MODELING DYNAMICS OF POST DISASTER RECOVERY

A Dissertation

by

ALI NEJAT

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2011

Major Subject: Civil Engineering

MODELING DYNAMICS OF POST DISASTER RECOVERY

A Dissertation

by

ALI NEJAT

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,	Ivan Damnjanovic
Committee Members,	Stuart D. Anderson
	Kenneth F. Reinschmidt
	Sergiy Butenko
	Arnold Vedlitz
Head of Department,	John Niedzwecki

August 2011

Major Subject: Civil Engineering

ABSTRACT

Modeling Dynamics of Post Disaster Recovery. (August 2011)

Ali Nejat, B.S., Zanjan University, Zanjan, Iran;

M.S., Islamic Azad University, Tehran, Iran

Chair of Advisory Committee: Dr. Ivan Damnjanovic

Natural disasters result in loss of lives, damage to built facilities, and interruption of businesses. The losses are not instantaneous, but rather continue to occur until the community is restored to a functional socio-economic entity. Hence, it is essential that policy makers recognize this dynamic aspect of the losses incurred and make realistic plans to enhance recovery. However, this cannot take place without understanding how homeowners react to recovery signals. These signals can come in different ways: from policy makers showing their strong commitment to restore the community by providing financial support and/or restoration of lifeline infrastructure; or from the neighbors showing their willingness to reconstruct. The goal of this research is to develop a model that can account for homeowners' dynamic interactions in both organizational and spatial domains. The spatial domain of interaction focuses on how homeowners process signals from the environment, such as neighbors reconstructing and local agencies restoring infrastructure, while the organizational domain of interaction focuses on how agents process signals from other stakeholders that do not directly affect the environment like insurers do. The hypothesis of this study is that these interactions significantly influence decisions to reconstruct and stay, or sell and leave. A multi-agent framework is used to capture emergent behavior such as spatial patterns and formation of clusters. The developed framework is illustrated and validated using experimental data sets. The results from simulation model confirm that spatial and organizational externalities play an important role in agents' decision-making and can greatly impact the recovery process. The results further highlight the significant impact of discount factor and the accuracy of the signals on the percentage of reconstruction. Finally, cluster formation was shown to be an emergent phenomenon during the recovery process and spatial modeling technique demonstrated a significantly higher impact on formation of clusters in comparison with experimental model and hybrid model.

DEDICATION

To my parents and my brother.

ACKNOWLEDGMENTS

I would like to take this opportunity to acknowledge the excellent academic guidance and financial assistance offered by Dr. Ivan Damnjanovic during my graduate studies at Texas A&M University (TAMU). Without his guidance, this dissertation would have not become a reality. Working with Dr. Damnjanovic was a wonderful experience in many ways and I will never forget him in my life. I also sincerely appreciate the excellent guidance and financial assistance offered by Dr. Stuart Anderson during my studies as a PhD student and I am very grateful for all my research opportunities that were offered by him. I would also want to extend my gratitude to Dr. Kenneth Reinschmidt for his excellent guidance, support and feedbacks on various aspects of my studies including this dissertation. I also sincerely appreciate the excellent guidance and support provided by Dr. Butenko and Dr. Vedlitz on the different aspects of my doctoral research. In general, I am very fortunate to have an extraordinary advisory committee with a wide range of expertise that helped me view the challenges from multiple perspectives and shape this dissertation in its current form.

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

Page

LIST OF TABLES

Page

1. INTRODUCTION

1.1. PROBLEM STATEMENT

Pre-disaster planning is the key to effective recovery from natural catastrophes, such as hurricanes, earthquakes, and tsunamis, or human-induced events such as acts of terrorism or accidents. In anticipation of these high-impact low-probability events, communities and their public and business decision-makers need policies, contingency plans, procedures, and guidelines to implement recovery actions. Typically these actions include evaluations of damage, removal of debris, and restoration of essential infrastructure and services to then allow for a market-driven reconstruction of homes and businesses.

In late summer of 2005, two major storms tested the ability of coastal communities in the United States to achieve recovery goals. Hurricane Katrina, and a few weeks later Hurricane Rita, exposed the flaws and deficiencies in the existing policies, plans and budgets to meaningfully and quickly restore damaged infrastructure and promote residential and business reconstruction. The scenes of damaged and unserviceable buildings and even entire neighborhoods in New Orleans and other gulf coast communities are constant reminders that the disaster is not over until the people have returned, and the affected area has been restored to a functioning social, political and economic entity.

This dissertation follows the style of *Natural Hazards Review,* ASCE.

Following the extensive media coverage, government agencies and the academic community have initiated a number of studies to identify hazard-specific design deficiencies, develop more effective emergency and evacuation plans, predict the extent of structural damage, assess short-term recovery efforts, and model long-term economic effects of market-driven reconstruction. However, very few studies, if any, have focused on identifying the forces driving such long-term market-driven reconstruction.

1.2. DISSERTATION GOAL

The goal of this dissertation is to study how agents (i.e. homeowners) process signals from spatial and organizational environment during long-term market-driven recovery. A successful modeling effort requires capturing agents' behavior as well as dynamics of their interactions over extended period of time. Although there are research efforts on modeling the recovery process, they fail to capture the complexity of interactions among the agents in a multi-domain environment (i.e. spatial as well as organizational).

There are a number of beneficiaries of this research. Public officials can use the developed models to evaluate recovery plans and strategically "seed" the reconstruction efforts in areas that can maximize the speed of recovery. Transportation agencies can use the model to evaluate effectiveness of restoration dynamics, while regulatory agencies can use it to increase bargaining power of homeowners following the disaster.

1.3. SCOPE

The scope of this research is limited to modeling behavior of two key stakeholders: *homeowners*, agents seeking to rebuild; and *insurers*, agents that maximize short-and long-term utility. The scope indirectly includes public agencies as they control many parallel parameters. Even though this assumption constrains the real life application of the developed model, it allows for marginal assessment of the effects of spatial and organizational externalities on the recovery process. Note that the models do not attempt to fully explain a very complex post-disaster reconstruction process, nor heterogeneity in homeowners' behavior, but to provide a theoretical foundation for investigating the emergent spatial phenomenon (i.e. clusters) and decision-making under uncertainty.

1.4. RESEARCH OBJECTIVES

This subsection presents research objectives formulated as research questions. The research questions have been divided into two categories: 1) micro-level research questions, and 2) macro-level research questions. The former category focuses on how the agents interact in both spatial and organizational domain respectively, while the latter category focuses on how such micro-level behaviors affect macro-level phenomena such as spatial cluster formation.

1.4.1. Micro-level Research Questions

1.4.1.1. RQ1: How do the agents interact in the spatial domain?

The first micro-level objective of this research is solely focused on how agents make decisions in a spatial environment. In other words, this question aims to capture how an individual reconstruction decision-making is affected by its neighbors' decision-making. The solution to this question unveils the logic behind how agents' update their beliefs regarding the value of reconstruction given what they observe in the neighborhood.

Data Source: The dataset used to address this question comes from an experimental study conducted in Fall 2010 in the department of Civil Engineering at Texas A&M University. Study participants were the students of a junior-level civil engineering course. The participants were faced with similar conditions as homeowners in affected area would face after a disaster and were asked to choose among different strategies.

Research Method**:** The methodology proposed for this research question is based on a two-pronged approach. In the first *theoretical* approach, homeowners make decisions based on their updated beliefs about their spatial surroundings. As reconstruction unfolds, they update their beliefs accordingly. This process is captured using Bayesian statistics. The outcome of the first approach is a closed-form theoretical solution to the probability of reconstruction.

The goal in the second approach is to develop and estimate an *empirical* model using previously defined datasets. The outcome of the second approach is a multinomial logistic regression model to predict the probability of reconstruction. The reason behind having two approaches is to cover the different aspects of spatial interactions independently. In the first theoretical approach, the focus is only on the temporal aspect of spatial interactions, which is solely based on assessment of how agents' actions (i.e. neighbors reconstruction actions), influence the dynamics of reconstruction-value in the affected area. On the other hand, the second approach aims to capture broader effects than just neighbors' reconstruction decision. The empirical model is developed to capture the confluence of different spatial parameters such as availability of infrastructure.

Model Validation: The results from both models are tested for their capability of delivering logically expected results.

1.4.1.2. RQ2: How do the agents interact in the organizational domain?

This research question aims to investigate how market conditions, government regulation, and incentives affect the ability of homeowners to secure equitable treatment when negotiating with large for-profit institutions such as insurers. In other words, the objective is to investigate how agents' risk attitudes affect their financial negotiations with insurers. There is ample anecdotal evidence of price gouging and failure to pay claims by some insurers after natural disasters. Indeed, it is not surprising for one party to leverage a stronger bargaining position to take advantage of the reduced bargaining strength of the other party (e.g. homeowners seeking to rebuild). Thus, in the second proposed domain of interactions (organizational domain), the bargaining power of the "stressed" agents is studied.

Data Source: The dataset used to address this research question is based on a bargaining experiment that was conducted in Fall 2010 in the department of Civil Engineering at Texas A&M University. Like in the previous experiment, study participants were the students of a junior-level civil engineering course. The experimental bargaining scenario mimicked what might happen after disaster between homeowners and insurers. Participants were divided into two categories (homeowners and insurers), and were asked to choose from the available options in respond to a received offer.

Research Method: Much like the methodology used for RQ1, the proposed approach to address this research question is two-fold: *theoretical* and *empirical*. In the theoretical part, the bargaining problem is modeled based on the concepts of the bargaining theory. In the empirical model, the approach to the bargaining problem is based on analyzing the collected data from the experiment.

Model Validation: The results from both models are tested to check for their capability of delivering logically expected results.

1.4.2. Macro-level Research Question

After separately investigating agents' interaction in both spatial and organizational domains, an integrative framework is designed to capture the effects of agents' behavior at a macro-level. This integrative framework is based on a multi-agent system (MAS) simulation approach. There are a number of advantages associated with applications of agent-based modeling technique, which make it a desirable approach to address the macro-level research question. These benefits include: 1) the ability to tackle the complexity of the research problem, 2) ability to capture the dynamics of the system during the simulation period, and 3) ability to test different behavioral models.

1.4.2.1. RQ3: Does the spatial interaction of agents result in formation of clusters of reconstructed properties?

The macro-level objective of this dissertation is to detect for any emergent phenomena such as spatial cluster formation due to agents' interactions. Spatial data suggest that reconstruction, much like other neighborhood phenomena such as foreclosures, is *contagious* and is nucleated first in small neighborhood areas.

Research Method: For this research question the methodology includes the following steps: 1) developing a MAS model, 2) detecting spatial clusters in MAS model using clustering algorithms, 3) hypothesis testing to determine the significance of the results from the second step, and 4) contrasting the results from theoretical and empirical spatial models to check for the factors that have the most significant influence on the formation of clusters.

1.5. ORGANIZATION OF THE DISSERTATION

Section 2 outlines the existing literature on modeling disasters. The section starts with introducing loss models and then proceeds to cover the literature on recovery models.

The section then continues to highlight the existing gap in the literature and is concluded by an introduction on the approach to overcome the shortcomings.

Section 3 introduces the research methodology to address the objectives of this dissertation. It starts with a discussion on the general framework and is further extended to capture the multi-domain framework of interactions and experimental data sets characteristics.

Section 4 covers the modeling procedure for the spatial domain of interactions. It starts with a discussion on the theoretical model and its solution. To follow, the section proceeds with the empirical model formulations and is continued by its associated statistical analysis. To conclude, summary of findings is presented.

Section 5 captures the modeling of the organizational domain of interactions. It begins with the theoretical model and proceeds to derive the solution. The section then continues with an introduction on empirical model formulation, parameter estimation and its associated statistical analysis. It then concludes by the summary of findings.

Section 6 extends on multi-domain MAS model. It starts with an introduction on MAS models, and their specifications. To follow, the simulation setups are discussed which are then followed by simulation results, research hypotheses, and testing methods. The section ends with a discussion of the results, which is continued by summary of the findings.

Finally, Section 7 outlines the summary of the dissertation, which is then proceeded by the areas requiring future research.

2. LITERATURE REVIEW

This section outlines the existing literature on the broad subject of disaster modeling. More specifically, the literature review is categorized into two typical modeling areas: 1) loss modeling, and 2) recovery modeling. To conclude, the section captures the need and the research problem listed as the objectives of this dissertation.

2.1. DISASTER MODELING

In the literature of disaster modeling, hazard is the incident of the physical occurrence whereas disaster is the subsequent aftermath Okuyama and Chang (2004). The studies on the impact of natural hazards on the socio-economic condition of affected areas gained significant attention due to a series of disasters which took place during the mid 1990s such as Northridge earthquake in 1994 and Great Hanshin (Kobe) earthquake in 1995 (Okuyama, 2007). These events followed by more recent catastrophes such as hurricane Katrina in 2005 and hurricane Ike in 2008 highlight the vulnerability of the urban infrastructure in modern cities and support the need for a better understanding of multidimensional socio-economic impacts and the way the homeowners and public sector respond.

Economic losses from both natural and anthropogenic disasters do not take place instantly; rather they are accumulated over the time of recovery. This implies that to assess the scale of losses, it does not suffice just to incorporate the initial losses. In other words, the direct losses can trigger spillover effects which in turn can cause indirect losses that are as significant, if not more, than the initial losses. In such settings, the dynamics of post disaster recovery plays an important role. This is clearly shown in Figure 2-1 where three different disaster cases are compared to each other (Chang and Miles, 2004). It is assumed that in all the three cases the economy faces a significant initial loss due to the occurrence of the disaster. In Case A, the reconstruction stimulus has led the economic equilibrium to a curve which dominates the baseline. This indicates future potential gains in the long run that will reimburse the initial losses. On the other hand, Case C shows that the trend has come to equilibrium below the base line which denotes that the reconstruction stimulus was not able to compensate the losses. In case B, the economy has a short-term updrift before it converges to the baseline. Figure 2-1 illustrates how application of different policies during the recovery process can affect the magnitude of the total losses.

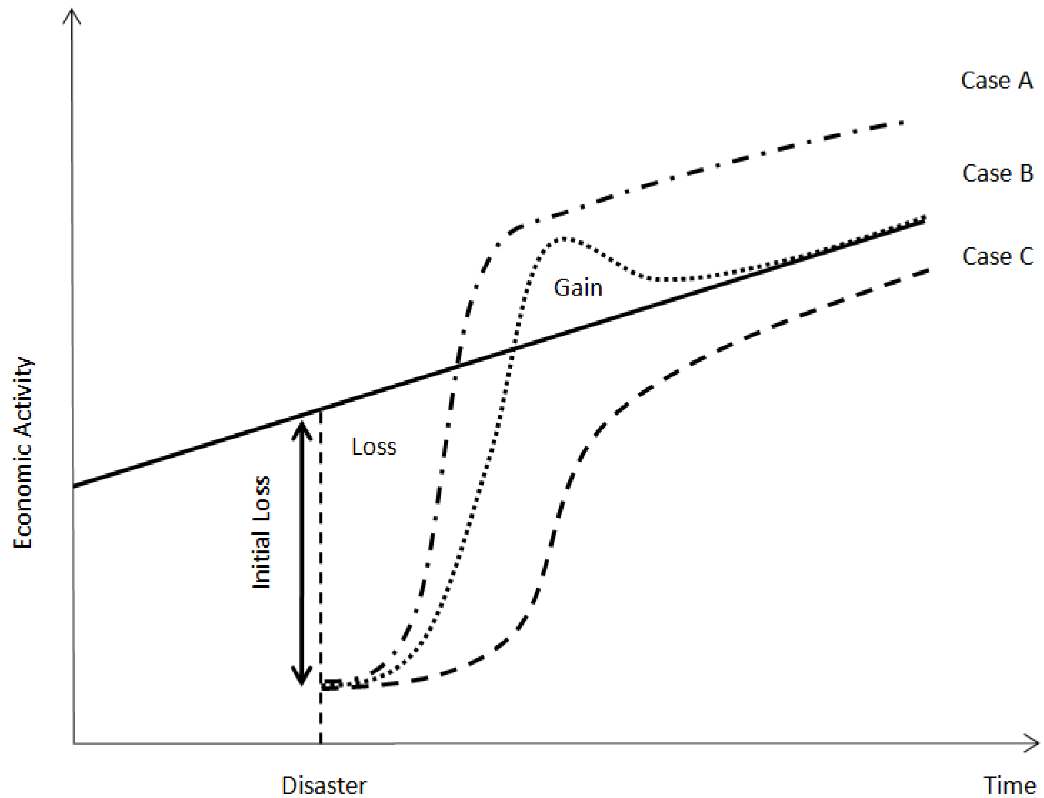


Figure 2-1. Post-disaster recovery adapted from Chang and Miles (2004)

The economic impacts of natural disasters can be categorized into two major categories, which are 1) direct losses, and 2) indirect losses. Differentiating between these two terms has been a matter of controversy in the existing literature. While Applied Technology Council (1991) and Heinz Center (2000) defined direct losses as property damages and indirect losses as business disruptions, Albala-Bertrand (1993) characterized indirect losses as a possibility rather than a reality, and Cochrane (2004) classified indirect losses as those which are not directly caused by a disaster. Rose et al. (1997), defined direct losses as those which incorporate property damage together with its following interruptions to directly affected businesses, and indirect losses as those which are associated with disruptions in businesses that are not directly influenced by a disaster. Rose (2004) proposed the use of "higher-order effects" term as an alternative to indirect effects to avoid the conflict with other economic modeling terminology especially input-output (I/O) models. The term was intended to encompass both input-output interdependencies and general equilibrium effects which can be attributed to price changes in product markets.

Therefore direct losses can be classified as those that are attributed to the damages and destructions to built environment, infrastructure, lifelines, and economic sectors and inter-industry linkages. Indirect losses, on the other hand, represent losses which are associated with the disturbances caused by the direct losses in economic sectors that are not directly affected. This includes the imposed interruptions in economic activities such as reductions in supply and demand. In other words, indirect losses can be described as a byproduct of the direct losses. Models with a focus on incorporating economic losses are represented as loss models whereas those which are centered around integrating parameters that affect recovery time path are denoted as recovery models. These two models are elaborated in the following subsections.

2.1.1. Loss Modeling

Loss models focus on capturing the initial losses rather than incorporating the dynamics of a recovery process (Chang and Miles, 2004). There are a variety of classifications for loss models in the literature. Brookshire et al. (1997) categorized direct loss estimation methods into two categories which are: 1) loss estimation based on primary data such as surveys in the affected areas, and 2) loss estimation founded on secondary data such as insurance claims, and loans and highlighted their weak prognostic aptitude. Furthermore, in the context of loss modeling, input-output (I/O) models are the most prevalent and dominating modeling framework to capture the regional economic impacts and higher-order effects of disasters (Rose 2004). I/O models are linear models which integrate the sales and purchases in different segments of an affected economy. I/O models can exhibit the interdependency of economic activities and economic sectors including producers and/or consumer (Brookshire et al. 1997). This ability makes I/O models a good candidate to study the domino effects caused by a disruption in an economic sector. Furthermore, the simplicity of I/O models allows integrating engineering models to estimate the higher-order effects of a disaster (Okuyama, 2007).

For example, Gordon and Richardson (1996), Gordon et al. (2004), Choe et al. (2001), and Sohn et al. (2004) used the I/O modeling approach to study transportation impacts, while Rose (1981), Rose et al. (1997), Rose and Benavides (1993, 1998) applied this model to assess lifeline impacts. Furthermore Cochrane et al. (1997), and Hewnigs and Mahindhara (1996) applied I/O models to capture the overall impacts of a disaster whereas Rose et al. (1997), Cole (1998), and Rose and Benavides (1999) applied I/O models to optimize recovery.

To overcome the limitations of I/O models such as their linear and rigid structure, and lack of resource constraints (Okuyama, 2007), more complex models have been developed by Boisvert (1992), Cochrane (1997), Davis and Salkin (1984).

In addition to traditional I/O models, econometric models are also used to capture losses. The econometric models are statistically rigorous, data-intensive, and capable of forecasting post-disaster conditions. Moreover, they fall short of differentiating between direct and high-order impacts (Rose, 2004). The third alternative to I/O models is Computable General Equilibrium (CGE) model. CGE models represent optimized behavior of consumers and firms in response to price changes in a multi-market framework (Rose 2004). These models can be seen through the works of Boisvert (1992), Brookeshire and Mckee (1992), Rose and Guha (2004), and Rose and Liao (2005). In contrast to I/O models, CGE models are non-linear, less rigid and capable of incorporating supply constraints. In most CGE models, the basis is founded on an extended I/O tables to account for separate institutional factors (Rose 2004). This includes Social Accounting Matrices to represent the higher order effects (Cole 1995; 1998; 2004). A summary of these methods together with their strength and weakness was summarized by Okuyama (2011) and is shown in Table 2-1.

Table 2-1. Summary of more comprehensive loss models with their associated strengths and weaknesses adapted from Okuyama (2011)

Model	Strengths	Weaknesses
IO models	• simple structure • detailed inter-industry linkages • wide range of analytical techniques available • easily modified and integrated with other models	• linear structure • rigid coefficients • no supply capacity constraint • no response to price change • overestimation of impact
SAM models	• more detailed interdependency among activities, factors, and institutions • wide range of analytical techniques available • used widely for development studies	• linear structure • rigid coefficients • no supply capacity constraint • no response to price change • data requirement • overestimation of impact
CGE models	• non-linear structure • able to respond to price change • able to cooperate with substitution • able to handle supply capacity constraint	• too flexible to handle changes • data requirement and calibration • optimization behavior under disaster • underestimation of impact
Econometric models	• statistically rigorous • stochastic estimate • able to forecast over time	• data requirement (time series and cross section) • total impact rather than direct and higher-order impacts distinguished

Although this subsection briefly outlined the most comprehensive methodologies to estimate losses, there are additional studies aimed to capture the shortcomings of these methodologies. These efforts include: 1) studies performed by Cole (1988, 1989) and Okuyama et al. (2004) to capture the temporal aspect of recovery by introducing a disrupted expenditure structure and sequential inter-industry model respectively, 2) studies performed to incorporate the spatial impact of disasters such as an interregional IO structure to assess higher order effect such as Okuyama (1999) and Sohn et al. (2004), and 3) studies by Rose and Liao (2005), Tierney (1997), Okuyama et al. (1999) to capture the behavioral changes due to disasters (Okuyama 2007).

2.1.2. Recovery Modeling

Despite the substantial literature on post-disaster loss modeling, only few studies (in relative terms) have focused on the dynamics of recovery (Chang and Miles 2004). The existing literature on modeling the recovery process can be grouped into five major categories: 1) Studies with a focus on recovery as a temporal process: This includes modeling temporal aspect of factory closure (Cole 1988 1989), interregional input-output analysis (Okuyama et al. 2004), as well as recovery optimization by minimizing economic losses (Rose et al. 1997), 2) Studies founded on a conceptual recovery framework introduced by Haas et al. (1977) in which the recovery process was modeled as a four-stage sequential incident. This study was followed by case studies by Hogg (1980), Rubin and Popkin (1990), Rubin (1991), Berke et al. (1993), and Bolin (1993) which extensively questioned this four-stage sequential approach to recovery, its predictability, and argued that the order of the sequence can be different from what was suggested by Haas et al. (1977). These subsequent studies characterized recovery as an uncertain event affected by social disparities and decision-making, 3) Studies centered around disparities in recovery, which were pursued by a two-pronged effort. The first effort captured disparity in social classes among people (see Hewitt (1997), Blaikie

(1994)), where the second effort covered the recovery issues associated with disparities in businesses (see Durkin (1984), Kroll et al. (1991) Tierney and Dalhamer (1998), and Alesch and Holly (1998)), 4) Studies attempted to capture the effect of spatial externality on different aspects of disaster recovery. Among those the spatial impact of lifeline infrastructure was studied by Gordon et al. (1998), while Chang and Miles (2004) proposed an object modeling technique to capture interactions between industry sectors and community planning, and finally 5) Studies to determine the key performance measures and indicators to capture the different aspects of the recovery process. These include psychological or perceptional measures related to stress and frustration, to more objective indicators such as regaining income, employment, household assets, and household amenities (Bates 1982, 1993, 1994; Bolin and Bolton, 1983; Bolin and Trainer, 1978; Peacock et al., 1987).

2.2. RESEARCH PROBLEM

While these efforts captured different aspects of the problem, an integrative spatial-organizational agent-based model is still missing. An example of the existing literature on modeling the recovery process through an agent-based approach is the model presented by Chang and Miles (2004). Although the model is agent-based, the agents do not exist spatially. Hence, this research aims to develop a theoretical link between the existing efforts in modeling recovery with a focus on macro-level patterns and socio-economic impact and those that are aimed at modeling micro-level behavior of "stressed" agents. This integration will be conducted in a multi-agent system simulation environment to capture the effects of time and the emergent system behavior. In other words, the proposed model can capture 1) the behavior of homeowners in the presence of spatial externality (being located among other homeowners), 2) the behavior of homeowners while bargaining with high-marketing-power entities such as insurers under stressed conditions and 3) the sensitivity of these two types of behaviors to a variety of parameters such as availability of infrastructure, and market conditions.

3. RESEARCH METHODOLOGY

3.1. GENERAL FRAMEWORK

Capturing the complexity of homeowners' multi-domain interactions requires an integrative framework, which should allow for flexibility of separately modeling domain-specific interactions, while providing a means to account for cross-domain phenomena. Multi-agent system (MAS) simulation framework facilitates this process by integrating the behaviors of participating agents in two different domains. In addition, it provides a framework where temporal and behavioral phenomena from interactions such as cluster formation and reduced bargaining power of "stressed agents" can be observed.

Furthermore, the multi-agent framework also addresses the shortcoming of the previous studies in modeling a real spatial environment by assigning a precise location to each of the agents in the spatial environment. Therefore, the research approach used in this dissertation is based on a series of overlapping steps which are: 1) developing theoretical and empirical models to account for spatial aspect, 2) developing theoretical and empirical approach to account for bargaining situation, 3) developing integrative MAS model, 4) incorporating spatial and organizational behavior among the agents, and 5) observing the spatial phenomena such as cluster formation. These steps are shown in Figure 3-1.

