(n, 1, t), s(n + 1, 1, t)));        % apply O5 to the row
    neighbors
    v(n, k, t + 1) = max(s(n, 1, t), max(s(n, 2, t), s(n, k, t)));      % apply O5 to the
    column neighbors
    s(n, 1, t + 1) = max(h(n, 1, t + 1), v(n, 1, t + 1));    % max-rule
    % s(n, 1, t + 1) = min(h(n, 1, t + 1), v(n, 1, t + 1));    % min-rule
elseif n == N
    h(n, k, t + 1) = max(2, max(s(n, 1, t), s(n - 1, 1, t)));
    v(n, k, t + 1) = max(s(n, 1, t), max(s(n, K, t), s(n, k, t)));
    s(n, 1, t + 1) = max(h(n, 1, t + 1), v(n, 1, t + 1));    % max-rule
    % s(n, 1, t + 1) = min(h(n, 1, t + 1), v(n, 1, t + 1));    % min-rule
else
    h(n, k, t + 1) = max(s(n - 1, 1, t), max(s(n, 1, t), s(n + 1, 1, t)));
    v(n, k, t + 1) = max(s(n, 1, t), max(s(n, 2, t), s(n, K, t)));
    s(n, 1, t + 1) = max(h(n, 1, t + 1), v(n, 1, t + 1));    % max-rule
    % s(n, 1, t + 1) = min(h(n, 1, t + 1), v(n, 1, t + 1));    % min-rule
```

```
    end

        if (s(n,1,t) == 0) & (s(n,1,t+1) == 2)
            U(n,k,t+1) = U(n,k,t) + Delta − Y1(1);   % apply y1 (0 → 2)
        elseif (s(n,1,t) == 0) & (s(n,1,t+1) == 1)
            U(n,k,t+1) = U(n,k,t) + Delta − Y1(2);   % apply y2 (0 → 1)
        elseif (s(n,1,t) == 1) & (s(n,1,t+1) == 2)
            U(n,k,t+1) = U(n,k,t) + Delta − Y1(3);   % apply y3 (1 → 2)
        else
            U(n,k,t+1) = U(n,k,t) + Delta;
        end
        if U(n,k,t+1) < 0
            s(n,k,t+1) = s(n,k,t);
            U(n,k,t+1) = U(n,k,t) + Delta;
        end
        value(1,t)=value(1,t)+s(n,k,t+1);
    % Row 2 to K − 1
        ...
    % Row K
        ...
end

performance;
x = 0;
for k = 1 : 1 : K
for t = 1 : 1 : T
    x = x + value(t);
end

average_value = x/T;
end
```

8.3 NetLogo code for Chapter 5

The following NetLogo code is applied in Section 5.3 for both the base case analysis and the experimental design analysis. The statement following ;; is a comment. The code to set up each network structure is consistent with the algorithms introduced in Chapter 2, so omitted here.

```
globals [ entrepreneurial-ratio ]

    ;; nodes to be occupied
    breed [ nodes node ]
    nodes-own [
        is-occupied?
        actor-id
    ]
    ;; actors occupy nodes
    breed [ actors, actor ]
    actors-own [
        node-id
        my-value          ;; ω_{i,t}
        my-feedback       ;; λ_{ij,t}
        my-feedback-0     ;; λ_{ij,0}
        action?           ;; z_{i,t}
    ]

    ;; create link breeds (undirected - symmetric links, directed - asymmetric links)
    undirected-link-breed [ s-links s-link ]
    directed-link-breed [ a-links a-link ]

    ;; generate a list of an actor's neighbors
    to-report my-neighbors
        report [who] of link-neighbors with [is-occupied?]
    end

    ;; count the number of an actor's neighbors
    to-report n
        report count link-neighbors with [is-occupied?] + count out-link-neighbors with
        [is-occupied?]
    end
```

```
;; calculate the likelihood of taking entrepreneurial action
to-report R        ;; ∑_{j~i} E[λ_{ji,t} ω_{j,t−1}] in Equation 5.1
    report (sum [my-feedback * my-value] of people-on link-neighbors with [is-occupied?])
end

to-report Q        ;; ∑_{i~j} E[λ_{ij,t} ω_{i,t−1}] in Equation 5.1
    report (n * [my-feedback * my-value] of person actor-id)
end

to-report the probability
    let logit-prob ( R - Q + [my-value] of person actor-id)
    let prob exp (logit-prob) / (1 + exp (logit-prob))
    ;; debugging
    if (prob < 0 or prob > 1)
    [show "Probability is outside the allowed range!"]
    report prob
end

;; allocate actors to nodes
to occupy-node [id]
    set node-id id
    move-to node id
    ask node node-id [set is-occupied? true]
end

;; clear the world and set up the network structures
to setup
    clear-all

    if (network-type = "Square lattices") [setup-square-lattices]
    if (network-type = "Packs") [setup-packs]
    if (network-type = "Ring lattices") [setup-ring-lattices]
    if (network-type = "Random") [setup-random]
    if (network-type = "Small world") [setup-small-world]
    if (network-type = "Scale free") [setup-scale-free]
```

```
    foreach ([who] of nodes) [
        if (random-float 1 ¡ density) [
            create-actor 1 [
                set node-id ?
                occupy-node ?
                set shape "person"
                set color blue
            ]
        ]
    ]

    ask actors [
        ask node node-id [set actor-id [who] of myself]

        ;; set up the actor's initial value and degree of feedback against friction at time 0
        set my-value random-normal mean-value sd-value
        set my-feedback-0 random-normal mean-feedback sd-feedback
            ;; resample until the degree of feedback is within the allowed range [0,1]
            while [my-feedback-0 < 0 or my-feedback-0 > 1]
            set my-feedback-0 random-normal mean-feedback sd-feedback
        set my-feedback my-feedback-0
    ]

    reset-ticks
end

to go
    if ticks >= 365 [ stop ]

    update my-feedback for value creation in the next period
    ask actors [
        if else (random-float 1 <= [probability] of node node-id )
        [ set action? true
        set colour blue
        set my-feedback my-feedback-0 ]
```

```
      [ set action? false
      set colour red
      set my-feedback 0 ]
  ]

  ;; update the value
  ask actors with [action?] [ set my-value my-value + [R - Q] of node node-id]
  ask actors with [not action?] [ set my-value my-value+ [R] of node node-id ]

  do-plots
  tick
end

to do-plots
  set-current-plot “Entrepreneurial Action Ratio”
  set entrepreneurial-ratio (count actors with [action?] / count actors)
  set-current-plot-pen “ratio”
  plot entrepreneurial-ratio
end
```