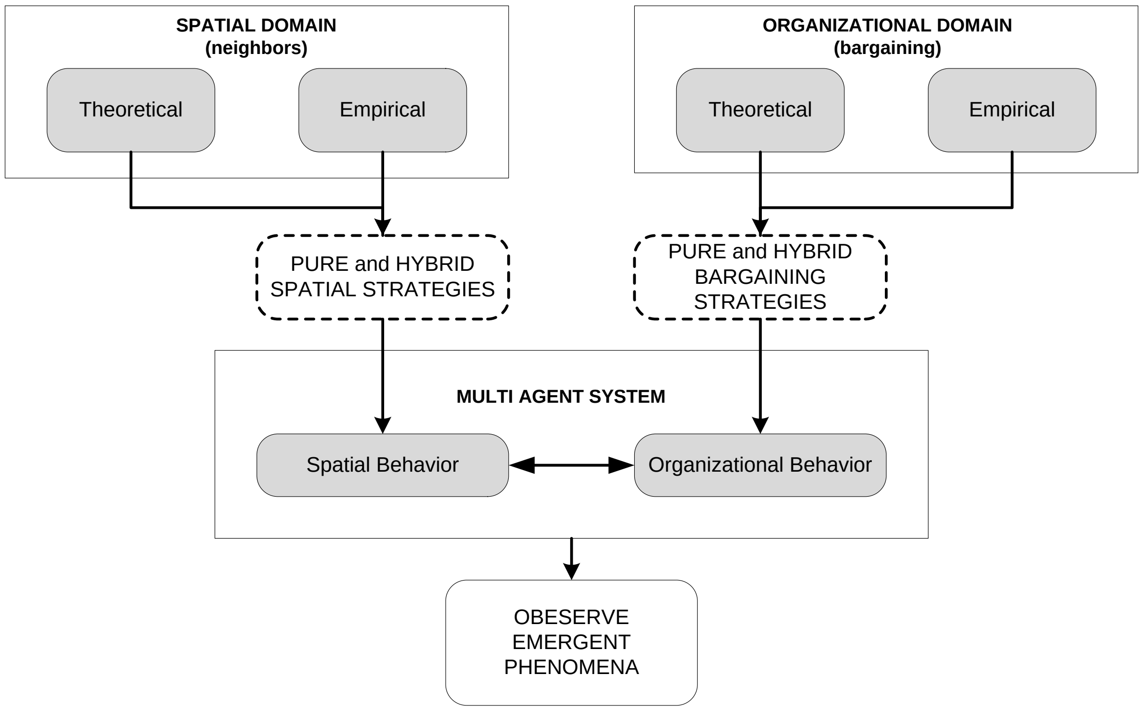


Figure 3-1. Research approach

As shown in the figure, for each of the spatial and organizational domains, two types of models are defined; theoretical and empirical. Each of these models can be separately chosen to model agents' interactions. This is called a pure strategy. On the other hand if agents' interactions is believed to be a consequence of the confluence of both models, one can assign different weights to each model and constitute a hybrid model. The most important advantage of this feature is its ability to simulate a variety of behaviors based on agents' rationality and their different decision making parameters. In spatial domain, one set of parameters captures the temporal aspect of spatial interactions whereas the other set covers the situational aspect of this interaction. Similarly, in the organizational domain, the first set of factors represents agents' negotiation based on the theoretical model while the other set of parameters capture a more realistic bargaining behavior of agents and is based on the empirical model.

3.2. MULTI-DOMAIN INTERACTIONS

In this dissertation, the *Multi-domain Multi-agent system (MD-MAS) model* is illustrated in Figure 3-2 as a 3-dimensional representation of the interaction domains. The two interaction domains are: 1) spatial domain of interaction among the agents defined by their spatial position (e.g. multi-layered networks of residential and commercial properties, as well as different infrastructure systems including essential lifelines, such as transportation, water, and electric power, and other more indirect yet still very important systems such as schools, hospitals, and others); and 2) organizational domain of interaction defining logical relationships among the stakeholders at the micro-social level. As shown in the figure, the key micro-social organizational agents are homeowners and insurers. While this list can be expanded to include other important stakeholders, this research is guided by the principle of parsimony, in which the complexity of model specification is determined by its *predictive capability*. In the MD-MAS model, **R** represents a homeowner (homeowner), and **I** characterizes an insurer. Following a disaster, homeowners decide about reconstruction of their property based on the availability of resources coming from the insurer and/or the governing authorities, while observing the actions of other homeowners.

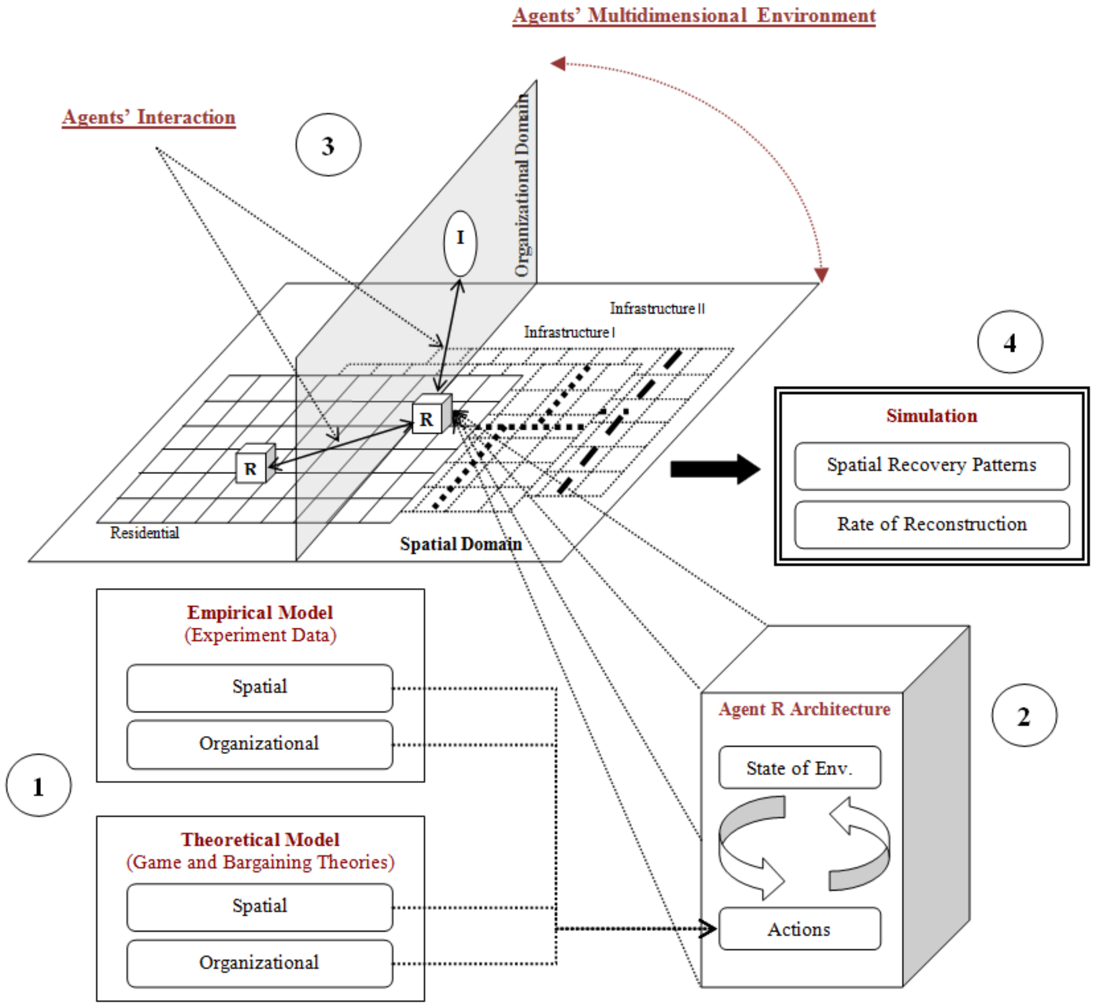


Figure 3-2. Interactions in multi-domain environment

As shown in the figure, two major parameters drive homeowners' actions regarding reconstruction. The first is homeowners' decision making structure which can be either theoretical (based on agents rationality) or empirical and the second is homeowners' perception of environment. Both of these factors are dynamic. The interaction starts at time zero when there is no reconstruction in the environment. Figure 3-2 shows the sequence of steps in the MD-MAS model. At Step 1, agents' decision-making structure is formed which leads to the corresponding actions in Step 2. Step 3 shows the effect of agents' actions on the environment and vice versa. Finally, in Step 4, the outcomes of these iterative interactions over time are discovered. These outcomes can be divided into two categories, which are 1) rate of reconstruction, and 2) spatial recovery patterns.

3.3. EXPERIMENTAL SETUP

As stated before, the empirical model formulation was based on the experiments. The experiments in this dissertation were conducted in the form of surveys. Participants in these surveys were chosen from a class of a CVEN junior level course in Zachry Department of Civil Engineering, Texas A&M University. To preserve anonymity, participants were asked to just communicate with the principal investigator through emails. Proper care was taken to make sure that the identity of participants was kept confidential and was not disclosed to any other participant. All the steps in the experiments were taken by using emails between participants and principal investigator. In other words where applicable, the principal investigator played the role of a proxy between two interacting participants. Details regarding each of the experiments are presented below.

3.3.1. Spatial Interactions Experimental Setup

In this experiment, the participants were asked to select a reconstruction strategy under various overriding spatial and financial settings. Spatial configurations were governed by the availability of infrastructure and the severity of damages. These configurations resulted in 6 different scenarios. Financial viability of reconstruction was controlled by the rate of availability of the funds and the cost of reconstruction. The available reconstruction strategies were 1) reconstruct immediately, 2) wait for 6 months and observe neighbors' actions and decide accordingly and 3) take insurance money and buy a housing alternative somewhere else in town. In this survey, 80 students participated. Details regarding the survey together with instructions to participants are included in Appendix A.

3.3.2. Bargaining Situation Experimental Setup

In this experiment, the students were divided into two groups and each group was assigned a different role. The first group played the role of insurer while the second participated as clients. Clients were supposed to maximize their claims while insurers tended to minimize their losses. A total of 77 students participated in the experiment. Six of the participants were assigned the role of insurer. Each of the insurers was responsible for 10 to 12 clients. This was performed to differentiate the participants from each other based on their attitude toward risk. Since insurers have the option of diversifying their risk through multiple clients, they were assumed to be risk neutral. The clients on the other hand, not having such an option, were assumed to be risk averse. Identity of clients was kept confidential and transmission of information between the insurers and the clients were managed through the proxy of the principal investigator.

3.4. SUMMARY

The objective of this section was to elaborate on the general framework of this dissertation and explain the methodology to approach its goals. The following chapters will sequentially complement this section by each focusing on a specific research question.

Section 4, starts with the micro-level objectives of this dissertation by focusing on the spatial domain and tackling agents interactions with each other. Furthermore, Section 5 expands on the micro-level objectives by capturing the organizational domain and addressing the interactions between homeowners and insurers. To continue, Section 6 elaborates on developing an integrative multi-domain agent based model that can incorporate the outcomes from Section 4 and Section 5. This integrative model is used to address the macro-level objective of this dissertation by looking for any emergent phenomena such as formation of clusters. Finally Section 7 presents the summary of findings and highlights the issues require future research.

4. MODELING SPATIAL INTERACTIONS

4.1. INTRODUCTION

This section presents the first micro-level objective of this dissertation by providing the answer to the question: "How agents process the information from the neighborhood?" The section starts with a presentation of a theoretical model in which the homeowners are modeled as rational agents seeking to maximize their utility. This utility is assessed in terms of homeowners' gains/losses from the reconstruction. Based on this structure, at each time step, the agents compute their expectation from two actions which are: 1) an immediate reconstruction, and 2) waiting and making the decision in the next stage. These expected values are directly influenced by the actions of neighboring homeowners and eventually dominate agents reconstruction decisions.

To proceed, the section focuses on defining the waiting game among homeowners and is extended to derive an equilibrium solution for the game each homeowners "plays" with the other in the neighborhood. The section then continues with introducing an empirical model which can account for a confluence of factors such as homeowners financial status, intensity of damages in the area, and availability of infrastructure. The empirical model is based on an experiment designed to establish similar conditions to what agents would be facing following a disaster. The reason behind developing the empirical model was to incorporate the situational aspect of spatial interaction that the theoretical model does not consider. To conclude, the summary of findings is presented which is then followed by the list of limitations of the model and the need for future data collection and work.

4.2. THEORETICAL MODEL

Faced with property damage and partial or even complete destruction of neighborhoods, the homeowners often question whether to rebuild the property immediately, or to wait and collect more information about the future value of such an action. This new information comes from signals from other homeowners in the immediate and extended neighborhood as well as policy makers and community leaders. If there is observed value in reconstruction (e.g. property values are restored as the community is being fully rebuilt), a homeowner will rebuild as well; otherwise, he/she may wait until the next time period to observe the value of reconstruction and then make the decision. In fact, the choice of "do-now" versus "wait-and-see" has been extensively studied in multiple applications where uncertainty is resolved sequentially.

Given that the value of neighboring reconstruction has a direct impact on the future value of the yet-to-be reconstructed properties, it is essential for homeowners to update their beliefs of the value of spending a substantial portion of their available resources to reconstruct. This externality, the effect of decision making of a set of property homeowners on the rest of the homeowners without considering their interests, normally leads to a free-rider effect in which some homeowners prefer to wait and observe the state of the world while some other homeowners rebuild. By doing this, homeowners reduce the risk of reconstructing when the community has not recovered to a functioning level. However, waiting may not always be the optimum strategy as homeowners have limited resources for reconstruction that are decreasing as the they wait to reconstruct and the benefits arising from the rebuilt properties are foregone. In other words, waiting is costly and associated with various costs such as house rentals which accumulates over the time and decrease financial flexibility of the homeowners in regard to reconstruction.

The free-rider problem caused by externalities has been extensively studied by economists. Groves and Ledyard (1977) presented a solution for optimizing the allocation of public goods by formulating a specific allocation-taxation scheme, while Porter (1995) studied its effect on the government's decision making regarding oil and gas leases. Also, Hendricks and Porter (1996) presented a Bayesian approach to capture its effect on timing of exploratory drilling on wildcat tracts. Much like the theoretical model introduced by Hendricks and Porter (1996), homeowners in this research are assumed to have an updating-belief structure which is presented below.

4.2.1. Signals and Uncertainty

Assume that homeowner y makes the reconstruction decision in a neighborhood of N homeowners. Homeowners' future property values (e.g. homeowner y's (x_y) and that of the $N-1$ neighbors $x_i \in X$, $i=1,...,N-1$), are assumed to be random variables from a lognormal distribution with geometric mean $\exp(\alpha)$ and precision (inverse of the variance) β. Therefore by transforming x_i to z_i where $z_i = \ln(x_i)$, $i=1,...,N$, it can be concluded that z_i would be a random draw from a normal distribution with mean α and precision β. Without loss of generality, precision β is normalized to 1. In this section, the logarithms of homeowners' future property values (z_i) are considered for the purpose of mathematical derivation where $z_1,...,z_N \sim N(\alpha,1)$. It is assumed that homeowner y's property value before damage is v_y, reimbursements from insurer is i_y, reconstruction cost is c_y and the reconstruction period is limited to time T. Hence, the net present value (NPV) of homeowner y's utility at time t can be expressed as:

$$NPV(U(y),t) = \gamma^t U(y) = \gamma^t \left[z_y - \left(\ln(v_y c_y / i_y) \right) \right] \quad \textbf{(4-1)}$$

where γ^t represents the discount factor for time period t and $U(y)$ denotes homeowner y's utility from reconstruction. Homeowner y's belief about the mean of future property values of all homeowners (α) together with its neighbors' beliefs about its actual future property value (z_y) are updated through future market appraisal information known as signals. For all homeowners, signals are considered to be normally distributed with mean z_i, and precision ρ_i where $i = 1,..., N$.

Signals represent a belief about the future property values. Therefore, homeowner y starts with its initial belief about the value of reconstruction in the neighborhood. This initial belief can be updated based on the signals (i.e. revealed property values from neighborhood). When the signals are observed, homeowner y updates its belief about the mean of future property values in the neighborhood. This further results in updating the belief of the other homeowners in the neighborhood about

z_y. This process continues until homeowner y reconstructs, or decides to sell at its fair market value or abandon the property and leave. Here, it is critical to understand how signals coming from different agents (e.g. neighbors reconstructing their houses) affect homeowners $y's$ perception of the value of reconstruction $(s_y \rightarrow z_y)$.

The belief-updating model used in this subsection is built upon previous studies that have investigated sequential decision-making and information updating (e.g. the "free-rider" problem, clock game, war of attrition, predator – prey waiting game, etc.). More specifically, the model extends the Hendricks and Porter (1996) study on the effect of timing on exploratory drilling, and develops a Bayesian value model to account for new information and signals. The signals are revealed sequentially as homeowners reconstruct $(s_i \rightarrow x_i)$. Following Bayes rule and ignoring prior beliefs, it can be shown that homeowners' belief about the mean of future property values in the neighborhood is a random draw from a normal distribution with the following parameters:

$$\mu = \frac{\sum_{i=1}^{N} [s_i \rho_i (1+\rho_i)^{-1}]}{\rho} \qquad \textbf{(4-2)}$$

$$\rho = \sum_{i=1}^{N} \frac{\rho_i}{(1+\rho_i)} \qquad \textbf{(4-3)}$$

The proof for Equations 4-2 and 4-3 are included in Appendix B. Additionally, homeowners' beliefs about $z_i, i = 1,..., N$(e.g. z_y) conditional on the observed signals from the neighborhood can be shown to be a random draw from a normal distribution with the following parameters:

$$\mu_{z_y} = \frac{\mu + \rho_y s_y}{1 + \rho_y} \qquad \textbf{(4-4)}$$

$$\rho_{z_y} = \frac{\rho(\rho_y + 1)^2}{\rho(\rho_y + 1) + 1} \qquad \textbf{(4-5)}$$

The proof for Equations 4-4 and 4-5 is included in Appendix C. Now if some (e.g. h number) of the homeowners reconstruct, homeowners' beliefs regarding the mean of the future property values in the neighborhood (α) will change respectively. The new value will depend on: 1) number of homeowners that reconstructed and have a revealed future value $(z_1,...,z_h)$; and 2) the remainder of the signals $(N-h)$ which, ignoring prior beliefs (using a non-informative prior), is a normal random variable with parameters shown in Equations 4-6 and 4-7 (Hendricks and Porter 1996). In these equations $\bar{z}$ denotes the average revealed future property value and N represents the total number of homeowners in the neighborhood.

$$\mu^h = \frac{h\bar{z} + \sum_{i=h+1}^{N} [s_i \rho_i (1+\rho_i)^{-1}]}{\rho^h} \qquad \textbf{(4-6)}$$

$$\rho^h = h + \sum_{i=h+1}^{N} \frac{\rho_i}{(1+\rho_i)} \qquad \textbf{(4-7)}$$

As shown in Equation 4-6, the new mean is a weighted mean of average revealed future property values and the sum of the remaining signals from properties on which reconstruction has not been started yet. Conditional on the signals and revealed property values, the posterior distribution for beliefs about homeowner y's future property value (z_y) will be represented by a normal distribution with the parameters shown in

Equations 4-8 and 4-9 where $\mu_{z_y}^h$ is the mean of homeowners' beliefs about z_y and $\rho_{z_y}^h$ is the precision of homeowners' beliefs about z_y given the new changes in the area.

$$\mu_{z_y}^h = \frac{\mu^h + \rho_y s_y}{1 + \rho_y} \quad \textbf{(4-8)}$$

$$\rho_{z_y}^h = \frac{\rho^h (\rho_y + 1)^2}{\rho^h (\rho_y + 1) + 1} \quad \textbf{(4-9)}$$

Therefore, homeowner y starts with its initial belief about the value of reconstruction in the neighborhood. This initial belief is updated based on the signals and revealed property values from neighboring property homeowners. When the signals are observed, homeowner y updates its belief about the mean of the future property values in the neighborhood. This will as well result in updating the belief of the other homeowners in the neighborhood about z_y. This process continues until homeowner y either reconstructs, or sticks to the do-nothing strategy and is shown in Figure 4-1.

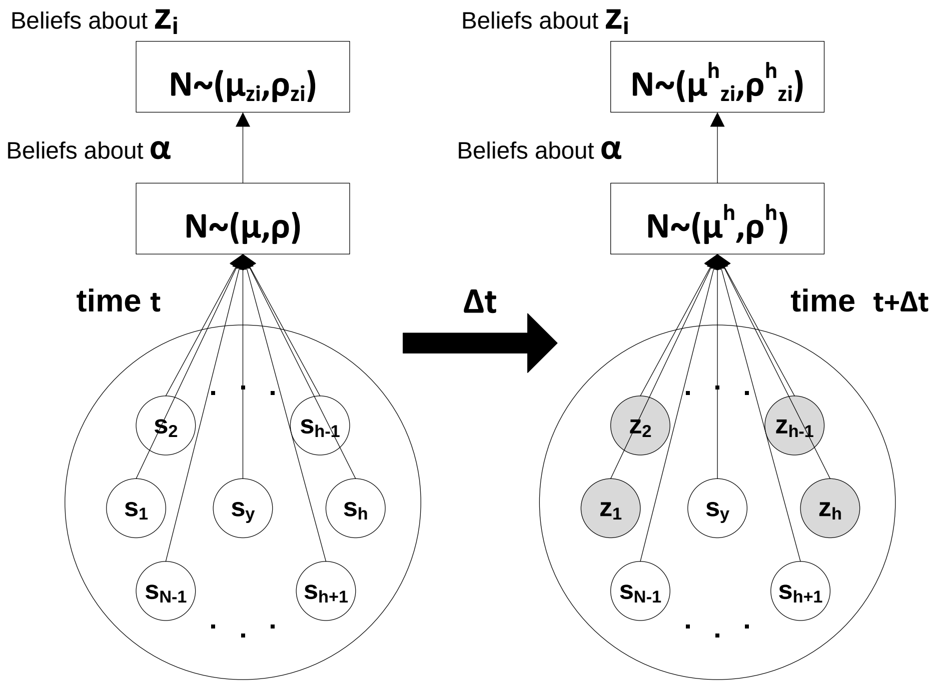


Figure 4-1. The updating process of the theoretical model

As shown in Figure 4-1, at time t, there are N homeowners in a given neighborhood where each has a signal and precision denoted as s_i and ρ_i. At this time, homeowners' beliefs about mean of the future property values in the neighborhood (α) and their own future property value (z_i) is based on these signals and precisions and are denoted as $N \sim (\mu, \rho)$ and $N \sim (\mu_{z_i}, \rho_{z_i})$ respectively. At time $t + \Delta t$, h number of the homeowners reconstruct in the neighborhood. Therefore based on the revealed values of those h homeowners, the rest of the homeowners update their beliefs about both mean of the future property values in the neighborhood ($N \sim (\mu^h, \rho^h)$) and their own future property value ($N \sim (\mu^h_{z_i}, \rho^h_{z_i})$). This iterative process continues until everyone reconstructs or wait till the last period.

4.2.2. Game and Behavior

In a multiagent setting, modeling human decision making becomes so complicated that it is usually a norm to believe that agents opt for Nash equilibrium strategies (Nash 1950). Nash equilibrium is the optimal solution of the game where neither of the players can improve their payoffs by unilaterally changing their strategy. Based on this premise, a game-theoretic model is developed to account for spatial interactions (e.g. the decision to reconstruct depends also on the neighbors and their decisions). In other words, the homeowners play a game with two strategies: wait, observe the signals, and reconstruct only when there is a sufficient value to do so; or reconstruct immediately, without waiting for the others. It is natural that homeowners with high value signals will select immediate reconstruction, while the rest will prefer to wait until a positive net value is secured.

However this wait-and-see strategy might not always be the optimal strategy due to the financial constraints (e.g. cost of renting). In cases where the net value from waiting exceeds that of immediate reconstruction, the game structure resembles war of attrition in which a follower may end up with a higher payoff than a leader. To illustrate the concept, a situation with only two neighbors (neighbor i and j) is considered in which $\mu(t)$, and $\rho(t)$ represent the mean and precision of future property values at the time of consideration (see Subsection 4.2.1). The logic behind a two-neighbor case consideration is two-fold: 1) its simplicity, and 2) the fact that the behavioral analysis for the multiple neighbor cases is not significantly different from the equilibrium solution for the two-neighbor case (Hendricks and Porter 1996). The expected payoff from immediate reconstruction for homeowner i considering no prior reconstruction can be shown as:

$$EVI[i \mid \mu(t), \rho(t)] = \int f(z_i \mid \mu(t), \rho(t)) U(i) dz_i \qquad \textbf{(4-10)}$$

where $EVI[i, t \mid \mu(t), \rho(t)]$ denotes the expected value from immediate reconstruction for homeowner i at time t given the current state of information about future property values in the neighborhood, $f(z_i \mid \mu(t), \rho(t))$ represents the normal probability density function of z_i with mean $\frac{\mu(t) + \rho_i s_i}{1 + \rho_i}$ and precision $\frac{\rho(t)(\rho_i + 1)^2}{\rho(t)(\rho_i + 1) + 1}$, and U_i represents the gained utility for owner i at time t. On the other hand, if homeowner i waits and observe its neighbor's (homeowner j) action, the state of information about the mean of future property values in the neighborhood changes to a new normal distribution with the following parameters (Hendricks and Porter 1996):

$$\mu(t + \Delta t) = \frac{[\mu(t)\rho(t) + (z_j - s_j \rho_j (1 + \rho_j)^{-1})]}{[\rho(t) + (1 + \rho_j)^{-1}]} \qquad \textbf{(4-11)}$$

$$\rho(t + \Delta t) = \rho(t) + \frac{1}{1 + \rho_j} \qquad \textbf{(4-12)}$$

As shown in Equation 4-11, homeowner i's belief about $\mu(t + \Delta t)$ is a function of homeowner j's property value which has not been revealed yet. It can be shown that $\mu(t + \Delta t)$ has a normal distribution with mean $\mu(t)$ and precision $\rho_t + \rho_t^2 (1 + \rho_j)$.

These derivations are shown in Appendix D. These derivations are used to compute the expected payoff of waiting for homeowner i at time t which can be denoted as:

$$EVW[i \mid \mu(t), \rho(t)] = \int \max[0, EVI(i \mid \eta, \rho(t+\Delta t))] \times f(\eta; \mu(t), \rho(t) + \rho(t)^2(1+\rho_j))d\eta \quad \textbf{(4-13)}$$

where $EVW[i \mid \mu(t), \rho(t)]$ denotes the expected value from waiting for homeowner i at time t given the current state of information about future property values in the neighborhood, $\eta = \mu(t+\Delta t)$ and $EVI(i \mid \mu(t+\Delta t), \rho(t+\Delta t))$ denotes the expected value from immediate reconstruction for homeowner i at time $t+\Delta t$. In equation 4-13, the expected payoff from waiting is assumed to be non-negative. This is attributed to the fact that in this model no direct waiting costs are considered for waiting and the act of other homeowners may hinder the homeowner reconstruction decision. Therefore as mentioned in Equation 4-10, the expectation from immediate reconstruction for owner i at time t is based on its belief about its future property value considering the present information about the future property values in the neighborhood. In contrast, owner i expectations from waiting depends on its gains from its updated information regarding the future property values in the area. This updating process is based on assumption that at time $t+\Delta t$ owner j reconstructs.

4.2.3. Game Solution

Based on these assumptions, the game between the homeowners (homeowners i and j) can be defined as a war of attrition where homeowners have two pure strategies, 1) starting the reconstruction, and 2) waiting for neighbors to reconstruct first and deciding accordingly. In the case where pure strategies do not result in equilibrium or homeowners are not determined about their reconstruction decisions, mixed strategies can solve the problem.

Mixed strategies are formed by assigning probabilities to pure strategies. Mixed strategies enable homeowners to randomly select between their pure strategies. For this game, the mixed strategy equilibrium can be expressed by the probability of reconstruction at each time period conditional on no prior reconstruction. The solution of this game can be found using backward induction. In the last period (T), homeowner i will start reconstruction if reconstruction has a positive expected value $(EVI(i \mid \mu(T), \rho(T) > 0)$. In period $T-1$, considering that no prior reconstruction has occurred, homeowner i has two options. If it chooses to reconstruct then its expected payoff of immediate reconstruction (EPI) would be the same as the last period. This is shown in equation 4-14.

$$EPI[i, \mu(T-1), \rho(T-1)] = \max[0, EVI[i, \mu(T-1), \rho(T-1)] \qquad \textbf{(4-14)}$$

If homeowner i chooses to wait, its expected payoff from waiting (EPW) depends on the probability of its neighbor (homeowner j) reconstructing ($P(R_j \mid T-1)$), where R_j denotes the action of reconstruction for homeowner j. Consequently homeowner i's payoff can be shown as:

$$EPW[i \mid \mu(T-1), \rho(T-1)] = \gamma \begin{bmatrix} P(R_j \mid T-1) EVW[i, \mu(T-1), \rho(T-1)] + \\ (1 - P(R_j \mid T-1)) \max(0, EVI(i \mid \mu(T-1), \rho(T-1)]) \end{bmatrix} \textbf{(4-15)}$$

The first part of the formulation shown in Equation 4-15 indicates the state in which homeowner j reconstructs and homeowner i updates its belief accordingly, while the next part refers to the state in which homeowner j does not reconstruct and homeowner i reconstructs if the payoff is positive. Homeowner i would be indifferent between immediate reconstruction and waiting if the payoffs are the same. Equating equations 4-14 and 4-15 leads to the equilibrium solution for the probability of reconstruction at each time period:

$$P(R_j \mid T-1) = \frac{(1-\gamma)\max[0, EVI[i \mid \mu(T-1), \rho(T-1)]}{\gamma\left(EVW[i \mid \mu(T-1), \rho(T-1)] - \max[0, EVI[i \mid \mu(T-1), \rho(T-1)]]\right)} \quad \textbf{(4-16)}$$

Considering no prior reconstruction, the same reasoning can be applied to other reconstruction periods. Hence, the probability computed in Equation 4-16 is the mixed strategy solution for the formulated game. This shows that if the payoff discrepancy between waiting and immediate reconstruction is not substantial, an increase in the probability of reconstruction will be expected. This can be attributed to signals with high precisions. On the other hand, under low precision signals condition, an increase in level of discounting will results in an increase in $(1-\gamma)/\gamma^{-1}$ ratio and increase the probability of reconstruction now.

4.2.4. MAS Integration

The result shown in Equation 4-16, indicates the mixed strategy equilibrium for homeowners at each period. As previously stated, this equilibrium strategy is denoted in the form of probability of reconstruction at each time considering no previous reconstruction. To integrate the result in the MAS model, at each period the expected value of instant reconstruction together with the expected value of waiting is computed for each homeowner. This will result in probability of reconstruction for each homeowner in that period. After computing this probability, a random number within the range of zero to hundred is assigned to each homeowner. If the probability of reconstruction for a given homeowner exceeds the value of the assigned random number divided by hundred exceeds, the homeowner will reconstruct and otherwise the homeowner will wait.

4.3. EMPIRICAL MODEL

This subsection presents an empirical model for making decisions regarding reconstruction of properties. The empirical model is based on an experiment designed to mimic a situation with conditions similar to real post-disaster conditions. The null hypothesis in this part of the study was that homeowners' decisions are not affected by the following variables: 1) availability of infrastructure, 2) percent of damages in the area, 3) homeowners' financial capacity, 4) property value before disaster, and 5) the value of a new housing alternative. These parameters were incorporated in the design of the experiment.

4.3.1. Experiment Design

The first step in designing the experiment was to define a scenario. In this experiment, it was assumed that a neighborhood with similar house plans and values was affected by a hurricane. This has caused a significant damage in the neighborhood, forcing homeowners to rent houses in other part of the town. At the same time homeowners need to make decisions about reconstruction. Under these circumstances, each individual has three reconstruction strategies: 1) to reconstruct immediately, 2) to wait six-months and observe the reconstruction in the neighborhood, and 3) to take the insurance money and buy a new housing alternative somewhere else in the town. Homeowners have no information about whether their neighbors will reconstruct but can observe if they will, by waiting. If a homeowner reconstructs right away and no one else reconstructs, there would be a significant chance that the value of his/her property will be less than the cost of reconstruction. In contrast, if they all reconstruct, there would be a high chance of getting a property value much higher than the cost of repair. After defining the scenario, the next step was to characterize the variables. These variables are assumed to drive participants' decision-makings and capture the different aspects of the initial hypothesis.

Variables defined for the experiment are as follow: 1) ratio of property values before damage to the values of a new housing alternative (r_1) that defines the effect of new alternative value by contrasting it to the original property value, 2) ratio of available funds to required expenses (r_2) which denotes homeowners' financial viability, 3) ratio of property value before damage to its damaged value r_3 that represents the influence of level of property damage over reconstruction decisions, 4) percent of damages in the neighborhood (pd), which is an ordinal variable and indicates the severity of damages in the area with respective values of 0 for damage percentages below 50% and 1 for damages more than 50%, and finally 5) availability of infrastructure in the area (ai) with three possible values of 0, 1, and 2 where 0 corresponds to the case where there is no infrastructure variable, 1 is the case that the infrastructure will be available in maximum 3 months, and 3 is the case where the infrastructure is available.

The ratios defined here were categorized into multiple categories to be also used as ordinal variables in the empirical model. The logic behind this step was to eliminate the need for a data-intensive model required for continuous variables such as these variables. Details regarding categories associated with variables are summarized in Table 4-1.

Table 4-1. Experiment factorial design

Factor	Type	Range	Subtotal
r_1	ordinal	$r_1 \leq 1,\ r_1 > 1$	2
r_2	ordinal	$r_2 \leq 1,\ 1 < r_2 \leq 1.5$ $1.5 < r_2 \leq 2,\ 2 < r_2 \leq 2.5$ $r_2 \geq 2.5$	5
r_3	ordinal	$r_3 \leq 3,\ r_3 > 3$	2
pd	ordinal	$pd \leq 50,\ pd > 50$	2
ai	ordinal	$ai = 0, ai = 1, ai = 2$	3
		Total	120

As shown in Table 4-1, based on this experiment design, a total of 120 cases were possible. Each case was replicated four times by randomly selecting values from each factor level. This led to a total sample size of 480 for the experiment. The designed experiment was then used to collect information about participants' chosen action with regard to various post-disaster conditions. As mentioned earlier, the number of participants in the survey was 80 and each participant was given 6 cases. A sample of this survey together with its associated instructions is included in Appendix A.

4.3.2. Model Formulation

The collected data was used to structure a decision making model. To form the model, logistic regression was used as the statistical modeling technique. Logistic regression is a form of statistical modeling which relates a set of explanatory variables to a categorical response variable. Response variables can either have two or more than two categories and are called dichotomous or polytomous, respectively. In the case of this survey, the response variable could take 3 different categories and as such is a polytomous variable. Now depending on the type of the response variable, there are two ways to approach logistic regression. If the response variable is ordinal, ordinal logistic regression (proportional odds model or cumulative logistic regression) are used (McCullagh 1980) whereas when the response variable in nominal, generalized logits (multinomial logistic regression) is employed. In this survey the three different values for response variable are 1) reconstruct immediately, 2) wait for 6 months, observe neighbors' action and decide accordingly, and 3) take insurance money and buy a housing alternative somewhere else. Since the responses are nominal, generalized logits is pursued to perform logistic regression. Generalized logit models are extended form of binary logit models in which instead of having a single logit model, multiple logits are modeled.

4.3.2.1. Binary logit models

Binary logit models are a member of generalized linear models or GLMs which were introduced by Nelder and Wedderburn (1972). Generalized linear models are characterized by three components which are: 1) a random factor which represents the probability distribution of the response variable; 2) a systematic component which denotes a linear function of explanatory variables that are used as regressors; and 3) the link which defines the functional relationship between the systematic component and the expected value of the random component (Agresti 1990). Binary response Y with outcomes 0 and 1 is a Bernoulli random variable with mean $E(Y) = 1 \times P(Y = 1) + 0 \times P(Y = 0) = P(Y = 1)$. By denoting this probability as $\pi(x)$ the variance of Y would be:

$$VAR(Y) = E(Y^2) - [E(Y)]^2 = \pi(x)[1 - \pi(x)] \qquad \textbf{(4-17)}$$

Now for the binary response variable, a linear probability model can be defined as:

$$E(Y) = \pi(x) = \alpha + \beta x \qquad \textbf{(4-18)}$$

The regression model shown in Equation 4-18 displays a major conceptual shortcoming associated with linear probability model, which is the occurrence of probabilities beyond the feasible range of 0 to 1. To address this defect, it would be more beneficial if a logistic regression function is used, which is s-shape and has a monotonic relationship with its regressor (Agresti 1990). This is shown in the following equation:

$$\pi(x) = \frac{\exp(\alpha + \beta x)}{1 + \exp(\alpha + \beta x)} \qquad \textbf{(4-19)}$$

As a result, the link function that should be used to make the logistic regression a GLM is a log odds transformation or the logit which is shown below (Agresti 1990):

$$\log\left(\frac{\pi(x)}{1-\pi(x)}\right)=\alpha+\beta x \quad \textbf{(4-20)}$$

4.3.2.2. Generalized logit model

Binary logit models can be extended to multinomial logistic model as follow. If response variable Y can take on categories $1,2,...,n$, choosing k as the reference category will result in:

$$\log\left(\frac{\pi_j}{\pi_K}\right)=\log\left(\frac{P(Y=j)}{P(Y=k)}\right)=x'\beta_j \quad \textbf{(4-21)}$$

In which k is the fixed category and j can take on values between 0 and n. In addition x' is the vector of covariates and β_j is the vector of regression coefficients for j^{th} logit. By assuming that the last response category is the same as the reference category, the response probabilities ($\pi_1,...,\pi_n$) can be shown as below (SAS 2011):

$$\pi_n=\frac{1}{1+\sum_{i=1}^{n-1}e^{x'\beta_i}} \quad \textbf{(4-22)}$$

$$\pi_j=\pi_n e^{x'\beta_j} \quad \textbf{(4-23)}$$

In other words, in generalized logit the log odds of being in one level to being in the reference category is computed. In the context of this dissertation, the aforementioned description can be interpreted as modeling the log odds of choosing a recovery strategy other than instant reconstruction to the recovery strategy of instant reconstruction. The vector of explanatory variables consists of $r_1, r_2, r_3, pd,$ and ai and the reconstruction strategy is the response (dependent) variable.

4.3.3. Parameter Estimation

Assuming N independent observations of the dependent variable, and multiple observations for each fixed x_i value, it can be concluded that $E(Y_i) = n_i \pi(x_i)$ where $i = \{1, ..., I\}$, and $n_1 + ... + n_I = N$. Given that the joint probability mass function of Y_1 to Y_I would be proportional to the product of I binomial functions or simply the joint conditional probability of the observations, therefore (Agresti 1990):

$$\prod_{i=1}^{I} \pi(x_i)^{y_i} [1-\pi(x_i)]^{n_i - y_i} = \left\{ \prod_{i=1}^{I} [1-\pi(x_i)]^{n_i} \right\} \exp\left[\sum y_i \log\left(\frac{\pi(x_i)}{1-\pi(x_i)} \right) \right] \quad \textbf{(4-24)}$$

and as a result the log- likelihood will be defined as:

$$L(\beta) = \sum_j \left(\sum_i y_i x_{ij} \right) \beta_j - \sum_i n_i \log\left[1 + \exp\left(\sum_j \beta_j x_{ij} \right) \right] \quad \textbf{(4-25)}$$

The next step is to differentiate the log-likelihoods with respect to the vector of β and equal the results to zero. This will results in the following equations:

$$\frac{\partial L}{\partial \beta_a} = \sum_i y_i x_{ia} - \sum_i n_i x_{ia} \left[\frac{\exp\left(\sum_j \beta_j x_{ij} \right)}{1 + \exp\left(\sum_j \beta_j x_{ij} \right)} \right] \quad \textbf{(4-26)}$$

which can be solved using Newton-Raphson method. There are several commercial programs which perform these procedures among which SAS was used for the purpose of this dissertation.

4.3.4. Experiment Results

The multinomial logistic regression model for this dissertation was approached through the use of LOGISTIC procedure in SAS. This procedure is capable of forming generalized logits which considering the type of response variable in this experiment, qualifies it for implementation. This procedure has also the feature of incorporating backward elimination technique in which insignificant covariates are eliminated from the model one at a time. For the purpose of backward elimination, the significance level was set to 95 percent. The detail results from regression analysis are included in Appendix E.

Interpretation of the results from LOGISTIC procedure starts with model information, model type, optimization technique, model convergence status and number of observations. In this experiment, a generalized logit model with 480 observations and 3 nominal categories was studied. The optimization technique was based on Newton-Raphson method. Model convergence was set to its default criterion (10^{-8}). The model convergence criterion denotes how well maximum likelihood procedure for parameter estimation is converging. In addition, the reference category was selected to be the immediate reconstruction strategy versus other reconstruction alternatives.

In each step of backward elimination procedure, model convergence status is checked, then model fit statistics are reported for the model with and without covariates. This is then followed by the results of hypothesis checking of model significance with regard to its covariates. This iterative process continues until all the parameters remaining in the model are statistically significant.

According to the results of this study, backward elimination process took 3 steps to finalize the model during which two of the parameters were removed from the model. These two predictors were r_1 and r_3. Predictor r_1 captured the effect of new housing alternative and independent variable r_3 was the effect of intensity of property damages on reconstruction decisions.

The fit statistics for the model can be divided into two categories. The first is an absolute fit statistic which in this study is McFadden's pseudo R-squared and the second is the relative fit statistics known as information criteria an includes AIC (Akaike Information Criterion), SIC (Schwarz Information Criterion), and negative two times the maximized log-likelihood ($-2\log L_{\max}$). These model fit statistics are defined below.

<u>McFadden's R-squared</u>: The structure of McFadden's pseudo r^2 is similar to the original R-squared with this fact that in original R-squared the variability of estimation error to that of the data is compared whereas in McFadden's the log-likelihood of models with and without covariates are compared to each other. This likelihood ratio indicates the level of improvement gained by the full model over the model without covariates (Academic Technology Services 2011). This is shown below.

$$r_{MF}^2 = 1 - \frac{\log L(F)}{\log L(I)} \qquad \textbf{(4-27)}$$

The results from regression analysis revealed a value of 0.203 for McFadden's R-squared. Although this value is substantially low compared to original and non-pseudo R-squared but still shows a satisfactory level. Although Hosemer and Lemeshow (2000) referred to the low McFadden's R-squared values as being a norm, Shtatland et al.

(NSEUG) argued that the interpretation of the statistic is more important than the range of its value. Following is the list of information criteria used for the model.

SIC/BIC (Schwarz/Bayesian Information Criterion): This information criterion is comprised of two components as shown in equation 4-28. The first term corresponds to maximized log-likelihood $\log L_{\max}$ whereas the next is the penalty term for overfitting in which r is the number of categories for response variable, s is the number of covariates in the model and f_i is the frequency value for i^{th} observation.

$$\text{SIC} = -2\log L_{\max} + \left((r-1)(s+1)\right) * \log\left(\sum_i f_i\right) \qquad \textbf{(4-28)}$$

AIC (Akaike Information Criterion) which like BIC is influenced by both maximized log-likelihood and overfitting penalty and is shown in Equation 4-29.

$$\text{AIC} = -2\log L_{\max} + 2\left((r-1)+(s+1)\right) \qquad \textbf{(4-29)}$$

During backward elimination these model fit statistics are computed for each iteration. The summary of these values are shown in Table 4-2.

Table 4-2. SAS results from multinomial logistic regression-Model fit statistics

Criterion	Intercept	Intercept & Covariates (Step0)	Intercept & Covariates (Step1)	Intercept & Covariates (Step2)
AIC	1039.386	841.318	840.080	841.189
SC	1047.734	891.404	881.818	874.580
$-2\log L$	1035.386	817.318	820.080	825.189

For all these model fit criteria, the lesser the value the better is the fit. This is clearly shown in Table 4-2 by contrasting the model with intercept and covariates to the model just with the intercept for each step.

Furthermore, the hypothesis of having statistically significant set of parameters is checked by integrating the following tests, 1) Likelihood Ratio Test, 2) Score Test, and 3) Wald Test. In these tests, the null hypothesis is that the covariates are equal to zero and therefore if p-values are not significant, it can be concluded that removing the explanatory variables will not affect the fitness of the model. Likelihood Ratio test checks the likelihood of data been regressed by an alternative model compare to its base model (null hypothesis). In this test the null hypothesis model is the one with just the intercept and the alternative model is the one with intercept and covariates. This statistic is shown below:

$$\mathrm{LRT} = -2[\log L_{\max 0} - \log L_{\max 1}] \qquad \textbf{(4-30)}$$

Likelihood Ratio test is based on the difference between the log-likelihood statistics of a model with and without covariates. The distribution of this difference is chi-square with degrees of freedom equal to the difference in degrees of freedom of the two models. On the other hand, Wald test examines whether a parameter is equal to a certain value. Wald test statistic is shown below:

$$WTS = \frac{(\hat{\theta} - \theta_0)^2}{\mathrm{var}(\hat{\theta})} \tag{4-31}$$

In the context of this dissertation, this certain value is equal to zero and therefore failing to reject the null hypothesis denotes that the parameter can be deleted from the model. This is because an independent variable with a very small coefficient compare to its standard error cannot have a significant effect on estimating the dependent variable. Score test perform a similar action to Wald test. The test statistic is shown below which takes a chi-square distribution under null hypothesis:

$$ST = \frac{U(\theta_0)^2}{I(\theta_0)} \tag{4-32}$$

In which $U(\theta) = \frac{\partial \log L(\theta \mid x)}{\partial \theta}$, $I(\theta) = -\frac{\partial^2 \log L(\theta \mid x)}{\partial \theta^2}$, and null hypothesis is $H_0 : \theta = \theta_0$. According to the results, for all elimination steps, the p-values for these 3 tests were less than 0.001 for all elimination steps and as a result the null hypothesis of having zero covariates was rejected.

To proceed, the analysis extends to cover the maximum likelihood estimates from multinomial logistic regression using LOGISTIC procedure in SAS. These estimates are shown in Table 4-3. The details regarding this model can be found in Appendix E.

Table 4-3. SAS results from multinomial logistic regression-Logistic procedure

Parameter	*option*	DF	Estimate	St. Err	Wald Chisq	Pr>Chisq
Intercept	2	1	2.0172	0.6538	13.660	0.0002
Intercept	3	1	1.7657	0.7237	4.3092	0.0379
r_2	2	1	-0.2456	0.1839	7.1375	0.0075
r_2	3	1	-0.1363	0.2119	1.6557	0.1982
pd	2	1	1.1990	0.2826	18.0035	<0.0001
pd	3	1	2.7347	0.3342	66.9698	<0.0001
ai	2	1	-1.1070	0.1910	33.5981	<0.0001
ai	3	1	-2.1986	0.2248	95.6897	<0.0001

During backward elimination process since parameters r_1 and r_3 did not meet the 0.05 significance level, were removed from the model. Therefore it can be concluded that for these parameters the null hypothesis cannot be rejected. This indicates that the effect of a housing alternative and level of property damages on reconstruction decisions was not significant.

As shown in Table 4-3, the parameter estimation results correspond to two sets of equations labeled as 2 and 3 in Table 4-3 under column "*option*". These labels refer to the categories defined for the response variable. Label 2 refer to the reconstruction strategy of waiting for 6 months and observe neighbors' action and decide accordingly whereas label 3 refers to the strategy of getting insurance money and buy a housing alternative somewhere else in the town. Regression results denote that both percent of damage (pd) and availability of infrastructure (ai) are statistically significant across the two models. Parameter r_2 while significant in the first model, is not significant in the second model in the presence of other parameters. The resulting equations are listed below:

$$\log\left(\frac{P(op2)}{P(op1)}\right) = 2.0172 - 0.2456 * r_2 + 1.1990 * pd - 1.1070 * ai \qquad \textbf{(4-33)}$$

$$\log\left(\frac{P(op3)}{P(op1)}\right) = 1.7657 - 0.1363 * r_2 + 2.7347 * pd - 2.1986 * ai \qquad \textbf{(4-34)}$$

4.3.5. Discussion of the Results

Equation 4-33 indicates that for every one unit increase in availability of infrastructure (ai), the log of probability of waiting over probability of immediate reconstructing (reference option or immediate reconstruction) is decreased by 1.1070. Similarly, a unit increase in parameters pd and r_2 will results in 1.1990 increase and 0.2456 decrease in the log-odds of waiting (option 2) to immediate reconstruction (option 1).

The same logic can be used to interpret the results for Equation 4-34. Other important conclusions are, 1) the more the r_2 the less the probability of waiting or leaving the area to immediate reconstruction. This means that if available funds exceed expenses, it would be less likely for an individual to pursue a reconstruction strategy other than the instant reconstruction, 2) the more the pd the more the likelihood of waiting or leaving. This indicates that if the percent of damages in a neighborhood increases, it would be more likely for an individual to opt for its second and third reconstruction strategies rather than reconstructing right away, and finally 3) the more the ai the less the odds of waiting or leaving to immediate reconstruction (option1). This signifies the fact that if infrastructure is more accessible in a neighborhood, individuals are more likely to stay and reconstruct rather than leave their property for other reconstruction strategies. The regression results are included in Appendix E.

4.3.6. MAS Integration

The results shown in Equations 4-33 and 4-34 indicate the log odds of choosing an alternative (waiting or leaving the area) to the reference category (reconstruct immediately) based on the three different independent variables. These variables are the ratio of available funds to the required expenses, the percent of damages in the area, and the availability of infrastructure. To integrate the results in the MAS model, a series of steps needs to be taken which are: 1) identifying the infrastructure in the area. In this research the only infrastructure that was considered in the multi-agent system model was transportation infrastructure; 2) assigning proper level of availability to the existing infrastructure based on the defined empirical model. These availability levels are: available status, available in three months status and not available status which are set based on the distance of the given infrastructure from the source of disaster; 3) assigning proper level of damage to each property based on its distance to the source of disaster. This will results in calculation of percent of damages in the neighborhood in the MAS model; 4) assigning financial resources and proper reconstruction cost to each homeowner based on its property level of damage. This will lead to calculation of the defined ratio (r_2) for each homeowner which denotes their financial flexibility. After accomplishing all the previously mentioned steps, the probabilities associated with each option for a homeowner can be computed using Equations 4-33, 4-34 and the fact that the sum of the probabilities should add up to 1. After computing the probabilities, just like the theoretical approach, a random number within the range of zero to hundred will be assigned to each homeowner. For each home owner, If the random number lies within the acceptable probability range of a strategy, that strategy will be the one that is assumed to be pursued by the homeowner.

4.4. SUMMARY

The objective of this section was to define a framework which can account for modeling agent's spatial interactions. The section started with a theoretical behavioral model which was solely focused on the neighboring aspect of homeowners' interaction. The result from the theoretical approach demonstrated that agents' actions are influenced by other agents in their surroundings. This conclusion was expressed as the probability of reconstruction at each time step based on the state of the environment. Furthermore to account for other factors, an experiment was designed and implemented with a goal of using the data to develop an empirical model.

The results from the empirical model show that in a more realistic post-disaster situation, the decision making of affected homeowners is significantly influenced by 3 variables: 1) severity of damages in the area which has a direct influence on choosing an alternative to reconstruct immediately, 2) availability of infrastructure in the area which in contrast to the previous parameter has a diverse effect on choosing an alternative to immediate reconstruction, and finally 3) the financial viability of homeowners which favors instant reconstruction. The next section proceeds to capture the next micro-level research question, which is how agents interact in the organizational domain.

4.5. LIMITATIONS

Although the results from both theoretical and empirical models yielded rational results, there were limitations associated with each modeling approach that might affect the broad applicability of the results. These limitations are listed separately for each model.

In the theoretical model, the defined utility for homeowners had a limited number of parameters in contrast to its complex structure in real conditions. Furthermore, other influencing parameters such as availability of infrastructure were not included in the model. In addition, the mixed strategy equilibrium for the probability of reconstruction at each time step was based on the assumption that the interaction between homeowners starts with a case where there are just two homeowners and this is not significantly different from the results of a sub-game perfect equilibrium. On the other hand, in the empirical model, the number of influencing variables were limited. in addition, due to the insufficient number of participants for the experiment, all the variables were defined as ordinal.

To overcome these limitations, the theoretical model should be extended to account for multi-neighbor cases. On the other hand due to the fact that in the empirical model, parameter estimation is based on maximum likelihood method, the more the data the better is the model. Therefore to have a better predictor of real conditions, more data is needed which requires a huge number of survey participants.

5. MODELING ORGANIZATIONAL INTERACTIONS

5.1. INTRODUCTION

The objective of this section is to address the second micro-level objective of this dissertation - how individuals interact in the organizational domain while negotiating with high-bargaining-power entities such as insurers. Much like the previous chapter, this section is divided into two subsections. The objective of the first subsection is to present a theoretical model of homeowner-insurer bargaining process, while the next subsection is focused on comparing the results from theoretical model with the data from an experimental study. The summary of findings is presented in the third subsection, which is then followed by the assumptions and limitations in this section.

5.2. THEORETICAL MODEL

5.2.1. Background

Bargaining situations from a broad perspective occur when individuals or organizations have a common interest in cooperation and conflicting interests in the form of cooperation (Muthoo 2002). An example of these situations is the common-conflicting set of interests with regard to division of a surplus between players.

Bargaining theory has been widely discussed in literature and applied to many research domains. The motivation behind implementation of bargaining theory is to capture the behavior of players in a game with mutual interests. Examples of bargaining situations in different research areas include bribery and corruption (Basu et al. 1992; Hindriks et al. 1999), wage negotiations (Gertler and Trigari 2009; Knabe 2009; Ellis and Fender 1985; Grout 1984; McDonald and Solow 1981), marriage (Lundberg and Pollak 1993; McElroy and Horney 1981; Manser and Brown 1980), coalition formation (Psathas and Stryker 1965), conflict analysis (Anbarci et al. 2002), bid bargaining games (Daniel et al. 1998), and war modeling (Reed 2003).

In the context of homeowner-insurer negotiations, the related studies include the availability of equilibrium in competitive insurance markets by Rothschild and Stiglitz (1976), the existence of equilibrium in reinsurance markets by Borch (1962), the effect of risk aversion on bargaining by Kihlstrom and Roth (1982), the analysis of monopolistic insurance markets by Stiglitz (1977), and the two-person insurance negotiation by Schlesinger (1984).

The focus of this subsection is on the application of bargaining theory in post-disaster negotiations; more specifically, to investigate the interactions between affected homeowners on one side, and insurers on the other. This is a very important, yet often overlooked aspect of the recovery process. There are numerous reported cases where insurance settlement offers were much lower than estimated losses and claims. Following Hurricane Katrina, National Public Radio (NPR) and Public Broadcasting Service (PBS) have extensively reported on the problems homeowners have in settling claims and obtaining insurance. A similar problem was reported by the Port of New Orleans. Here, the bargaining power of the insurers is much greater than the bargaining power of the homeowners. In such settings, "stressed" agents are often impatient and willing to accept offers they might not otherwise have considered.

Therefore there is a need to model this process so that public agencies can react correspondingly. In this section the goal is to address the same need using both theoretical and empirical models. While theoretical model conceptually approaches the problem, the empirical model reflects the results from the experiment.

5.2.2. Model Formulation

The bargaining model presented here is designed to capture the interaction between players in the incidence of a disaster. In this settings, the two players are 1) insurer and 2) homeowner. In addition, it is assumed that the players are bargaining over the difference between the maximum claim amount and no compensation.

Homeowners seek to maximize their claims while insurers try to minimize their losses. Under this bargaining situation, one of the major driving factors is the available strategies for both players. Each strategy will result in a payoff, which in bargaining literature is divided into two categories. The first category is attributed to the payoffs that are acquired while players are still in-play, negotiating to achieve an agreement and is called an inside option. The other category is related to payoffs gained by players due to quitting the game without reaching to an agreement (Muthoo 1999). In the theoretical owner-insurer negotiation framework of this dissertation, while no specific inside option was considered for players, the only available outside option was the payoff from referring the case to court.

The model was designed in such a way that it can mimic a bargaining situation in a case of a disaster. Following a disaster, bargaining starts between the affected population and their insurers regarding the amount of compensation for the incurred damage. Subsequent to the incidence, an insurer and homeowner start negotiating to reach an agreement. The players are assumed to be rational players and therefore maximizing their utilities.

The sequence of this bargaining game is as follows: The insurer starts the negotiation by offering a claim amount to the homeowner. To respond, the homeowner has three strategies: 1) accept the insurer's offer, 2) reject and continue negotiation by making a counteroffer, and 3) reject and take the case to the court in the next period. If the homeowner chooses the first strategy the game is finished, if it prefers to take the case to court both players will get their undiscounted court payoffs; and finally if the homeowner opts for a counteroffer, the insurer has the option to either accept or reject this counteroffer. In the next period, if the insurer accepts the offer, the game ends and if he rejects, the case will be taken to court in which both players will get their court payoffs. The homeowner's court payoff is assumed to be a random draw from a uniform distribution, (in this study distribution parameters are assumed to be $a = 0.7$ and $b = 0.9$) of the maximum claim amount which will be discounted by a common discount factor (assumed to be $\delta = 0.9$) for each time step that an agreement is not achieved. For simplicity the maximum claim amount is assumed to be 1. The discount factor is incorporated in the model to account for the costly nature of waiting. Furthermore, both players have a unique outside option, which is pursued by taking the case to court. It is also assumed that the bargaining problem is a multi-period process, which will be resolved in two-steps. In this model delay can be costly and in equilibrium condition, the very first offer is accepted.

5.2.3. Model Solution

Since the bargaining problem in this research is a finite sequential process, the extensive form of the game can be used to find the equilibrium strategy for the players. The extensive form of the game is shown in Figure 5-1. In the extensive from, the game is broken down into its feasible sets of strategies called subgames. The next step is to check for Nash equlibria in each subgame. A Nash equilibrium is an optimal solution for a game in terms of strategies for players, in which none of the players can improve their payoffs by unilaterally changing their strategy. This process leads to finding the subgame perfect Nash equilibria for the game. In the context of this dissertation, the goal is to find an equilibrium offer in the insurer-homeowner negotiations. This equilibrium strategy implies the amount of offer that should be made by insurer in the first period to make the homeowner indifferent between accepting and rejecting and eventually accepting the offer. The idea of subgame-perfect equilibrium for extensive-form games was initiated by Selten (1978). A subgame perfect Nash equilibrium is a strategy which leads to the Nash Equilibrium of every subgame of the original game. To compute subgame perfect Nash equilibria, backward induction method is used. Backward induction is an iterative process in which the optimal strategy is initially found for the last period of the game and is subsequently used to find the optimal strategies for the previous stages. This backward process continues until all players' actions are being determined. In this study the game in its extensive form (Figure 5-1), is a finite sequential game in which the game starts with a first offer, continues with a possible counteroffer and ends with acceptance or the court payoffs.

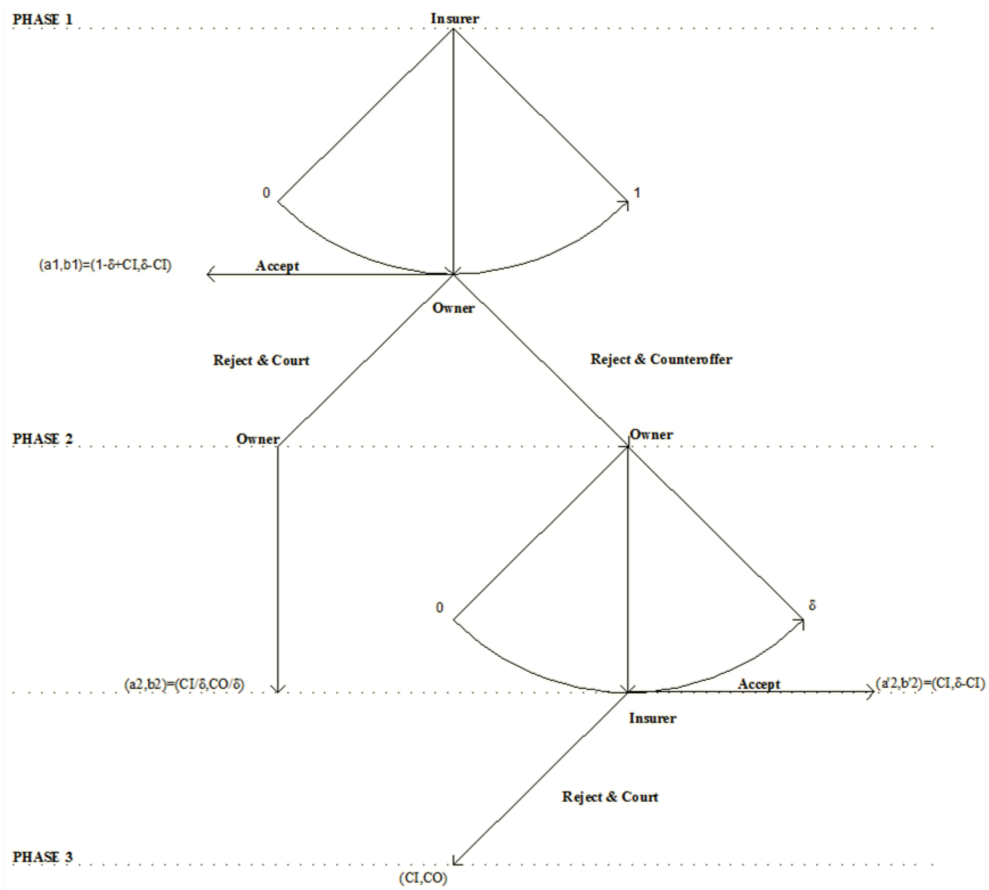


Figure 5-1. Extensive form of the bargaining game

Consider the backward induction process for the extended form of the game in Figure 5-1, it is shown that in the 3rd period, if they do not reach the agreement beforehand, both players will get their court payoffs C_I, C_o. C_I is insurer's court payoff whereas C_o is homeowner's court payoff. In this period the negotiation value has been discounted twice, therefore $C_I + C_o = \delta^2$. Now by moving one step backward in period 2, there are two strategies available for the homeowner. The first is to reject insurer's offer (from the first period) and go to the court whereas the second is to reject the offer and make a counteroffer. If homeowner chooses the first option the payoffs for insurer and homeowner would be $\frac{C_I}{\delta}, \frac{C_o}{\delta}$ respectively.

On the other hand if homeowner chooses to make a counteroffer the payoffs will change to $C_I, \delta - C_I$. This is due to the fact that the homeowner knows that if insurer does not accept the offer, the case will be directed to court and insurer will get its court payoff. Therefore homeowner will make its offer to be the same as insurer's court payoff. In addition, since in this period the negotiation value has been discounted once. Proceeding with the backward process in period 1, there is a unique strategy for the insurer to start the bargaining process.

Since insurer knows that in period 2, homeowner will opt for the second strategy which is rejecting and making a counter offer (since the outcome of this strategy for the homeowner is always higher than the outcome from directing the case to court), insurer will make its offer to be the same as homeowner's highest payoff in the 2nd period. As a result insurer's equilibrium strategy would be to offer $\delta - C_I$ for homeowner and keep $1 - \delta + C_I$ for himself. This strategy profile concludes the theoretical approach to solve the bargaining game. The next subsection will approach the problem from an empirical point of view to contrast the results to that of a theoretical approach.

5.2.4. MAS Integration

The result from the theoretical approach to capture the organizational behavior of homeowners was presented as an equilibrium offer from insurer in the first period. The structure of this equilibrium offer is very similar to the alternating offer bargaining model by Rubinstein (1982). This equilibrium offer is based on three variables which are: 1) discount factor, 2) maximum bargaining value, and 3) Insurer's court payoff wghich are initially defined for the model. Therefore integration of these results in the MAS model requires entering the proper values for each variable and for each homeowner in the model.

5.3. EMPIRICAL MODEL

5.3.1. Experiment Design

The empirical model studied in this dissertation is based on an experiment designed to capture a similar situation to what occurs between insurer and homeowner following a disaster. The experiment was designed to pose a situation that maybe more familiar to the participants (i.e. undergraduate students). Among the possible options, a case of a car accident seemed to be a good example due to its nature and the way the negotiations between players take place. This is due to the fact that the strategies defined for both parties are the same as those identified for the theoretical model. Therefore, the game starts with insurer's offer to car-owner. The car-owner can accept the offer, reject- go to court, and reject-make a counter offer. The next step starts with insurer's either accepting or rejecting car-owner's offer. Failing to reach an agreement in the second period, will result in court payoffs for both parties. The details regarding the experiment together with the instructions to participants are included in Appendix F. Results from this experiment were used to formulate an empirical model to estimate more realistic choices and compared to the theoretical model to check for similarities and dissimilarities.

5.3.2. Model Formulation

Unlike the previous section, in the empirical model formulation there is no equilibrium offer available for the insurer to start the negotiation. In other words, an empirical model considers a payoff structure for players which is formed by incorporating their strategies and the associated probabilities with each of the strategies. The objective of this subsection is to estimate these strategies and probabilities by incorporating the data from the experiment and test for several hypotheses related to the empirical model presented below:

$$b_1 = P_{11}(b_1^{'}) + P_{12}(b_2) + P_{13}(\frac{C_O}{\delta}) \quad \textbf{(5-1)}$$

$$b_2 = P_{21}(C_O) + (1 - P_{21})(b_2^{'}) \quad \textbf{(5-2)}$$

In equations above $b_i, i \in \{1,2\}$ is car-owner's payoff in the i^{th} period, $P_{ij}, i \in \{1,2\}, j \in \{1,2,3\}$ is the probability of incurring event j at period i, C_O is car-owner's court payoff, δ is the common discount factor for both of the players, $b_1^{'}$ is insurer's offer to the car-owner in the first period, and finally $b_2^{'}$ is the car-owner's offer in the second period. As shown in Equations 5-1 and 5-2, in the first period car-owner's expected payoff would be a combination of its payoffs from various game outcomes with their associated probabilities.

There are three strategies available for the car-owner in this period, the first is to pursue its court payoff which is the third term in Equation 5-1 (C_O / δ), the next is to reject insurer's offer and make a counteroffer which corresponds to the second term of the equation (b_2), and finally the last is to accept the insurer's offer which corresponds to the first term in the equation (b_1'). Similarly in the second period the car-owner's expected payoff is a combination of its payoff from 1) court payoff due to insurer's rejection (C_O), and 2) its own offer due to insurer's acceptation of the offer (b_2') and their associated probabilities.

5.3.3. Model Fitting

The subsequent step to model formulation is to estimate the parameters in Equations 5-1 and 5-2 by formulating and testing the hypotheses. The null hypotheses formed for this purpose are as following: 1) insurer's initial offer to homeowner (b_1) does not follow a specific distribution, 2) car-owners' decision following insurer's initial offer is not associated with the size of insurer's initial offer. This hypothesis is to check whether probabilities associated with homeowner's response ($P_{11}, P_{12},$ and P_{13}) to insurer's initial offer (b_1) is significantly related to the size of the offer from insurer (b_1), 3) car-owner's counter offer (b_2) is not associated with insurer's initial offer (b_1), 4) insurer's decision to car-owner's counteroffer is not related to the magnitude of the counteroffer (b_2'). The assumptions were statistically analyzed to check for validity and significance. The whole process is shown in Figure 5-2.

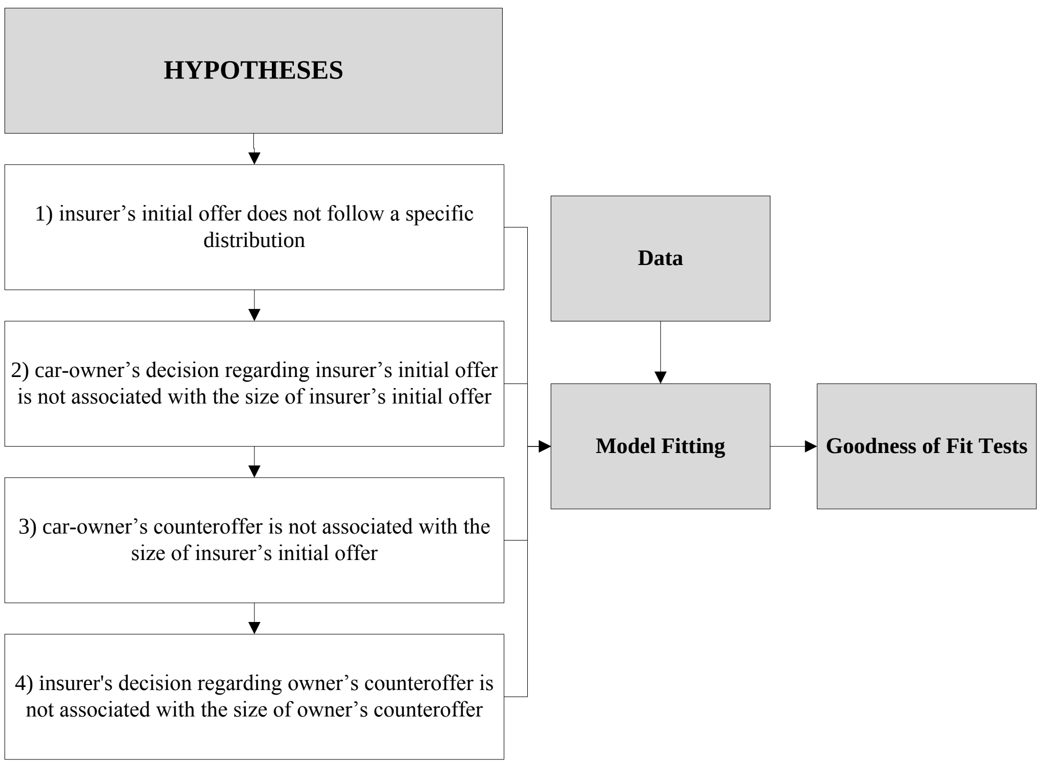


Figure 5-2. The process of experimental model development

5.3.3.1. *Null Hypothesis 1: "Insurer's initial offer does not follow a specific distribution"*

The null hypothesis is that the observed data from insurer's offer are not random draws from a specific distribution. A variety of methods can be used to fit distributions to data and check for their statistical significance. These fitting procedures can either be empirical (nonparametric) or parametric. Each of these methods has its own benefits and drawbacks. Nonparametric models are usually easier to use but at the same time need larger sample sizes. Parametric models are more complicated but are capable of estimating parameters inside the feasible range and outside the observed data (Vose, 2008).

For the purpose of this dissertation since regression outcome is intended to be directly used in the MAS model, the preference was given to a parametric regression. To accomplish this, a wide range of possible distributions were checked for the observed data through ModelRisk by Vose Software in which a total of 51 continuous univariate distributions where fitted to data.

In this approach Maximum Likelihood Estimation (MLE) technique was used for parameter estimation. The fitting results were rank ordered based on their information criteria. Three information criteria were used to rank the fitted distributions. These information criteria were: 1) SIC (Schwarz Information Criterion); 2) AIC (Akaike Information Criterion); and 3) HQIC (Hanna-Quinn Information Criterion). Information criteria were used as replacements for popular goodness of fit statistics such as Chi-Square, Kolmogorov-Smirnoff, and Anderson-Darling. The reason is a set of drawbacks associated with them such as, 1) they present the probability that data generated from the fitted distribution has a goodness of fit statistic as low as the observed data instead of providing a probability that observed data are necessarily random draws from the fitted distribution, and 2) they cannot integrate censored, truncated, or binned data (Vose 2008).

For information criteria, the lower the values are the better the fit will be. The other main benefit of using information criteria is that they penalize the model for overfitting which is caused by additional parameters in the model to increase the likelihood. The first two information criteria were described earlier in the chapter. Similar to AIC and SIC, HQIC is also comprised of a separate component for the maximized likelihood and a penalizing component for the number of parameters. This is shown in Equation 5-3.

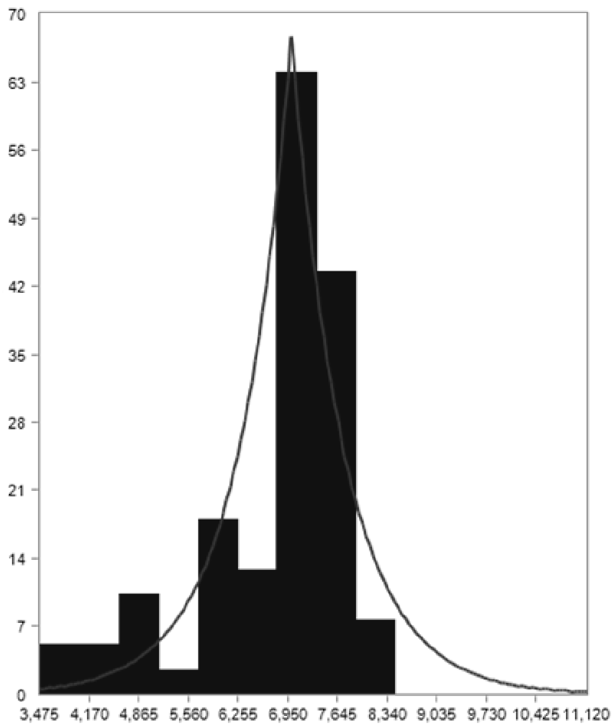
$$\mathrm{HQIC} = -2\log L_{\max} + 2\ln[\ln[n]]k \qquad \textbf{(5-3)}$$

in which n is the number of observations, and k is the number of predictors. Among these criteria SIC is the one with more penalizing power and AIC is the one with the least (Vose 2008). The summary of fitting results rank ordered by their fitting statistics is shown in Table 5-1. As shown in the table the best fit resulted from a Laplace distribution with location parameter (μ) of 7000 and scale parameter (b) of 1044.7.

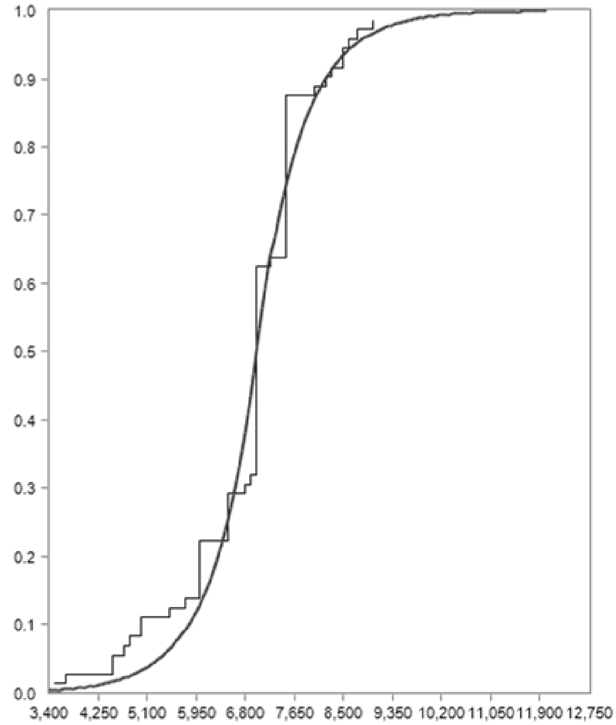
Table 5-1. List of the top 3 fitted distributions

Distribution	AIC	SIC	HQIC
Laplace	-1186.853	-1182.504	-1184.127
Log-Laplace	-1194.104	-1187.674	-1190.015
GLogistic	-1195.233	-1188.803	-1191.144

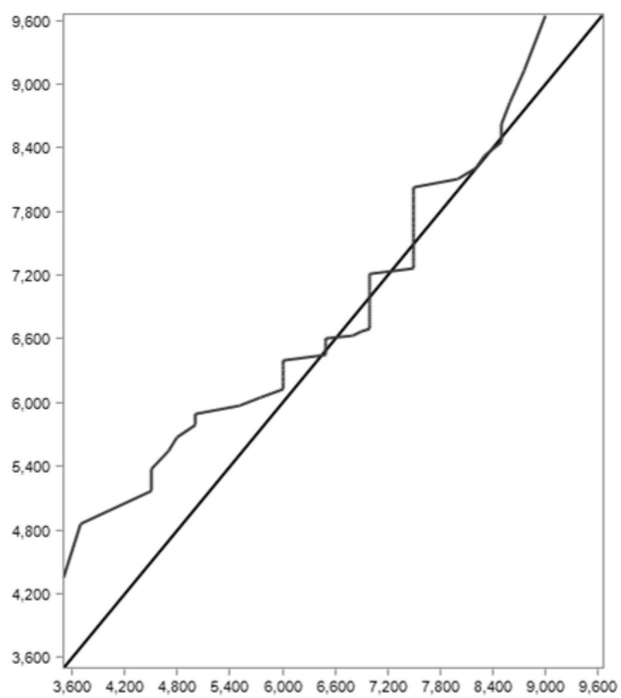
Apart from model fit statistics, goodness of fit plots are also a good measure to visually check the overall fit of a proposed model. Figure 5-3 shows these plots taken from the output of ModelRisk software. The plots are 1) histogram of the observed data versus PDF of the fitted distribution, 2) cumulative histogram of the observed data versus CDF of the fitted model, 3) Q_Q plot or Quantile-Quantile plot which is a probability plot that contrast two probability distributions (observed against fitted) by plotting their quantiles against each other, and 4) P_P plot or Probability-Probability plot which is a graphical representation of comparing two cumulative distributions (observed against fitted) against each other. In the first two plots, the goodness of fit can be visually checked by observing how the histograms of the observed data match the PDF and CDF of the fitted distribution. In Q-Q and P_P plots, the goodness of fit can be observed by checking how close the quantiles and cumulative distributions from observed data match up with the same values for the fitted distribution. In an ideal case the values should lie on the diagonal line shown in Figure 5-3.



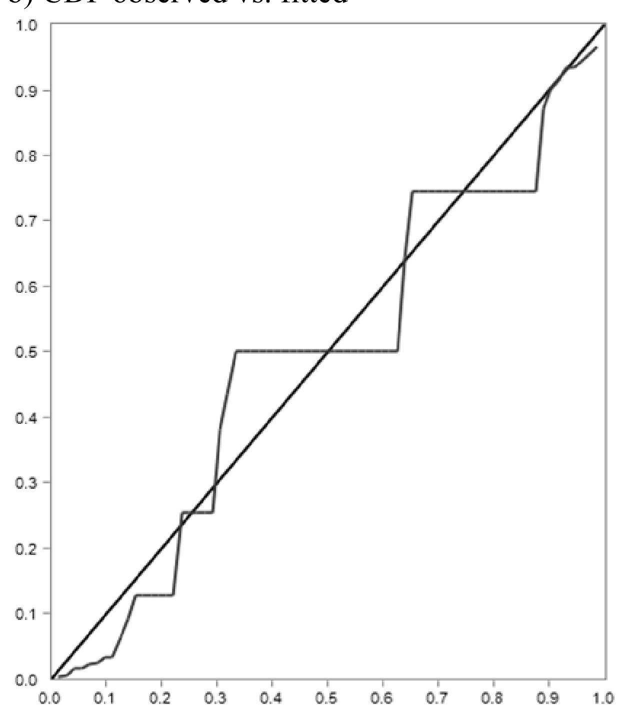
a) PDF observed vs. fitted



b) CDF observed vs. fitted



c) P-P plot



d) Q_Q plot

Figure 5-3. Goodness of fit plots (ModelRisk Vose Software)

Since information criteria such as AIC do not provide test statistics, a similar approach was performed in another commercial statistical software, EasyFit, in which the Laplace distribution was contrasted to four major univariate distributions which were Lognormal, Gamma, Normal and Weibull. The results from EasyFit statistical analysis are shown in Figure 5-4 and Table 5-2. The results demonstrated that the Laplace distribution fairly predicted the data, had the highest overall ranking, and as such rejected the first null hypothesis that the data are not random draws from a specific distribution.

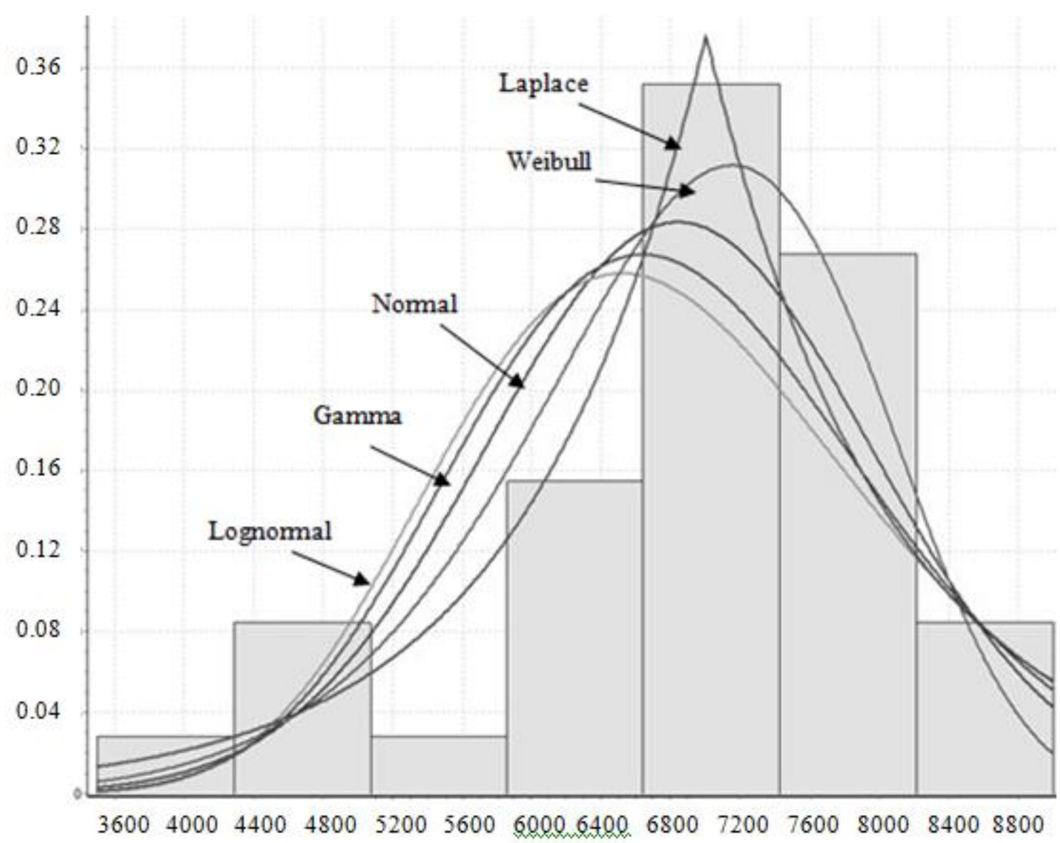


Figure 5-4. Fitted distributions to the data (EasyFit Software)

Table 5-2. EasyFit statistical analysis result for fitted distributions (numbers in parentheses denote distribution ranking for each test)

	Kolmogorov Smirnoff		Anderson Darling		Chi-Squared	
Distributions	Statistic	Pvalue	Statistic	Pvalue	Statistic	Pvalue
Laplace (1,2,4)	0.19718	0.00679	2.495	NS	29.269	2.05E-5
Gamma (4,4,1)	0.25145	1.92E-4	3.8225	S	11.988	0.03496
Lognormal (5,5,5)	0.25827	1.15E-4	4.3173	S	39.649	1.76E-7
Normal (3,3,3)	0.233	7.139E-4	2.9838	S	24.869	1.477E-4
Weibull (2,1,2)	0.19823	0.00639	2.193	NS	23.767	2.41E-4

The results from hypothesis testing in this subsection showed that insurer's initial offer (b_1) can be fitted to a Laplace distribution with parameters $\mu = 7000$ and $b = 1044.7$ via significant goodness of fit statistics. This is clearly shown in Table 5-2. In this table for each fitted distribution, three goodness of fit statistics are presented together with their respective Pvalues. Furthermore the ranking of each distribution for those statistics are given. Based on these information, the Laplace distribution had the best overall ranking of 1st for Kolmogorov Smirnoff, 2nd for Anderson Darling, and 4th for Chi-squared. This denotes that the first hypothesis indicating that insurer's initial offer is not a random draw from a specific distribution can be rejected.

5.3.3.2. *Null Hypothesis 2: "There is no association between insurer's offer and car-owner's following actions"*

The next step to integrate the bargaining game in the MAS model is to inspect the effect of changes in the value of the insurer's offer on car-owner's decision making in the first bargaining period. This requires a statistical modeling technique in which the outcome variable is categorical. In this phase of bargaining there are 3 available options for the car-owner which are 1) accept the offer, 2) reject and make a counter offer, and 3) reject and go to court. Since the response variable is nominal and has more than 2 categories, multinomial logistic regression would be the proper modeling technique. The modeling procedure is the same as the one described for spatial experiment. Results from SAS statistical modeling software for multinomial regression is summarized in Table 5-3. The details are included in Appendix G. Since no ordinal classification can be assigned to the different levels of dependent variable, generalized logits is again employed for the analysis. The reference category for analysis was set to car-owner's last option which is to accept the offer. The second option was set to be the owner's counteroffer and finally the third option is to refer the case to court.

Table 5-3. SAS results from multinomial logistic regression-Logistic procedure

Parameter	act	DF	Estimate	St. Err	Wald Chisq	Pr>Chisq
Intercept	2	1	4.3344	0.6538	4.6156	0.0317
Intercept	3	1	3.5939	0.7237	2.1046	0.1469
Offer	2	1	-0.00068	0.00029	5.4247	0.0199
Offer	3	1	-0.00072	0.000365	3.8889	0.0486

The results from regression analysis indicates that the value of the offer in the first period is statistically significant across the two models. The outcomes of this logistic regression analysis can be shown in the following two equations:

$$\log\left(\frac{P_{12}}{P_{11}}\right) = 4.3344 - 0.00068 * b_1' \qquad \textbf{(5-4)}$$

$$\log\left(\frac{P_{13}}{P_{11}}\right) = 3.5939 - 0.00072 * b_1' \qquad \textbf{(5-5)}$$

Equation 5-4 indicates that for every one unit increase in insurer's initial offer (b_1'), the log of probability of choosing the counteroffer strategy over probability of accepting the offer (reference option) is decreased by 0.00068. Similarly in Equation 5-5, a unit increase in insurer's initial offer (b_1') will result in 0.00072 decrease in the log-odds of choosing the court option instead of accepting the offer. Furthermore these equations indicate that the more the offer is, the less would be the likelihood of preferring any other options over accepting the offer. The results from multinomial logistic regression in this part, contribute to finding the probability associated with owner's different strategies ($P_{11}, P_{12},$ and P_{13}) in Equation 5-1, in response to insurer's initial offer (b_1').

5.3.3.3. Null Hypothesis 3: "Car-owner's counter offer is not associated with insurer's offer in the first bargaining phase"

The third step was to check the hypothesis of not having an association between insurer's actions and car-owner's counter-offer. The hypothesis is checked by fitting a linear model to the data and check for the significance of the results.

There are four major criteria to be checked for a linear relationship between two variables, these criteria are: 1) linearity, which is to check whether the predictor and the response variable have a linear relationship. This can be checked by plotting the residuals against fitted values and check whether the distribution of the points is symmetrical along the horizontal line, 2) independence, which is to inspect whether there is a correlation among residuals which can indicate that there is a potential for model improvement. Independence can be checked by computing the autocorrelation among the residuals, 3) homoscedasticity, which is to check for the homogeneity of the variances and can be checked by inspecting the residual versus predicted values plot and look for any heterogeneity, and 4) normality, which is to check whether the errors are normally distributed in the model. Failing to demonstrate normally distributed errors in the model can be a good indication of having an outlier. This significantly affects parameter estimation, which in turn relies on minimizing the squared errors. This phenomenon can be detected by drawing the normal probability plot of the residual and check whether the points are randomly distributed along the diagonal line (Decision Forecasting 2011).

The analysis of data for linear regression was performed in both R and SAS programming environment. Table 5-4 summarizes the result from the original data in R. The results from linear regression denotes a significant linear relationship between car-owner's counter offer and insurance initial offer and as a result the null hypothesis of not having an association between these two parameters is rejected.

Table 5-4. R results from linear regression modeling for car-owner's counter offer

Parameter	**Estimate**	**St. Err**	**t value**	**Pr>|t|**
Intercept	2671.4749	814.7944	3.279	0.00343
Insurance-Offer	0.8449	0.1242	6.803	7.78e-07

In addition to Table 5-4, Figure 5-5 presents model's goodness-of-fit plots. As shown in the figure, there is a clear indication of having an outlier in the model. This can be detected by observing: 1) the residuals are not normally distributed along the horizontal line shown in the upper left side of the graph labeled as "Residuals vs Fitted", and 2) there is a point on "Residual vs Leverage" graph with a Cook's distance higher than 1, and 3) in the "Scale-Location" graph, there is a distinct trend in the distribution of the points.

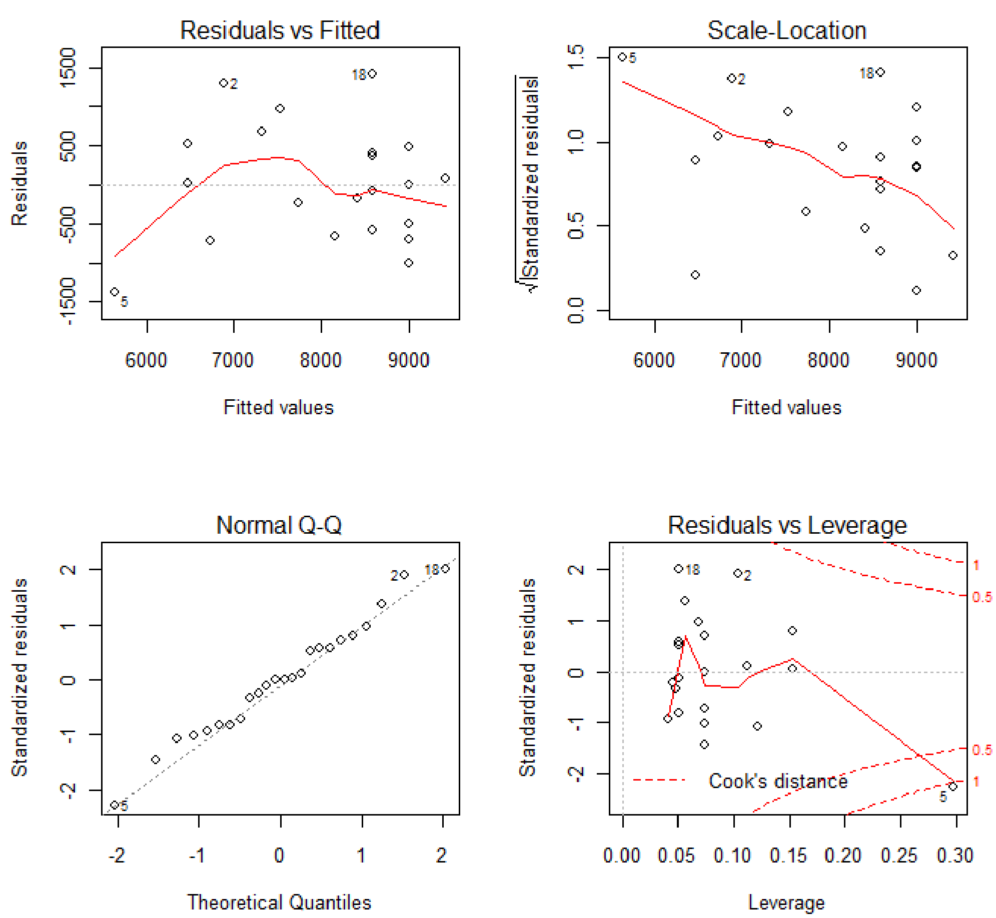


Figure 5-5. Model fit plots (R)

To address the problem the fifth observation was treated as an outlier and was deleted from the data (as labeled in the graphs) and the new data was analyzed. The goodness-of-fit plots are shown in Figure 5-6, while regression results are shown in Table 5-5.

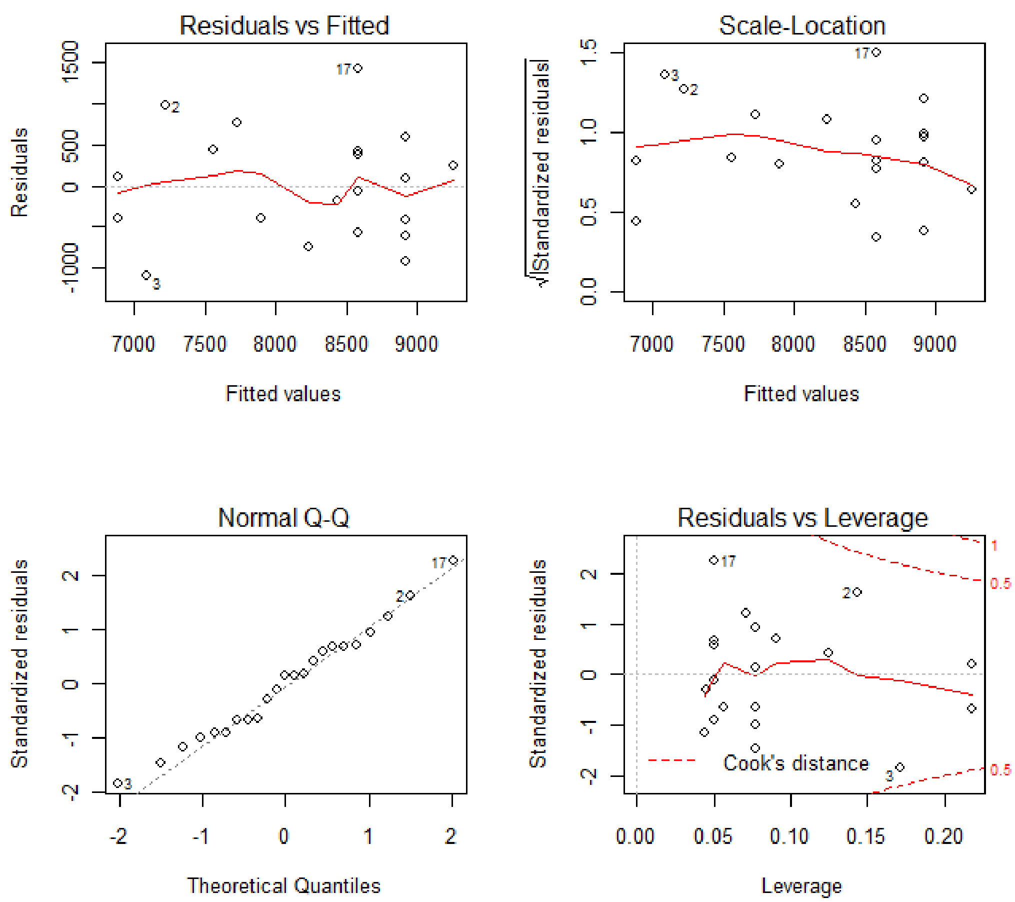


Figure 5-6. Model fit plots-Without outlier

Table 5-5. R results from linear regression modeling for car-owner's counter offer-without outlier

Parameter	Estimate	St. Err	t value	Pr>|t|
Intercept	3854.0463	865.5643	4.453	0.00022
Insurance-Offer	0.6743	0.1299	5.190	3.83e-05

As shown in Figure 5-6, the violations for linear regression criteria in the first model was fairly addressed by eliminating the fifth observation. Results from SAS linear regression analysis revealed a better linear fit compare to the original data. The details regarding this analysis are shown in Appendix H.

The statistical analysis results demonstrated a significant linear relationship between insurer's initial offer and owner's counteroffer. Therefore it can be concluded that the third null hypothesis of not having any association between these two values is rejected. This enables the model to predict owner's counteroffer (b_2') in Equation 5-2 based on the insurer's initial offer (b_1') in Equation 5-1.

5.3.3.4. Null Hypothesis 4: "Insurer's action following car-owner's counteroffer is not associated with the value of car-owner's counter-offer"

Finally, the last part of incorporating the bargaining concept into the MAS model was to check for any association between the value of car-owner's counteroffer and the probability of acceptance by insurer. Since under these settings, the response variable is categorical and has just two categories (accept or reject), binomial logistic regression was selected for modeling. Parameter estimation and optimization technique for binary logit models were previously described in the Section 4. Table 5-6 shows the regression results. The details regarding the regression results are included in Appendix I.

Table 5-6. Results from binomial logistic regression - R

Parameter	Estimate	St. Err	Z Value	Pr(>|Z|)
Intercept	-1.565e+1	7.427	-2.107	0.0352
offer	1.99e-03	9.089e-04	2.190	0.0285

The outcome from logistic regression indicates a statistical significance for the influence of car-owner's counteroffer on insurer's acceptance and hence the null hypothesis of having no association between these parameters is rejected. The resulting equation can be written as below:

$$\log\left(\frac{P_{21}}{1-P_{21}}\right) = -15.65 + 1.99e - 03 * (b_2') \qquad \textbf{(5-6)}$$

Equation 5-6 indicates that for every one unit increase in car-owner's counteroffer, the log of probability of rejection versus acceptance increases by 1.99*e-03. Furthermore this shows that the more the counteroffer is the less would be the likelihood of accepting the offer by the insurer. The results obtained here help predict the probabilities regarding insurer's accepting or rejecting owner's counteroffer (P_{21}) in Equation 5-2 and conclude the simulation of empirical bargaining procedure in the MAS model.

5.3.4. Estimation Results

As previously mentioned, data from the experimental study was used for estimating parameters of the empirical model (see Equations 5-1 and 5-2). These parameters include insurer's first offer (b_1'), car-owner's counter offer (b_2') and probabilities associated with each of the actions ($P_{11}, P_{12}, P_{13},$ and P_{21}). For the insurer's first offer, the statistical analysis showed that the hypothesis of having a model to significantly fit the data is valid and the model is a Laplace distribution. Furthermore, the results from multinomial regression analysis showed that the owner's probability of accepting the insurer offer, rejecting it, or making a counter offer is significantly associated with the amount of insurer's offer. In addition, the analysis indicated that the owner's counteroffer is a significant linear relation with the amount of insurer's offer. Finally the statistical analysis showed that the insurer's reaction to owner's counteroffer is significantly associated with the amount of owner's counteroffer. The generalized bargaining model helps automate the empirical bargaining process in the MAS model and reveals how agents would behave under various post disaster bargaining situations.

5.3.5. MAS Integration

To integrate the results in the MAS model the following steps should be taken: 1) to code a program which can generate random variables from a Laplace distribution with its given parameters, 2) calculate the probabilities associated with homeowners' action based on the value generated from the Laplace distribution using Equations 5-5 and 5-5, 3) calculate homeowner's counter offer based on insurer's initial offer using the results shown in table 5-5, and finally 4) compute the probabilities associated with insurer's action in response to homeowner's counter offer using Equation 5-6. Accomplishing these steps leads to calculate the expected value of homeowners payoff in the first period (b_1) and concludes this subsection.

5.3.6. Summary

The objective of this section was to define a framework which can represent agents' organizational behavior while negotiating with higher bargaining power entities such as insurers. The section started with a theoretical model to present the optimal bargaining solution under post disaster conditions. The second part of the section was focused on capturing the same aspect of organizational interaction but from a more realistic point of view. To accomplish this task, an experiment was designed to support building an empirical model. Data collected from the experiment was used for parameter estimation for the empirical model using various statistical analysis methods. The next section introduces the multi agent framework and elaborates on how the models presented in Sections 4 and 5 will be incorporated in such a framework.

5.4. LIMITATIONS AND FUTURE WORK

Similar to the previous chapter, there are a few assumptions and limitations associated with this section which are: 1) simplifying the theoretical bargaining process in a 3-period bargaining model; 2) using a common discount factor for both of the insurer and homeowner in the theoretical model; 3) assuming no inside option and a unique outside option for both of the players; 4) assuming certain court payoffs for both players; 5) assuming a different hypothetical scenario for the empirical model, and 6) not having a large number of participants for the empirical model.

Future work is needed to address the aforesaid limitations. The theoretical model needs to integrate additional parameters including inside options or additional outside options. This can include the outside option of selling properties to other entities with a higher bargaining power rather than facing the insurer directly. Regarding the empirical model, a large number of participants is required to address the need for the intensive data requirement of model fitting due to the maximum likelihood method.

6. MULTIAGENT SYSTEM SIMULATION MODEL

6.1. INTRODUCTION

The objective of this section is to present a framework, which is capable of integrating the proposed spatial and organizational models, and analyze the results. Due to the complex nature of post-disaster recovery, this framework was based on previously discussed Multi-dimension Multi Agent Systems (MD-MAS) model. This MAS model selection allowed for simulating every single agent (homeowner) and their actions under the governing conditions and assessing the outcomes of their mutual interactions. The section starts with an introduction to MAS and extends to capture the structure of the model and its specifications. To proceed, the section presents a case study that considers both theoretical and empirical models to assess the recovery dynamics in the two-pronged spatial-organizational domain. The result from the model is then checked for sensitivity to different simulation set-up parameters. Finally the section ends with the summary of key discoveries and directions for future research.

6.2. MULTI AGENT SYSTEMS

The Multi Agent Systems (MAS) approach is applied in many research domains that require capturing dynamic interactions among multiple stakeholders. Examples of MAS application covers a wide range of domains including land-use and land-cover change (Parker et. al. 2003), epidemiology (Yergens et al. 2006), and traffic and transportation in complex networks (Burmeister et al. 1997). The MAS results often reveal the hidden behavior by accounting for temporal spatial interactions.

The MAS model is based on simulation of intelligent agents designed to achieve a variety of goals. The agents may have common or conflicting goals and may interact with other agents directly or indirectly (Bellifemine, 2007). Wooldridge and Jennings (1995) classifies intelligent agents as being reactive, proactive, and social. Furthermore, Padgham and Winikoff (2004) define an intelligent agent as an autonomous system situated in an environment, which is reactive to the changes in the environment, pursues its objectives determinedly while being flexible, recuperates from failures, and finally interacts with other agents.

The MAS model features have led to their implementation in different research areas such as modeling population dynamics based on economic status and cultural identity (Benenson, 1998), spatial patterns of unemployment (Conley and Topa, 2002), firms' spatial competition (Collins and Sherstyuk, 2000), complexity in human-environment interaction (An et al., 2005), land-use and land-cover change (Parker et. al, 2003), technology diffusion, resource use changes and policy analysis (Berger, 2001), and residential land use patterns (Irwin and Bockstael, 2002).

This wide range of applications for MAS models shows its high potential in handling the real-world complexities and as such qualifies it as an ideal candidate to represent a framework for modeling interactions among the homeowners and other agents during the post disaster recovery process.

6.3. MAS-MODEL STRUCTURE AND SPECIFICATIONS

In this section, the structure of the MAS model is presented in 4 sequential subsections. The first subsection named as *import-world* module, elaborates on the multi-agent framework chosen for the model and extends on how real world data was imported into this framework. To illustrate the process, a neighborhood in College Station, Texas is selected and is subsequently used to show model sensitivity to both theoretical and empirical models, and initial parameters. The second subsection presents the details of homeowners' decision making structure for both spatial and organizational domains and is named as *agent-setup* module. This is succeeded by the third subsection named as *run* module, which controls the details regarding each run of the simulation by incorporating the temporal and organizational aspect of recovery. Finally the last subsection illustrates the methods used to capture emergent spatial phenomena such as formation of clusters resulting from agents' interactions and was described as *cluster* module.

6.3.1. "import-world" Module

The multi-agent framework chosen for this dissertation was Netlogo (Wilensky, 1999). Netlogo started as StarlogoT in 1997 by Uri Wilensky and was named as Netlogo in 2002. Netlogo is a Java-based multi-domain multi-agent framework and has been used to capture the complexity of a variety of topics in the literature. This include population variation (BenDor et al. 2009), financial market (Dréau et al. 2009), green house effect (Shultz 2009), infection and epidemic dynamics (Kleczkowski and Maharaj 2010) and forest fire simulation (Niazi 2010).

One of the great advantages of multi-agent frameworks such as Netlogo is their ability to model spatial aspects of the problem. This plays a crucial role in the context of recovery dynamics where the recovery is significantly linked to the distribution of agents' location around the source of the disaster or its focal point. For the purpose of this dissertation, the same feature was used to import the real conditions to the simulated model.

There are two ways to import location data in Netlogo. In the first, the program detects subjects based on their color. This makes it easier for programming but at the same time impedes its applicability for the cases where there are a wide range of gradient colors and the cases where a color is shared among different subjects. In contrast to the first approach, the next method is based on using the GIS extension of the program. This extension enables the model to import GIS data in two forms of data files, which are ascii grid file and shape files. Ascii grid files include raster data whereas shape files include vector data such as points, lines and polygons (Wilensky 1999). The disadvantage regarding the second approach is its shortcoming in the types of imported data. This shortcoming can be attributed to the fact that the software is incapable of importing data from Google Earth© which is one of the most popular mapping software and browser.

Programs such as Google Earth© provide users with universal GIS data. However, this data cannot be saved as compatible formats with Netlogo. The outputs from Google Earth© have another file format named as Keyhole Markup Language (KML) which is the Extensible Markup Language (XML) form of the graphical data for the use in maps and map browsers. To address this shortcoming, a KML to shape file convertor (Zonum Solutions 2011) was used to convert data from KML extension to shape files that are usable in Netlogo framework. This enabled the model to benefit from the integrated features in Google Earth© such as pinpointing the targets and drawing polylines and polygons. The steps taken to import geographical information in Netlogo is described below for a selected neighborhood in College Station, Texas. Figure 6-1 shows this area.

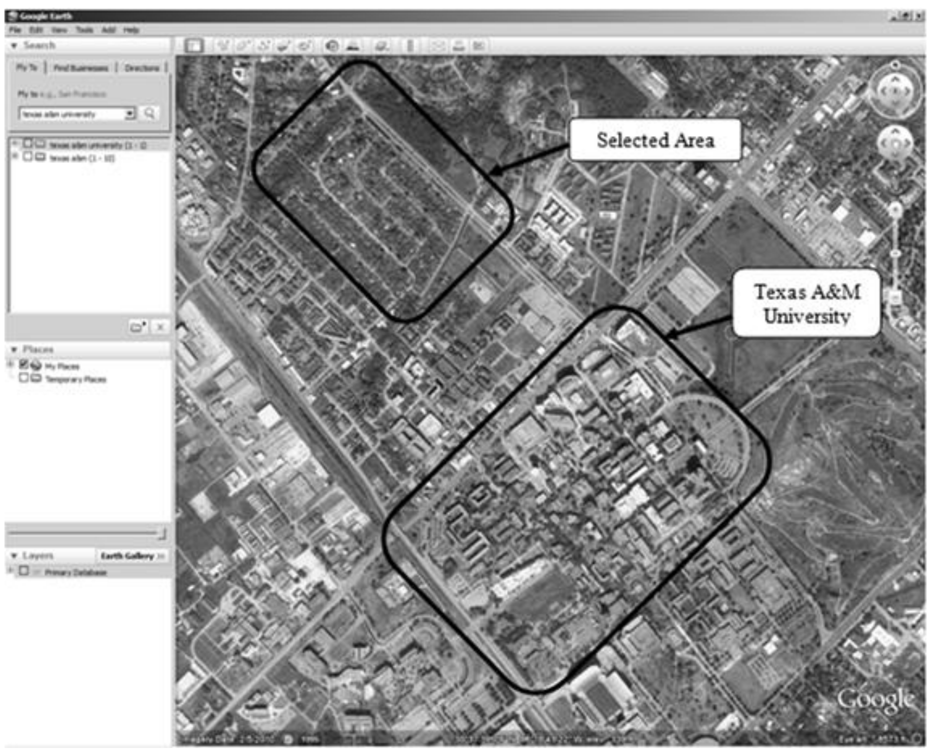


Figure 6-1. Area selection in Google Earth©

After area selection, the next step was to pinpoint targets (homes) and draw the polylines (streets) to import them as points and lines in the model. This step was performed using Google Earth© features and is shown in Figure 6-2 and Figure 6-3.

a) aerial map

b) aerial map with points

Figure 6-2. Aerial map with points

Figure 6-3 displays the added polylines to the area in Google Earth© that characterized the streets for model simulation.

Figure 6-3. Aerial map with points and polylines

After defining targets (homes) and polylines (streets), the next step was to import the data in Netlogo modeling framework. The importing procedure was accomplished by performing different subroutines and functions, list of which is shown in Figure 6-4 below. As shown in the figure, homes were detected as black dots whereas the streets or other infrastructure were distinguished as black polylines.

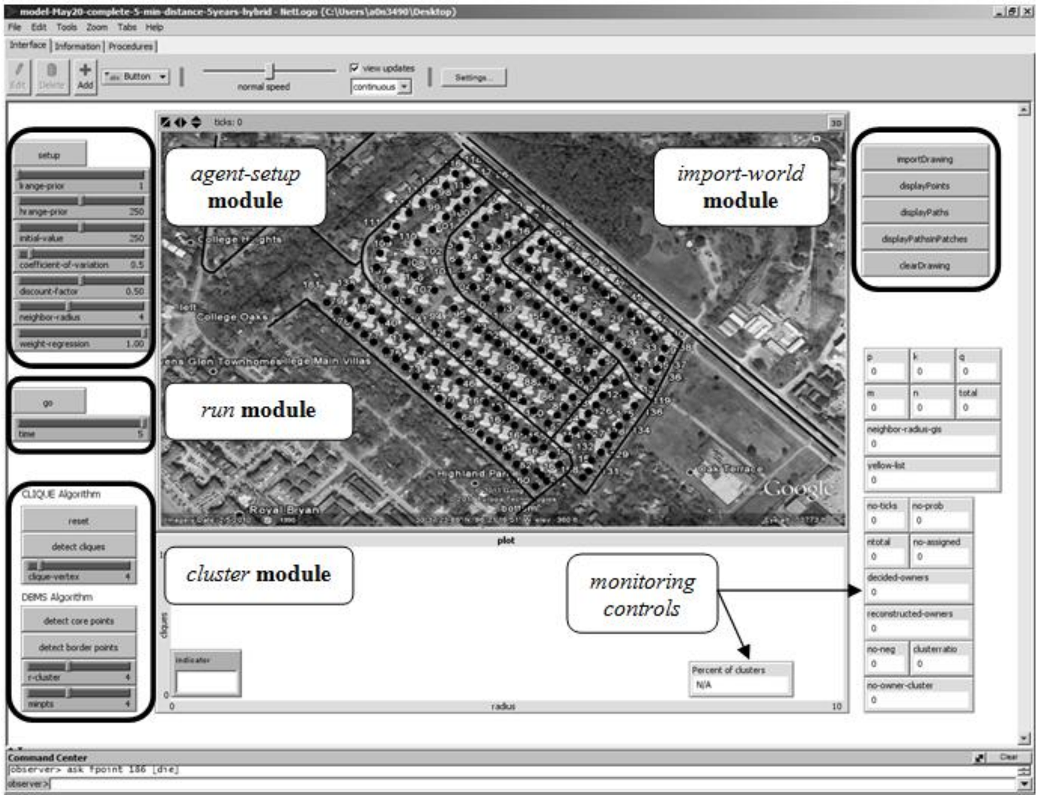


Figure 6-4. Imported area in Netlogo framework

In this figure, subroutines, functions, and controllers for each module known as programming components (PC) are presented. These programming components are separately illustrated for each module in their corresponding subsection. For the *import-world* module these components are listed in Figure 6-5.

```
SUB import-world
     import-drawing
     import-points
     import-paths
     detect-paths (as patches)
     clear-drawing
END
-------------------------------------------------------
FUNCTION import-drawing
     load(aerial-photo)
END
-------------------------------------------------------
FUNCTION import-points
     connect(points-database)
     define j = 0
     set i number of points in database
     while j <= i
     load(i)
     j = j + 1
END
-------------------------------------------------------
FUNCTION import-paths
     connect(paths-database)
     define j = 0
     set i number of points in database
     while j <= i
     load(i)
     j = j + 1
END
-------------------------------------------------------
FUNCTION detect-path (as patches)
     ask patches if [intersect(patch,path)] = true
     [set patch as path]
END
```

Figure 6-5. "import-world" pseudo code

After successfully importing the geographical data in Netlogo, The next step is to identify each agent and assign its properties. This is the objective of the next subsection.

6.3.2. "setup-agent" Module

The goal of this simulation step is to setup homeowners' decision-making structure and characterize a hypothetical case of a disaster. This was followed by defining variables that were previously introduced for both the theoretical and empirical models and was accomplished through a series of actions, 1) define the source of disaster, 2) characterize the points as homeowners by assigning them a decision-making structure for both theoretical and empirical models, and 3) assign proper level of damage to both homes and infrastructure based on their distance from the source of disaster. These are shown in Figure 6-6.

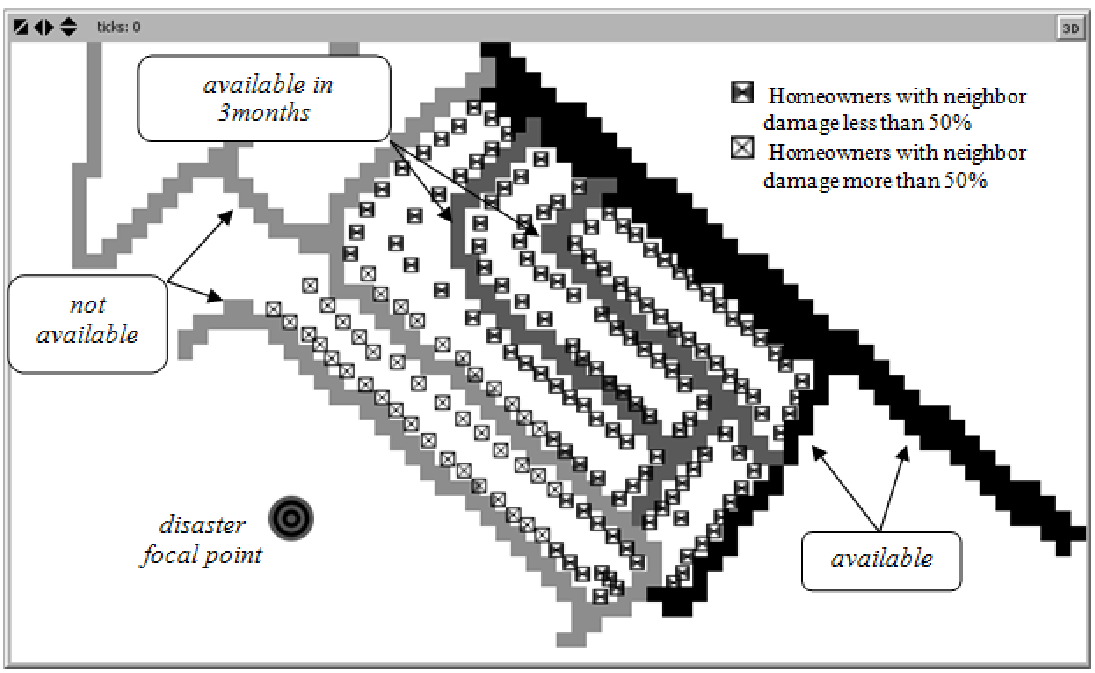


Figure 6-6. Characterized model in Netlogo

Parameters modeled in Figure 6-6 are the same as those resulted from the data used in spatial experiment in Section 4. According to the experiment results, homeowners' reconstruction decision is significantly associated with three variables which are: 1) the ratio of available funds to reconstruction costs; 2) percent of damages in the neighborhood which was categorized into two categories of below and over 50 percent of damages by using different icons; and 3) availability of infrastructure which was classified in three groups of not available, available in three month and available, by using different color codes.

Therefore the sequence of events in this subsection is as follow, initially the disaster took place in the area and affected both homeowners and infrastructure. Subsequent to this incident, homeowners are assigned a signal value, which is indicative of their future property value if they reconstruct. The range of the signal value and its precision together with homeowners' initial property value and discount factor are among the control simulation set-up parameters defined in this module.

At the same time, homeowners start bargaining with insurance companies to secure funds for future reconstruction. This bargaining procedure is approached by both theoretical and empirical models. This is then followed by defining neighborhood for each homeowner. This allows for updating beliefs in homeowners regarding the mean of property values in the neighborhood and their own future properly value. The parameter denoting the radius of each homeowner's neighborhood can also be set by the last control parameter in this module. These steps are shown in Figure 6-7.

```
SUB setup-agent
     disaster
     setup-homeowner
END
-------------------------------------------------------
FUNCTION disaster
     damage(infrastructure)
     damage(homeowners)
END
-------------------------------------------------------
FUNCTION damage(i)
     if i=infrastructure [set category]
     if i=homeowners [set percent-damage]
END
-------------------------------------------------------
FUNCTION setup-homeowner
     assign(signal, precision)
     assign(insurance)
     assign(neighbor)
     assign-belief
END
-------------------------------------------------------
FUNCTION assign-belief
     set-belief(mean-future-property-values)
     set-belief(own-future-property-value)
END
```

Figure 6-7. "setup-agent" pseudo code

After setting up the belief structure for homeowners, the next part is to simulate their actions based on the existing conditions in the area. This is the objective of the next subsection.

6.3.3. "run" Module

This module captures the temporal behavior of homeowners including the way they update their beliefs at each time step during the recovery process. As previously mentioned, two approaches were integrated in the model to capture the spatial and organizational interactions of agents. In the theoretical-spatial model, homeowners' behavior is based on the concepts of game theory and their mixed reconstruction strategy, whereas in the empirical-spatial model this behavior is a function of homeowners' available funds versus cost of reconstruction, percent of damages in the environment and availability of infrastructure. Similarly for the organizational domain, the theoretical model is based on bargaining theory whereas the empirical model captures the results from the experimental study. Agents' decisions in each of these approaches relies on their beliefs at the time of simulation which is updated in every time step using this module.

Furthermore to generate hybrid models, a parameter was defined to assign weights to each model. The sequence of events for each run of the model is as follows: 1) homeowners observe the current conditions in the area and update their beliefs accordingly; and 2) homeowners calculate their probability of reconstruction based on their updated beliefs and act respectively. This is shown in details in Figure 6-8.

```
SUB run
Loop
[
     I = I + 1:I = total number of agents [stop]
     select agent:select neighbor
-----------Reconstruction Strategy based on Experiment-----------
     Log(P(W)|P(R))=f(r2,pd,ai)
     Log(P(L)|P(R))=f'(r2,pd,ai)
     Calc-P(R) (Probability of Reconstruction)  (EQUATION 4-33 & 4-34)
     Calc-P(W) (Probability of Wait)            (EQUATION 4-33 & 4-34)
     Calc-P(L) (Probability of Leaving)         (EQUATION 4-33 & 4-34)
-----------Reconstruction Strategy based on Theory--------------
     [Update-Belief agent→(Signals Only)
     if neighbor.reconstruct = true then
     [Update-Belief agent](Signals & Real values)
     endif
     Calc-EVI (Immediate)
     Calc-EVW (Waiting)
     Calc-P(R) [reconstruct] [wait] (EQUATION 4-16)
-----------Bargaining Strategy based on Theory--------------
     Calc-Eq(offer) (SUBSECTION 5-2-3)
-----------Bargaining Strategy based on Experiment--------------
     Calc-b1 (expected payoff first round) (EQUATION 5-1)
     Calc-b2 (expected payoff counteroffer) (EQUATION 5-2)
     T= T + 1
]
END
```

Figure 6-8. "run" pseudo code

6.3.4. "cluster" Module

The first three subsections addressed how the micro-level objectives of this dissertation were incorporated in the multi-agent environment. The last subsection will focus on the macro-level objective of this dissertation. Therefore, the objective of this subsection is to create a feature in the multi-agent framework, which can detect any emergent phenomena such as spatial cluster formation.

For the purpose of recovery pattern recognition, two clustering algorithms were proposed: 1) Density Based Spatial Clustering of Applications with Noise (DBSCAN) proposed by Ester et al. (1996); and 2) Clique algorithm. The results from both algorithms were contrasted to each other to identify the best algorithm for the purpose of this dissertation.

6.3.4.1. DBSCAN clustering algorithm

DBSCAN is one of the most frequent clustering algorithms cited in the literature with the ranking of 22nd in the field of data mining (Microsoft 2010). In this algorithm, the main idea behind detecting clusters is that for each point of a given cluster, the neighborhood with a given radius must have at least a given number of members. Therefore a cluster can be characterized by two key parameters: 1) Neighborhood, which is the neighboring area within a given radius; and 2) Minimum points, which are the minimum number of points that must exist within a cluster.

Based on these definitions, three classifications are illustrated founded on the concept of points reachability, which are: 1) *Directly Density Reachable,* which is the case where a point exists within the neighborhood of another point and that point satisfies the minimum points criterion for clusters; 2*) Density Reachable,* in which a point is not directly reachable by another point but is reachable through a set of intermediate directly reachable points; and 3) *Density Connected,* which is the case where two points are neither directly density reachable nor density reachable but are density reachable to a single common point (Ester et al. 1996).

Now, according to these definitions, a cluster is a set of density-connected points which is maximal with regard to density reachability. The pseudo code of this algorithm is shown in Figure 6-9, in which D is the set of points, eps is the radius defining the neighborhood, and $MinPts$ is the minimum amount of points required to form a cluster (Ester et al. 1996).

```
FUNCTION DBSCAN(D, eps, MinPts)
   C = 0
   foreach point P in D if P.flagged = False
   set P as flagged
   N = countNeighbors (P, eps)
      if size(N) < MinPts
         set P as NOISE
      else
         set C as New(cluster)
   checkCluster(P, N, C, eps, MinPts)
END
------------------------------------------------------
FUNCTION checkCluster(P, N, C, eps, MinPts)
   cluster(C) = cluster(C) + P
   foreach point Q in N
   if Q.flagged = False
         set Q as visited
         M = countNeighbors(Q, eps)
   if sizeof(M) >= MinPts
            set N = N + M
   if Q.ismemberofCluster = False
            cluster(C) = cluster(C) + Q
END
```

Figure 6-9. DBSCAN pseudo code

6.3.4.2. Clique algorithm

The goal of clique algorithm is to find a set of complete sub-graphs within a graph that satisfies a certain criterion. The clique algorithm was initiated by Luce and Perry (1949) who used it in social networks and to find people who all know each other, and became very popular afterwards.

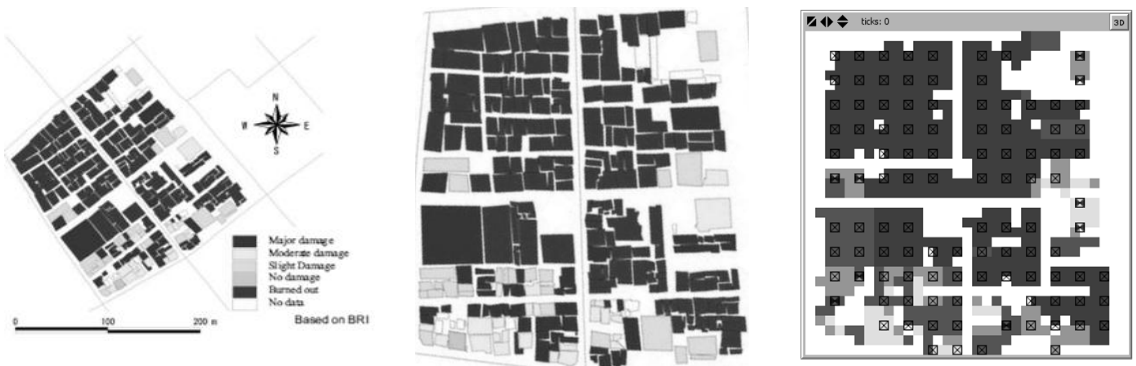
In this algorithm, the research problem is modeled as a connected graph $G(V, E)$ that consists of a set of vertices V and a set of unordered pairs, called edges E. Cliques are any subsets of vertices T in G where any pair of vertices forms an edge in G. Then the objective is to detect the maximum and maximal cliques. Maximal cliques are those that cannot be extended by including any more adjacent vertices, while maximum cliques are the ones with maximum number of vertices. For the purpose of this research, the vertices represent the reconstructed homeowners and the edges denote the distance between any pair of homeowners. In this subsection, the objective was not to detect maximal or maximum cliques but to find the number of homeowners who were a part of a clique with size of n, where n denotes the minimum number of homeowners. The following pseudo code displays how this algorithm was integrated in the multi-agent system. As shown in Figure 6-10, for every point in each sub-graph, the criteria of forming a clique of size n are checked, and therefore the results are optimal by brute force, in which all possible candidates for problem solutions are checked.

```
SUB clique
   dim D
   dim K(D)
   D = set of homeowners
   foreach point P in D if P.reconstructed
   foreach point M in neighbor-radius point P
   if M.reconstructed
   create a link from P to M
   set K(P)=K(P)+M
   next
   next
   checkClique(P,K(P),no-clique)
END
------------------------------------------------------
FUNCTION checkClique(P,K(P),no-clique)
   dim N
   foreach point N in K(P)
   foreach point L in K(N)
   if point L is a member of K(K(P))
   set sum(N) = sum(N) + 1
   next
   next
   foreach point D in K(P)
   if sum (D) >= no-clique
   set D member of Clique(P,K(P),no-clique)
END
```

Figure 6-10. Clique pseudo code

6.3.4.3. Evaluation of cluster-detection algorithms

In this part, the objective is to contrast the aforementioned algorithms. To accomplish this task the MAS model was used for a new case study. The case study was related to a region affected by Kobe earthquake in Nagata area by Maki et al. (2007). The area was imported in Netlogo by detecting the regions based on their colors. Figure 6-11 shows the original and the imported maps converted to the grayscale format. Since in the original photo the exact number of properties was not specified, in the simulated model for each colored region, properties with equal distance from each other were automatically created. The next step was to assign proper level of damage to each homeowner. This was performed by the color coding on the original map in which red showed major damage, yellow was moderate, blue indicated no damage, green was slight damage, pink was burned out, and white showed no information.



a)original (Maki et al. 2007) b)edited c)imported in Netlogo

Figure 6-11. Case study – Kobe earthquake

Although the multi agent model developed here has its own simplifications, the goal was to examine its ability to capture the major concepts. After defining the model, both clustering algorithms were applied to the model. Figure 6-12 shows the results from a single run of the model for the Kobe case study.

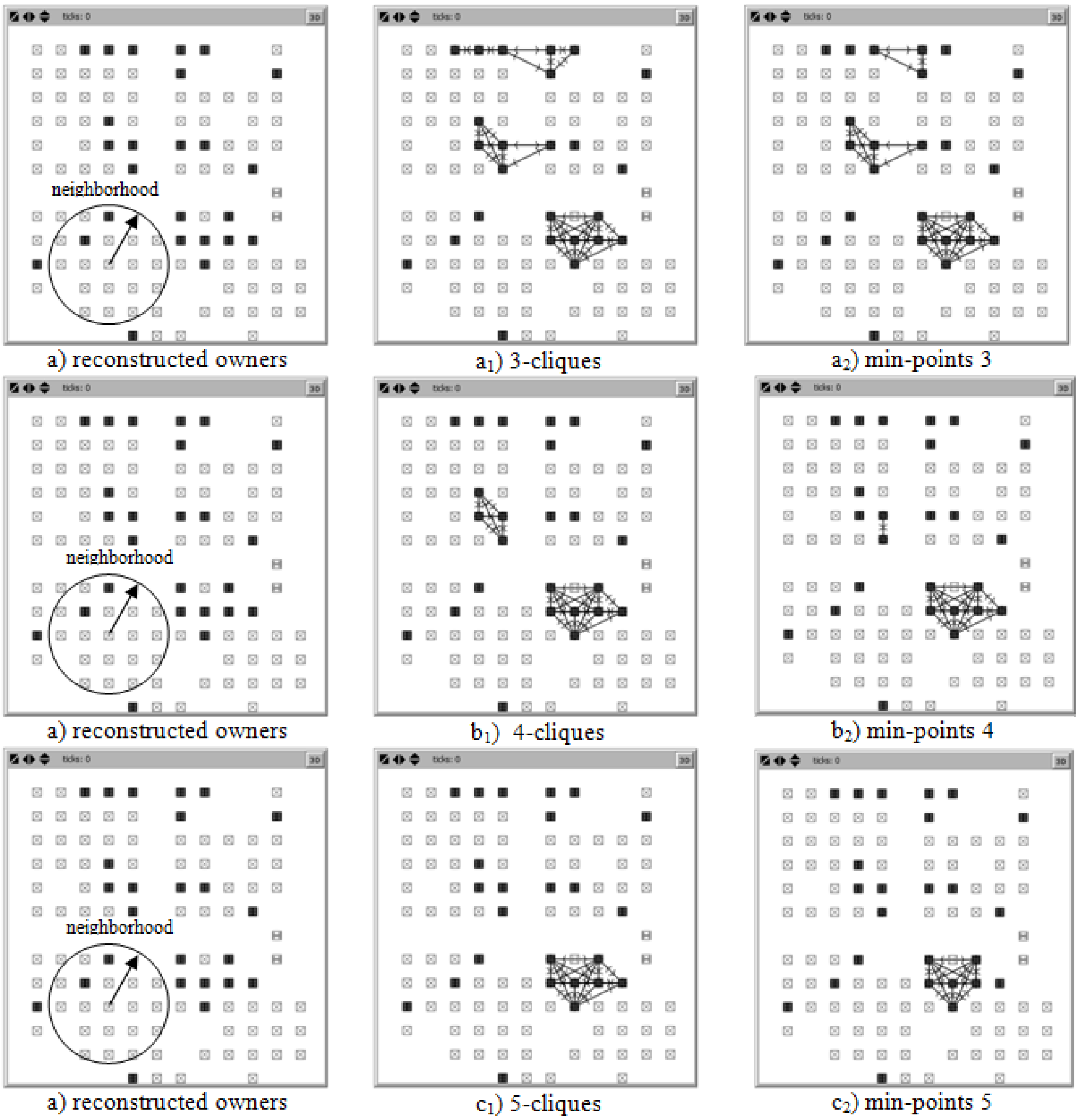


Figure 6-12. Comparison of the two cluster-detection algorithms

In this case study, the figures on the left are all identical and represent the initial phase of the study. The black squares denote the properties that have been reconstructed. The neighborhood defined for each property is shown by the drawn circle on the figure. The case was tested for different scenarios in which the neighborhood radius was kept the same and the minimum acceptable properties to form a cluster, was changed. This number was changed from a minimum of three to a maximum of five.

In Figure 6-12, the second column shows the results from application of the clique algorithm, whereas the third column shows the results for DBSCAN algorithm. Although there exist similarities between the two methods, Clique algorithm being optimal, shows a better coverage of properties that are believed to form a cluster compared to the DBSCAN algorithm and, as such, was selected as the preferred cluster-detection algorithm in this dissertation. This is clearly shown in Figures 6-12-b_1 and 6-12-b_2.

6.3.4.4. Hypothesis testing

After selection of clique algorithm as the preferred cluster detection method for this research, the algorithm was used for Kobe case study to examine the level of significance of cluster formation in the model. This required developing a null hypothesis for the model. The proposed null hypothesis would have to be a certain percentage for cluster formation. Consequently performing the statistical procedure shows whether the percentage of cluster formation is significant assuming the proposed confidence level.

The hypothesis testing was formulated using a minimum rate of cluster-formation. This minimum rate was set to be 50 percent of reconstructed properties. Hence, accepting the alternate hypothesis would indicate that clustering in reconstruction occurs more than 50 percent of the time. Assuming normality and unknown variance for the population, a t-statistic was used for the test:

$$H_0 : \mu = \mu_0,\ H_1 : \mu > \mu_0,\ T_0 = \frac{\bar{X} - \mu_0}{S / \sqrt{n}},\ t_0 > t_{\alpha,n-1} \qquad \textbf{(6-1)}$$

where H_0 is the null hypothesis, H_1 is the alternative hypothesis, T_0 is the test statistic, and t_0 is the rejection criterion. Since the t statistic is bigger than the rejection criterion, the hypothesis of having a cluster formation equal to 50% is rejected and the alternative hypothesis is accepted. This denotes that the rate of cluster formation is higher than 50%. Table 6-1 shows the results.

Table 6-1. Results from *t* test

	t	**P-value**	**Low Interval**	**High Interval**
T test for $\mu = 0.5$	3.7438	2.375E-4	0.5452682	0.6460363

Based on the estimated *p*-values, it can be concluded having a level of cluster formation higher than 50 percent is statistically significant base on a 95% confidence level. Furthermore the confidence interval for the mean lies within the range of [0.5452,0.646].

6.4. MODEL VALIDATION

Model validation in simulation models in general and social dynamics models in particular is an inherently difficult task and a point of disagreement among the researchers. The contradiction lies in the very essence of the modeling philosophy, should models be the representative of the reality – as exists or built in future, or should models be purpose-driven and focus on authenticity rather than statistical results (Sterman, 2000). In this subsection, the goal is to pursue both approaches and strike the balance between the parsimony and accuracy.

To examine the robustness of the model, a series of sensitivity analyses was performed. These analyses started with the theoretical model by testing its reconstruction sensitivity to a set of parameters, such as: 1) accuracy of signals through coefficient of variation; and 2) economic parameters, such as discount factor. The base model was assumed to have a discount factor of 0.9, coefficient of variation of 0.5, neighbor radius of 4, initial value of $250K. Since discount factor and coefficient of variation were separately defined just for the theoretical approach of the spatial model, the following sensitivity analyses were performed for that specific part of the model.

To accomplish the task, two values were considered for each parameter. For discount factor these values were 0.9 and 0.5, whereas for coefficient of variation these values were 0.5 and 2. The logic behind these selections was that each represents an extreme for that parameter. For example, the discount factor of 0.5 indicates a high discounting which is in contrast to the discount factor of 0.9. On the other hand, the coefficient of variation of 2 denotes a high level of variance, which is in contrast to the coefficient of variation 0.5. The results from the simulation were depicted in Figure 6-13. Explanation of the results is separately shown for each parameter.

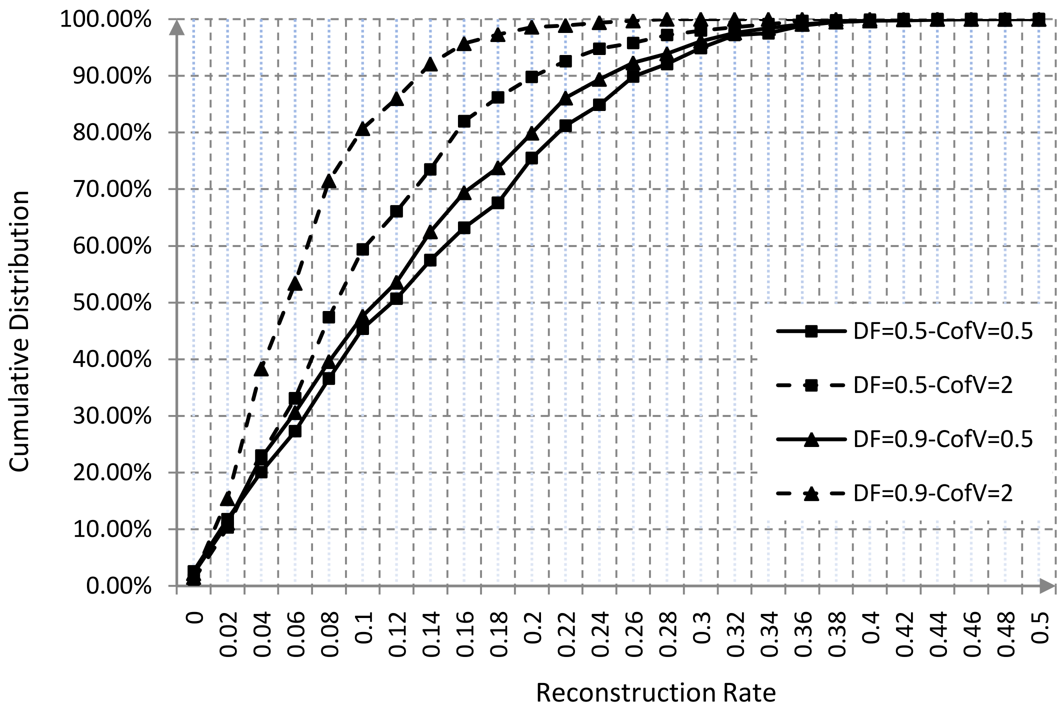


Figure 6-13. Model sensitivity to discount factor and coefficient of variation

6.4.1. Sensitivity to Coefficient of Variation

The first feature of the model is its sensitivity to accuracy of signals through coefficient of variation (CofV). As previously stated, a higher CofV indicates that the signal is a poor indicator of the true future value or in other words, denotes a high variance associated with the value.

The results show that given a fixed discount factor of 0.5, the reconstruction rate decreases as the level of uncertainty for the signals increases. This is clearly shown for the two sets of curves shown in Figure 6-13. The first two curves have a triangle marker whereas the other two have a rectangle marker. This is due to the fact that homeowners decide based on their observed signals from their surrounding neighbors. The accuracy of these signals is inversely proportional to their variance. Therefore with increasing variance (uncertainty), owners become more hesitant in starting reconstruction and prefer to wait and observe other neighbors' action to guarantee a positive net value for reconstruction.

6.4.2. Sensitivity to Discount Factor

The next characteristic of the model is its sensitivity to the level of discounting. The results show that given a fixed CoV, reconstruction rate increases as discount factor (DF) increases. This is again shown in for the two sets in Figure 6-13 displayed as full lines and dash lines.

The reason behind this behavior is that discount rate is one of the driving parameters in the process of decision making. Applying a high discount rate to the present value calculations assigns more weight to the current payoffs compared to payoffs anticipated in the future. Therefore one expects to observe an increase in the number of reconstructing owners by increasing the discount rate and vice versa. It is assumed that all the homeowners have the same discount rate.

6.4.3. Theoretical Model versus Hybrid and Empirical Model

The third sensitivity analysis was to contrast the different models to check for their effect on the rate of reconstruction. These different models consist of, 1) Theoretical model, 2) Empirical model, and 3) Hybrid model. For the hybrid model the assumption was to consider an equal weight for both theoretical and empirical models. The results from simulation is shown in Figure 6-14.

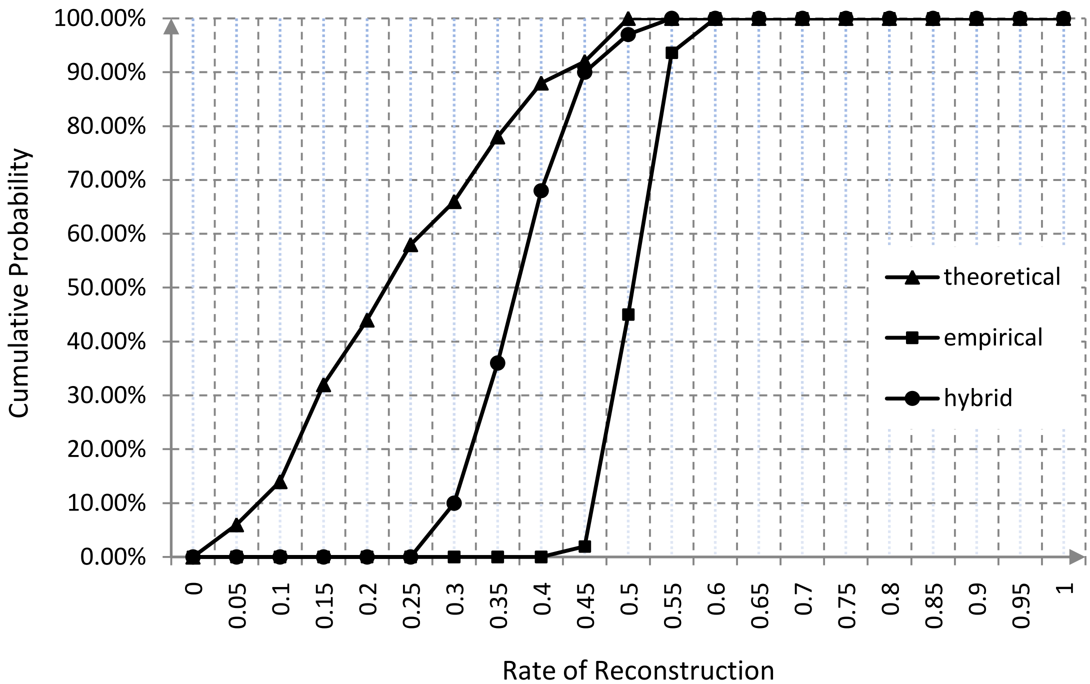


Figure 6-14. Sensitivity analysis for different models

For the purpose of simulation, a discount factor of 0.5 and a coefficient of variation of 0.5 was considered for the model. The results shown in Figure 6-14, denotes that the reconstruction rate in the empirical model has a very limited dispersion. This is due to the fact that in the empirical model, reconstruction decisions is based on three parameters which are: 1) ratio of available funds to reconstruction costs (r_2); and 2) percent of damages in the neighborhood and availability of infrastructure. Among these parameters, the availability of infrastructure does not change and as a result will not contribute to the variability of the reconstruction rate. On the other hand r_2 which is the only parameter that is directly affected by the assumed discount factor, is not as significant as the other two variables in the model. Therefore it is expected to have an almost constant rate of reconstruction for the empirical model. The other important issue shown in the figure is the substantially higher rate of reconstruction for empirical model in contrast to the theoretical model. This result is attributed to the fact that in the empirical model, the probability of reconstruction significantly increases by availability of infrastructure and percent of damage in the area. In the model used for simulation, almost half of the home owners have a damage level of less than 50 percent and are in vicinity of either available infrastructure or semi-available infrastructure. These parameters significantly contribute to the high rate of reconstruction in the empirical model.

In addition, the hybrid model exhibits the characteristics of both empirical and theoretical model. As shown in Figure 6-14, the level of dispersion has increased compared to the empirical model which is due to including the equal weight for both models. The rate of reconstruction is still higher than the theoretical model which is inherited from the empirical model.

7. CONCLUSIONS AND FUTURE RECOMMENDATIONS

7.1. CONCLUSIONS

Modeling the dynamics of post-disaster recovery can play an important role in providing public decision makers with analytical tools and methods to analyze policies that can promote fast recovery of the affected areas. To restore the community on a level of a functional socio-economic entity it is essential that policy makers and homeowners send signals of strong commitment. Without this, the reconstruction is often sporadic as spatial and information externalities dominate decisions to reconstruct and stay, or sell the property and leave.

This dissertation presents a multi-domain behavioral model that captures the homeowners' behavior when spatial externalities are present. The multi-domain considered for this model includes: 1) spatial domain of interaction in which the behavior of homeowners while interacting with each other was presented; and 2) organizational domain of interaction which analyzed the behavior of homeowners while interacting with insurers to secure funding for reconstruction.

A two-pronged approach was utilized, capturing the spatial and organizational externalities in this research. Regarding the spatial externality, the first approach was based on a theoretical approach to the existence of spatial externality which led to the free-rider problem. This results in the situation where homeowners may prefer to wait and observe the neighbors' actions rather than starting the reconstruction. As a result, the homeowners were assumed to have two pure strategies, which are: 1) immediate reconstruction; and 2) wait and observe the neighbors' action and act accordingly. Additionally from empirical approach this decision making is made based on a confluence of parameters such as availability of infrastructure, percent of damage in the area and financial flexibility of the homeowners. In this dissertation, the solution for theoretical part was approached through a mixed strategy equilibrium, where homeowners are indifferent between their strategies when the payoffs are the same. In addition, the solution for the experimental method was addressed through logistic regression modeling.

Regarding the organizational domain, the same set of approaches was applied to the model. The first approach was to capture the characteristics of homeowners' bargaining behavior in their interaction with insurers from a theoretical point of view, whereas the next approach was to tackle this problem from an empirical perspective and by running an experiment.

Based on the developed models, a multi-agent system simulation was developed to integrate these models and depict the emergent behavior. In this multi-agent model, homeowners were defined as intelligent agents with a belief structure which is updated based on the signals from their neighbors.

The results from simulation model confirm that spatial and organizational externalities play an important role in agents' decision-making and can greatly impact the recovery process. The results further highlight the significant impact of discount factor and the accuracy of the signals on the percentage of reconstruction. Finally, cluster formation was shown to be an emergent phenomenon during the recovery process and spatial modeling technique demonstrated a significantly higher impact on formation of clusters in comparison with experimental model and hybrid model.

The model assumed that reconstruction could peak out at less than 100 percent. Therefore if the property-owners cannot secure a positive payoff from reconstruction, they will not reconstruct but effectively leave the location eventually.

The issues deserving further attention are those which might have implications for policy holders. These include setting constraints for availability of funding in regards to reconstruction of residential units and transportation infrastructure, limiting the number of insured homeowners, optimizing the methods of resource allocation, incorporating the dynamics of the transportation infrastructure and others.

7.2. LIMITATIONS

As previously mentioned, this dissertation was intended to investigate the role of two key intelligent agents in the dynamics of post-disaster recovery and to capture the overall trend in post disaster reconstruction. While the number of affecting stakeholders could be much more than what has been considered, this research followed the principle of parsimony to clearly track the dynamics created in the system.

This model does not attempt to fully explain a very complex post-disaster reconstruction process, nor to capture heterogeneity in owners' behavior, but to provide a theoretical foundation for investigating the phenomenon of spatial cluster formation and decision-making under uncertainty.

It is also important to note that rezoning of the neighbors in abandoned areas and the impacts of other influencing parameters such as location, density, public policy, and others have not been considered in the model. Although the multi agent model developed here has its own simplifications, which include lack of heterogeneity of the agents, and availability of funds for reconstruction among others, it has an ability to capture the broad trends.

7.3. CONTRIBUTIONS

7.3.1. General Contributions

The general contributions of this model are: 1) providing a platform to spatially model the agents and investigate the resulting interactions; and 2) providing a platform with a potential to observe the impact of public policies on dynamics of post disaster recovery.

7.3.2. Engineering Contributions

From the engineering viewpoint, the key contribution of this research is to provide a framework which facilitates infrastructure-management in the context of natural hazards. The capability of incorporating a variety of parameters in the MAS model developed for this research allows for studying the impact of integrating different reconstruction and resource allocation polices in the affected areas, which, in turn, will lead to optimizing the available resources. This could be done in the model by capturing the process of *economic recovery* in the community until a full socio-economic restoration is realized.

Economic recovery is a critical parameter facing communities affected by disasters. The economic losses after disasters do not occur instantly but accumulate over the duration of recovery. In other words, the immediate economic losses have a domino effect on other sources of economic viability in a community.

For example, in Hurricane Katrina the economic losses other than those resulted from immediate destructions were due to: 1) damages to industry by disruption in the oil supply due to the destructions in oil refineries and platforms; 2) damages due to disruption in commerce attributable to the destruction of highway infrastructure in the Gulf Coast; 3) damages due to interruption in operation of US ports; and 4) damages due to job losses and businesses (United States Department of Commerce, 2006). Similar conditions were present for other natural disasters, such as the incurred economic losses in Des Moines, Iowa due to the closure of the water treatment plant and disruption of railroad traffic due to the damages to the flooded tracks; the economic losses suffered due to the collapse of Oakland Bay Bridge, which included the disruptions created by the destruction of major highway corridors; and the closure of local airport during the Loma Prieta earthquake. Furthermore, loss of tourism was also among one of the major sources for economic losses which were experienced in the affected communities, especially in Sun Belt (FEMA 421, 1998).

Additionally, as shown in Figure 7-1, economic growth and recovery is among the three pillars of a sustainable design of engineering structures (Adams 2006) and together with public safety are the two driving factors for post disaster planning.

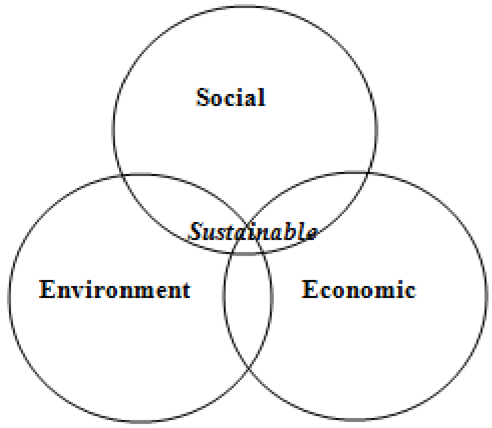


Figure 7-1. Three pillars of a sustainable design

Therefore, the main idea behind this research was to provide engineers and researchers with a new platform, in which the influential parameters with regard to economic recovery of an affected area could be modeled. This will eventually result in better post-disaster planning, leading to enhanced economic viability, which, in turn, results in a sustainable design.

Additionally, having an accurate knowledge of disasters' ripple effect enables policy makers to contrast the effect of policies on the relative, not necessarily on the absolute basis to determine the policies that are relatively more effective for the recovery process when contrasted to the existing policies. This will also help decision makers to bring together the best technical with the best socially and politically acceptable solutions to create a set of policies that are acceptable to the relevant stakeholders and the public.

REFERENCES

Academic Technology Services (2011). *Introduction to SAS*. UCLA, Statistical Consulting Group. <http://www.ats.ucla.edu/stat/sas/notes2> (May 24, 2011).

Adams, W.M. (2006). *The future of sustainability: re-thinking environment and development in the twenty-first century*. Report of the International Union for Conservation of Nature Renowned Thinkers Meeting, <http://cmsdata.iucn.org/downloads/iucn_future_of_sustanability.pdf> (May 23, 2010)

Agresti, A. (1990). *Categorical data analysis*. John Wiley & Sons, New York, NY.

Albala-Bertrand, J.M. (1993). *The political economy of large natural disasters: with special reference to developing countries*. Clarendon Press, Oxford, UK.

Alesch, D. J. and Holly J. N. (1998). *Small business failure, survival, and recovery: lessons from January 1994 Northridge Earthquake*. NEHRP Conference and Workshop on Research on the Northridge, California Earthquake, Richmond, CA

An, L., Linderman, M., Qi, J., Shortridge, A. and Liu, J. (2005). "Exploring complexity in a human–environment system: An agent-based spatial model for multidisciplinary and multiscale integration." *Annals of the Association of American Geographers*, 95, 54–79.

Anbarci, N., Skaperdas, S., and Syropoulos C. (2002). "Comparing bargaining solutions in the shadow of conflict: How norms against threats can have real effects." *Journal of Economic Theory*, 106(1), 1-16.

Applied Technology Council (1991). *ATC-25: Seismic vulnerability and impact of disruption on lifelines in the conterminous United States*. Federal Emergency Management Agency, Applied Technology Council, Redwood City, CA.

Basu K., Bhattacharya S., and Mishra A. (1992). "Notes on bribery and the control of corruption." *Journal of Public Economics,* 48(3), 349-359.

Bates, F. L. (1982). "Recovery, change and development: A longitudinal study of the Guatemalan Earthquake." University of Georgia, Department of Sociology, Athens, GA.

Bates, F. L., and Peacock , W. G. (1993). *Living conditions, disasters and development*. University of Georgia Press, Athens, GA.

Bates, F. L., and Pelanda, C. (1994). "An ecological approach to disasters." R.R. Dynes and K. J. Tierney (eds.), *Disasters, collective behavior, and social organization*. University of Delaware Press, Newark, 149-159.

Bellifemine, F., Caire G., and Greenwood D. (2007). *Developing multi-agent systems with JADE*. John Wiley & Sons, New York.

BenDor, T., Westervelt, J., Aurambout, J. & Meyer, W. (2009). "Simulating population variation and movement within fragmented landscapes: An application to the gopher tortoise (*Gopherus polyphemus*)." *Ecological Modeling,* 220(6), 867-878.

Benenson, I. (1998). "Multi-agent simulations of residential dynamics in the city." *Computers, Environment, and Urban Systems,* 22 (1), 25-42.

Berger, T. (2001). "Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis." *Agricultural Economics*, 25, 245–260.

Berke, P. R., Kartez, J. and Wenger D. (1993). "Recovery after disaster: Achieving sustainable development, mitigation and equity." *Disasters,* 17(2), 93-109

Blaikie, P., Cannon, T., Davis, I., and Wisner B. (1994). *At risk: natural hazards, people's vulnerability, and disasters*. Routledge, New York.

Boisvert, R. (1992). "Indirect losses from a catastrophic earthquake and local, regional, and national interest." *Indirect economic consequences of a catastrophic earthquake*, National Earthquake Hazards Reduction Program, Federal Emergency Management Agency, Washington, DC, 207–265.

Bolin, R. C. (1993). *Household and community recovery after earthquakes*. Institute of Behavioral Science, University of Colorado Boulder, CO.

Bolin, R. C., and Bolton P. (1983). "Recovery in Nicaragua and the USA." *International Journal of Mass Emergencies and Disasters,* 1(1), 125-152.

Bolin, R. C. and Trainer P. (1978). "Modes of family recovery following disaster: A cross national study. " E. Quarantelli (ed.), *Disasters: Theory and research*. Sage, Beverly Hills, CA, 1978, 234-247.

Boisvert, R. (1992). "Indirect losses from a catastrophic earthquake and local, regional, and national interest." in: "Indirect economic consequences of a catastrophic earthquake", National Earthquake Hazards Reduction Program, Federal Emergency Management Agency, Washington, DC, 207–265.

Borch, K. H. (1962). “Equilibrium in a reinsurance market.” *Econometrica*, 30, 424-444.

Brookshire, D. S., Chang, S. E., Cochrane, H., Olson, R. A., Rose, A. and Steenson, J. (1997). “Direct and indirect economic losses from earthquake damage.” *Earthquake Spectra*, 13(4), 683-701.

Burmeister B., Haddadi, A., and Matylis, G. (1997). “Application of multi-agent systems in traffic and transportation.” *IEEE Proceedings on Software Engineering*, 144(1), 51-60.

Chang, S. E. and Miles S. B. (2004). “The dynamics of recovery: A framework.” Y. Okuyama and S. E. Chang (eds), *Modeling the spatial economic impact of disasters*. Springer-Verlag, Berlin, 181-204.

Cho, S., Gordon, P., Moore II, J.E., Richardson, H.W., Shinozuka, M. and Chang, S.E. (2001). “Integrating transportation network and regional economic models to estimate the costs of a large urban earthquake.” *Journal of Regional Science*, 41, 39–65.

Cochrane, H.C., Chang, S.E. and Rose, A. (1997). “Indirect economic losses”, *Earthquake loss estimation methodology: HAZUS technical manual*, National Institute of Building Sciences, Washington, DC.

Cochrane, H. C. (2004). “Indirect losses from natural disasters: Measurement and myth.” Y. Okuyama and S.E. Chang (eds), *Modeling spatial and economic impacts of disasters*. Springer, New York, NY, 37-52.

Cole, S. (1995). “Lifelines and livelihood: A social accounting matrix approach to calamity preparedness.” *Journal of Contingencies and Crisis Management*, 3, 1-11.

Cole, S. (1998). “Decision support for calamity preparedness: socioeconomic and interregional impacts.” M. Shinozuka et al. (eds.), *Engineering and socioeconomic impacts of earthquakes: An analysis of electricity lifeline disruptions in the new Madrid area*. Multidisciplinary Center for Earthquake Engineering Research (MCEER), Buffalo, NY.

Cole, S. (2004). “Geo-hazards in social systems: An insurance matrix approach, Y. Okuyama and S.E. Chang (eds), *Modeling spatial and economic impacts of disasters*. Springer, New York, NY, 103-118.

Collins, R. and Sherstyuk, K. (2000), “Spatial competition with three firms: an experimental study.” *Economic Inquiry*, 38, 73–94.

Conley, T. G. and Topa, G. (2002), "Socio-economic distance and spatial patterns in unemployment." *Journal of Applied Econometrics*, 17, 303–327.

Daniel, T. E., Seale, D. A., and Rapoport, A. (1998). "Strategic play and adaptive learning in the sealed-bid bargaining mechanism." *Journal of Mathematical Psychology*, 42(2-3), 133-166.

Davis, H.C. and E. L., Salkin (1984). "Alternative approaches to the estimation of economic impacts resulting from supply constraints." *Annals of Regional Science*, 18, 25–34.

Dréau, D., Stanimirov, D., Carmichael T., & Hadzikadic M. (2009). *An agent-based model of solid tumor progression*. Paper presented at the 1st International Conference on Bioinformatics and Computational Biology, New Orleans, LA.

Durkin, M. E. (1984). *The economic recovery of small businesses after earthquakes: the Coalinga experience*. International Conference on Natural Hazards Mitigation Research and Practice, New Delhi, India.

Ellis, C.J. and Fender, J. (1985). "Wage bargaining in a macroeconomic model with rationing." *Quarterly Journal of Economics*, 100, 625-650.

Ester, M., Kriegel HP, Sander J., and Xu X. (1996). *A density-based algorithm for discovering clusters in large spatial databases with noise*. Proceedings of 2nd International Conference on Knowledge Discovery and Data Mining (KDD-96), Portland, Oregon.

FEMA (1998). *Planning for post-disaster recovery and reconstruction*., Federal Emergency Management Agency. <http://www.fema.gov/library/viewRecord.do?id=1558> (June 23, 2010)

Gertler, M., and Trigari A. (2009). "Unemployment fluctuations with staggered Nash wage bargaining." *Journal of Political Economy,* 117(1), 41-86.

Gordon, P. and Richardson, H.W. (1996). *The business interruption effects of the Northridge earthquake*. Lusk Center Research Institute, University of Southern California, Los Angeles, CA.

Gordon, P., Richardson, H.W. and Davis, B. (1998). "Transport-related impacts of the Northridge earthquake." *Journal of Transportation and Statistics*, 1, 22–36.

Gordon, P., Moore II, J.E., Richardson, H.W., Shinozuka, M., An, D. and Cho, S. (2004). "Earthquake disaster mitigation for urban transportation systems: an integrated methodology that builds on the Kobe and Northridge experiences." Y. Okuyama and S.E. Chang (eds.), *Modeling spatial and economic impacts of disasters*. Springer, New York, NY, 205–232.

Grout, P. A. (1984). "Investment and wages in the absence of binding contracts: A Nash bargaining approach." *Econometrica*, 52, 449-460.

Groves, T. and Ledyard, J. (1977). "Optimal allocation of public goods: a solution to the Free Rider problem." *Econometrica*, 45(4), 783-809.

Haas, J. E., Kates, R. W. and Bowden M. (1977). *Reconstruction following disaster*. MIT Press, Cambridge, MA.

Heinz Center for Science, Economics and the Environment (2000). *The hidden costs of coastal hazards: implications for risk assessment and mitigation*. Island Press, Washington, DC.

Hendricks, K. and Porter, R. (1996). "The timing and incidence of exploratory drilling on offshore wildcat tracts." *The American Economic Review,* 86(3), 388-407.

Hewitt, K. (1997). *Regions of risks: A geographical introduction to disasters*. Addison Wesley Longman Limited, Essex, UK.

Hindriks, J., Keen, M., and Muthoo, A. (1999). "Corruption, extortion and evasion." *Journal of Public Economics*, 74(3), 395-430.

Hogg, S. J. (1980). "Reconstruction following seismic disaster in Venzone, Friuli." *Disasters,* 4(2), 173-185.

Irwin E. G., and Bockstael, N. E. (2002). "Interacting agents, spatial externalities and the evolution of residential land use patterns." *Journal of Economic Geography,* 2(1), 31-54.

Kihlstrom, R. E. and Roth A. E. (1982). "Risk aversion and the negotiation of insurance contracts." *Journal of Risk and Insurance*, 49, 372-387.

Kleczkowski, A., Maharaj, S. (2010). *Stay at home, wash your hands: epidemic dynamics with awareness of infection*. Proceedings of Summer Computer Simulation Conference, Ottawa, Canada.

Knabe, A. (2009). "Implementing endogenous inside options in Nash wage bargaining models." *Mathematical Social Sciences*, 57(2), 161-176.

Kroll, C. A., Landis, J. D., Shen, Q., and Stryker, S. (1991). *Economic impacts of Loma Prieta earthquake: A focus on small businesses*. Paper No: 91-187, University of California Transportation Center and the Center for Real Estate and Urban Economics, University of California at Berkeley, CA.

Luce, R. D., and Perry, A. D. (1949). "A method of matrix analysis of group structure" *Psychometrika,* 14 (2), 95–116.

Lundberg, S., and Pollak., R. A. (1993). "Separate spheres bargaining and the marriage market." *Journal of Political Economy,* 101(6), 988-1010.

Maki, N., Kawakata, H., Yoshitomi, P. , Urakawa, V., Chan, K., Matsuura, H., Tatsumi, K., Hara, T., Inokuchi, M., Higashida, M., Hayashi, H. and Kawata, Y. (2007). "Building an integrated database system of information on disaster hazard risk, and recovery process-cross-media database." *Annuals of Disaster*, 50C, 63-67.

Manser, M., and Brown, M. (1980). "Marriage and household decision-making: A bargaining analysis." *International Economic Review,* 21, 31-44.

McCullagh, P. (1980). "Regression models for ordinal data (with discussion)." *Journal of the Royal Statistical Society*, series B, 42, 109-142.

McDonald, I. and Solow, R. (1981). "Wage bargaining and employment." *American Economic Review*, 71, 896-908.

McElroy, M. B., and Horney, M. J. (1981). "Nash-bargained household decisions: toward a generalization of the theory of demand." *International Economic Review,* 22, 333-349.

Microsoft Academic Search, <http://academic.research.microsoft.com/CSDirectory/paper_category_7.htm> (June 23, 2010)

Muthoo, A. (1999). *Bargaining theory with applications*. Cambridge University Press, Cambridge, UK.

Nelder , J., and Wedderburn, R. W. M. (1972). "Generalized linear models." *Journal of the Royal Statistical Society*, series A, 135, 370-384.

Niazi, M., Siddique, Q., Hussain, A., & Kolberg, M. (2010). *Verification and validation of an agent-based forest fire simulation model*. Agent-directed simulation Symposium, Spring Simulation Conference, Orlando, FL.

Okuyama, Y. (2011). "Economic impacts of natural disasters: development issues and applications", <http://nexus-idrim.net/idrim09/Kyoto/Okuyama.pdf>, (May 10, 2010)

Okuyama, Y. (2007). "Economic modeling for disaster impact analysis: past, present, and future." *Economic Systems Research,* 19(2), 115-124.

Okuyama, Y. and Chang, S.E. (2004). *Modeling spatial and economic impacts of disasters*. Springer, New York, NY.

Okuyama, Y., Hewings, G. J. D., and Sonis, M. (2000). *Sequential inter-industry model (SIM) and impact analysis: application for measuring economic impact of unscheduled events*. Paper presented at the 47th North American Meetings of the Regional Science Association International, Chicago, IL.

Padgham, L. and Winikoff, M. (2004). *Developing intelligent agent systems*. John Wiley & Sons, UK.

Parker, D. C., Manson, S. M., Janssen, M. A., Hoffman, M. J., and Deadman, P. (2003). "Multi-agent systems for the simulation of land-use and land-cover change: a review." *Annals of the Association of American Geographers*, 93(2), 314-337.

Peacock, W. G., Killian, C. D., and Bates, F. L. (1987). "The effects of disaster damage and housing aid on household recovery following the 1976 Guatemalan earthquake." *International Journal of Mass Emergencies and Disasters,* 5, 63-88.

Porter, R. H. (1995). "The role of information in U.S. offshore oil and gas lease auction." *Econometrica,* 63(1), 1-27.

Psathas, G., and Stryker, S. (1965). "Bargaining behavior and orientations in coalition formation." *Sociometry*, 28(2), 124-144.

Reed, W. (2003). "Information, power, and war." *American Political Science Association*, 94(4), 633-641.

Rose, A. (1981). "Utility lifelines and economic activity in the context of earthquakes." J. Isenberg (ed.), *Social and economic impacts of earthquake on utility lifelines*. American Society of Civil Engineers, New York. NY, 107-120.

Rose, A. (2004). "Economic principles, issues, and research priorities in hazard loss estimation." Y. Okuyama and S.E. Chang (eds.), *Modeling spatial and economic impacts of disasters*. Springer, New York, NY, 13–36

Rose, A. and Benavides, J. (1993). *Inter-industry models for analyzing the economic impacts of earthquakes and recovery policies*. Report to National Center for Earthquake Engineering Research (NCEER), Department of Mineral Economics, The Pennsylvania State University, University Park, PA.

Rose, A. and Benavides, J. (1998). "Regional economic impacts." M. Shinozuka, A. Rose and R.T. Eguchi (eds.), *Engineering and socioeconomic impacts of earthquakes*. Multidisciplinary Center for Earthquake Engineering Research (MCEER), Buffalo, NY, 95–123.

Rose, A. and Guha, G.S. (2004). "Computable general equilibrium modeling of electric utility lifeline losses from earthquakes." Y. Okuyama and S.E. Chang (eds.), *Modeling spatial and economic impacts of disasters*. Springer, New York, NY, 119–141.

Rose, A. and Liao, S.Y. (2005). "Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions." *Journal of Regional Science*, 45, 75–112.

Rose, A., Benavides, J., Chang, S.E., Szczesniak, P. and Lim, D. (1997). "The regional economic impact of an earthquake: direct and indirect effects of electricity lifeline disruptions." *Journal of Regional Science*, 37, 437–458.

Rothschild, M. and Stiglitz, J. E. (1976). "Equilibrium in competitive insurance markets: an essay on the economics of imperfect information." *Quarterly Journal of Economics,* 90, 629-649.

Rubin, C. B. and Popkin R. (1990). *Disaster recovery after hurricane Hugo in South Carolina*. Final report to the National Science Foundation, George Washington University, Washington, DC.

Rubin, C. (1991). "Recovery from disaster." T. E. Drabek and G. J. Hoetmer (eds.), *Emergency management: principles and practice for local government*. International City Management Association, Washington, DC, 224-259.

Rubinstein, A. (1982). "Perfect equilibrium in a bargaining model." *Econometrica,* 50, 97-109.

Selten, R. (1975) "Reexamination of the perfectness concept for equilibrium points in extensive games." *International Journal of Game Theory*, 4, 25-55.

Schlesinger, H. (1984). "Two-person insurance negotiation." *Insurance: Mathematics and Economics,* 3(3), 147-149.

Shultz, L. (2009). *Understanding the greenhouse effect using a computer model*. Master's thesis, University of Maine, Maine.

Sohn, J., Hewings, G.J.D., Kim, T.J., Lee, J.S. and Jang, S. G. (2004). “Analysis of economic impacts of earthquake on transportation network.” Y. Okuyama and S.E. Chang (eds), *Modeling spatial and economic impacts of disasters*. Springer, New York, NY, 233–256.

Sterman, J. (2000). *Business dynamics: systems thinking and modeling for a complex world*. McGraw Hill, New York, NY.

Stokes, M.E., Davis, C.S., and Koch, G.G. (2000). *Categorical data analysis using the SAS system*. SAS Institute Inc., Cary, NC.

Stiglitz, J. E. (1977). “Monopoly, non-linear pricing and imperfect information: the insurance market.” *Review of Economic Studies*, 44, 407-430.

United States Department of Commerce (2010). *Hurricane Katrina service assessment report*, <http://www.weather.gov/om/assessments/pdfs/Katrina.pdf. 2006> (03/03/2009)

Vose, D. (2008). *Risk analysis: A quantitative guide*. John Wiley & Sons, Chichester, West Sussex, UK.

Wilensky, U. (1999). NetLogo.< http://ccl.northwestern.edu/netlogo/>. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

Wilson, R. (1982). *Earthquake vulnerability analysis for economic impact assessment*. Information Resources Management Office, Federal Emergency Management Agency, Washington, DC.

Wooldridge, M. and Jennings, N. R. (1995). “Intelligent agents: theory and practice.” *The knowledge Engineering Review*, 10(2), 115-152.

Yergens D., Hiner, J., Denzinger, J., and Noseworthy, T. (2006). *Multi agent simulation system for rapidly developing infectious disease models in developing countries*. The 2nd International Workshop on Multi-Agent Systems for Medicine, Computational Biology and Bioinformatics as part of the 5th International Joint Conference on Autonomous Agents and Multi-agent Systems (AAMAS 2006), Future University, Hakodate, Japan.

Zonum Solutions, Online KML to SHP convertor <http://www.zonums.com/online/kml2shp.php>, (March 10, 2011)

APPENDIX A

INSTRUCTION TO PLAYERS-SPATIAL SURVEY

Assume that you live in a neighborhood with similar house plans, and that your neighborhood has been recently affected by a hurricane. Your property together with a few number of properties in your neighborhood have been significantly damaged and not suitable for living. As a result you as well as your neighbors are forced to rent houses in another part of the town.

You are about to make a decision what to do. You have three options; 1) to reconstruct your home immediately, 2) to wait six-months and see if any of your neighbors have reconstructed or not and reconsider reconstruction based on your observation, and finally 3) to take the insurance money and buy yourself a new house somewhere else in the town.

You have no information about whether your neighbors will reconstruct or not but you can observe if they will, by waiting. If you are to reconstruct right away and no one else reconstructs there would be a significant chance that the value of your property will be less than the cost of repair. In contrast if they all reconstruct there would be a high chance of getting a property value much higher than your cost of repair.

Common Assumptions

- Your neighborhood is the subdivision in which you are located
- It would cost you $1,500 per month to rent a house

Specific Assumptions

No	Specification	Value*
1	Your property value before damage	
2	Cost of a new property in other part of the town	
3	Your savings/mortgages	
4	Reimbursement from your insurance	
5	Your property cost of repair	
6	Your current (damaged) property value	

*Computer generated data (all values are in thousand dollars)

Based on the specific assumptions described in Table 1 and the different conditions showed in Table 2, pick an action from the following available options and email it back:

Different Options:

1) Reconstruct your home immediately

2) Wait for 6 months and observe your neighbors' actions and decide accordingly

3) Take the insurance money and buy yourself a house somewhere else in the town

Condition	Availability of Infrastructure In your neighborhood	Percent of significantly damaged properties in your neighborhood	What would you do? (either 1,2, or 3)
1	Not Available	Less Than 50%	
2	Available	Less Than 50%	
3	Available in 3 months	Less Than 50%	
4	Not Available	More Than 50%	
5	Available	More Than 50%	
6	Available in 3 months	More Than 50%	

APPENDIX B

PROOF FOR EQUATIONS 4-2 AND 4-3

Proof: The proofs for Equations 4-2 and 4-3 are elaborated below through a series of sequential steps. The proof starts with signal s_i and then integrates all the signals:

Given: $$\begin{aligned} &f(z_i) \sim N(\alpha, \beta = 1) \\ &f(s_i \mid z_i) \sim N(z_i, \rho_i) \end{aligned}$$

Assuming independency among variables: $f(z_i, s_i) = f(z_i) f(s_i \mid z_i)$

Marginal of s_i is proportional to: $\int_{-\infty}^{\infty} \exp\left(-\frac{1}{2}(\alpha - x)^2\right) \exp\left(-\frac{1}{2}\rho_i (s_i - x)^2\right) dx$

Now expanding the equations will result in:

$$\int_{-\infty}^{\infty} \exp\left(-\frac{1}{2}(\rho_i s_i^2 + \alpha^2)\right) \exp\left(-\frac{1}{2}\left(x^2(1+\rho_i) - 2(s_i\rho_i + \alpha)x\right)\right) dx$$

Completing the square: $\left(\sqrt{1+\rho_i}\,x - \frac{\alpha + s_i\rho_i}{\sqrt{1+\rho_i}}\right)^2$

$$\int_{-\infty}^{\infty} \begin{aligned} &\exp\left(-\frac{1}{2}(\rho_i s_i^2 + \alpha^2)\right) \exp\left(-\frac{1}{2}\left(\frac{-1}{1+\rho_i}(s_i\rho_i + \alpha)^2\right)\right) \\ &\exp\left(-\frac{1}{2}\left(x^2(1+\rho_i) - 2x(s_i\rho_i + \alpha) + \frac{1}{1+\rho_i}(s_i\rho_i + \alpha)^2\right)\right) dx \end{aligned}$$

Taking the integral will result in (function of α):

$$\exp\left(-\frac{1}{2}(\alpha^2 + s_i{}^2\rho_i - \frac{1}{1+\rho_i}(s_i{}^2\rho_i{}^2 + \alpha^2 + 2\alpha s_i\rho_i))\right)$$

Assuming independency of signals conditional on α results in following for all the signals:

$$\exp\left(-\frac{1}{2}\left[\sum_{i=1}^{N}\frac{\rho_i}{1+\rho_i}\alpha^2 - 2\sum_{i=1}^{N}\frac{s_i\rho_i}{1+\rho_i}\alpha + K\right]\right)$$

This is proportional to:

$$N\left(\frac{\sum_{i=1}^{N}\frac{s_i\rho_i}{1+\rho_i}}{\sum_{i=1}^{N}\frac{\rho_i}{1+\rho_i}}, \left(\sum_{i=1}^{N}\frac{\rho_i}{1+\rho_i}\right)^{-1}\right)$$

APPENDIX C

PROOF FOR EQUATIONS 4-4 AND 4-5

Proof: similar to the previous part, derivations for Equations 4-4 and 4-5 are presented below in a series of sequential steps. For simplicity, the derivations are shown for z_1 which is the same for other $z_i s$.

Given: $m(s_1, z_1, ..., s_N, z_N, \alpha) \propto m(s_1, z_1, ..., s_N, z_N \mid \alpha)$

Therefore:

$$m(s_1, z_1, ..., s_N, z_N, \alpha) = \prod_{i=1}^{N} f(s_i \mid z_i) f(z_i \mid \alpha)$$

This is proportional to:

$$\exp\left(-\frac{1}{2}\sum_{i=1}^{N}(z_i - \alpha)^2\right)\exp\left(-\frac{1}{2}\sum_{i=1}^{N}\rho_i(z_i - s_i)^2\right)$$

Now integrating out $x_2, ..., x_N$ will result in:

$$\exp\left(-\frac{\rho_1}{2}(z_1 - s_1)^2\right)\exp\left(-\frac{1}{2}(z_1 - \alpha)^2\right)\times$$
$$\iint ... \int \exp\left(-\frac{1}{2}\sum_{i=2}^{N}\left[\rho_i(z_i - s_i)^2 + (z_i - \alpha)\right]^2\right)dz_2 ... dz_N$$

This is proportional to:

$$\exp\left(-\frac{\rho_1}{2}(z_1-s_1)^2-\frac{1}{2}(z_1-\alpha)^2\right)\exp\left(-\frac{1}{2}(N-1)\alpha^2\right)\times$$
$$\iint\ldots\int\exp\left(-\frac{1}{2}\sum_{i=2}^{N}\left[z_i^{\,2}(1+\rho_i)-2z_i(\rho_i s_i+\alpha)\right]\right)dz_2\ldots dz_N$$

This is now proportional to:

$$\exp\left(-\frac{\rho_1}{2}(z_1-s_1)^2-\frac{1}{2}(z_1-\alpha)^2\right)\exp\left(-\frac{1}{2}(N-1)\alpha^2\right)\times$$
$$\exp\left(\frac{1}{2}\sum_{i=1}^{N}\frac{(\rho_i s_i+\alpha)^2}{1+\rho_i}\right)$$

Now to integrate out α :

$$\exp\left(-\frac{1}{2}(z_1-\alpha)^2-\frac{1}{2}(N-1)\alpha^2+\frac{1}{2}\sum_{i=2}^{N}\frac{2\alpha\rho_i s_i}{1+\rho_i}+\frac{1}{2}\alpha^2\sum_{i=2}^{N}\frac{1}{1+\rho_i}\right)$$

This is proportional to:

$$\exp(-\frac{1}{2}z_1^{\,2})\exp\left[(-\frac{1}{2}[\alpha^2\underbrace{(N-\sum_{i=2}^{N}\frac{1}{1+\rho_i})}_{*}-2\alpha(z_1+\underbrace{\sum_{i=2}^{N}\frac{\rho_i s_i}{1+\rho_i})}_{**}\right]$$

On the other hand derivation for part (*) of the bracket results in:

$$*\;N-\sum_{i=2}^{N}\frac{1}{1+\rho_i}=1+\sum_{i=2}^{N}(1-\frac{1}{1+\rho_i})=1+\sum_{i=2}^{N}\frac{\rho_i}{1+\rho_i}=1-\frac{\rho_1}{1+\rho_1}+\rho=\rho+\frac{1}{1+\rho_1}$$

Similarly derivation for part (**) of the bracket results in:

$$** \sum_{i=2}^{N} \frac{\rho_i s_i}{1+\rho_i} = \sum_{i=1}^{N} \frac{\rho_i s_i}{1+\rho_i} - \frac{\rho_1 s_1}{1+\rho_1} = \rho\mu - \frac{\rho_1 s_1}{1+\rho_1}$$

Therefore the original formulation will be proportional to (by completing the square for α):

$$\exp(-\frac{1}{2}z_1^{\,2})\exp(-\frac{1}{2}(\rho+(1+\rho_1)^{-1})(\alpha-\frac{z_1+\rho\mu-\rho_1 s_1(1+\rho_1)^{-1}}{\rho+(1+\rho_1)^{-1}})^2)\times$$
$$\exp(\frac{1}{2}\frac{(z_1+\rho\mu-\rho_1 s_1(1+\rho_1)^{-1})^2}{\rho+(1+\rho_1)^{-1}}$$

Which is proportional to the following:

$$\exp(-\frac{\rho_1}{2}(z_1-s_1)^2)\times\exp(-\frac{1}{2}z_1^{\,2})\times\exp\left(\frac{1}{2}\frac{(z_1+\mu\rho-\rho_1 s_1(1+\rho_1)^{-1})^2}{\rho+(1+\rho)^{-1}}\right)$$

This leads to:

$$\exp\left(-\frac{1}{2}[z_1^{\,2}(1+\rho_1-\frac{1}{\rho+(1+\rho_1)^{-1}})-2z_1(\rho_1 s_1+\frac{\rho\mu-\rho_1 s_1(1+\rho_1)^{-1}}{\rho+(1+\rho_1)^{-1}})]\right)$$

and finally it can be concluded that it is proportional to:

$$\exp\left(-\frac{1}{2}\left(1+\rho_1-\frac{1}{\rho+(1+\rho_1)^{-1}}\right)\times\left(z_1-\frac{\rho_1 s_1+\left(\dfrac{\rho\mu-\rho_1 s_1(1+\rho_1)^{-1}}{\rho+(1+\rho_1)^{-1}}\right)}{1+\rho_1-(\rho+(1+\rho_1)^{-1})^{-1}} \right)^2 \right)$$

This denotes that the distribution of $z_1 \mid s_1,\ldots,s_N$ is normal with the following parameters:

Mean: $$\frac{\rho_1 s_1+\left(\dfrac{\rho\mu-\rho_1 s_1(1+\rho_1)^{-1}}{\rho+(1+\rho_1)^{-1}}\right)}{1+\rho_1-\left(\dfrac{1}{\rho+(1+\rho_1)^{-1}}\right)}=\frac{\rho_1 s_1(\rho+(1+\rho_1)^{-1})+\rho\mu-\rho_1 s_1(1+\rho_1)^{-1}}{(1+\rho_1)(\rho+(1+\rho_1)^{-1})-1}$$

$$=\frac{\rho_1 s_1(\rho(1+\rho_1)+1)+\rho\mu(1+\rho_1)-\rho_1 s_1}{(1+\rho_1)(\rho(1+\rho_1)+1)-(1+\rho_1)}=\frac{\rho_1 s_1\rho(1+\rho_1)+\rho\mu(1+\rho_1)}{\rho(1+\rho_1)^2}=\frac{\mu+\rho_1 s_1}{1+\rho_1}$$

Precision: $$1+\rho_1-\frac{1}{\rho+(1+\rho_1)^{-1}}=\frac{(1+\rho_1)(1+\rho(1+\rho_1))-(1+\rho_1)}{1+\rho(1+\rho_1)}=\frac{\rho(1+\rho_1)^2}{1+\rho(1+\rho_1)}$$

APPENDIX D

PARAMETERS FOR $\mu(t+\Delta t)$ DISTRIBUTION

<u>Calculating mean</u>

Starting with the original formulation

$$\mu(t+\Delta t)=\frac{[\mu(t)\rho(t)+(x_j-s_j\rho_j(1+\rho_j)^{-1})]}{[\rho(t)+(1+\rho_j)^{-1}]}$$

Calculating the expectation of $\mu(t+\Delta t)$

$$E[\mu(t+\Delta t)]=\frac{\mu(t)\rho(t)+E[x_j]-s_j\rho_j(1+\rho_j)^{-1}}{\rho(t)+(1+\rho_j)^{-1}}$$

Using Equation 4-4, will result in

$$E[\mu(t+\Delta t)]=\frac{\mu(t)\rho(t)+[(\mu(t)+s_j\rho_j)(1+\rho_j)^{-1}]-s_j\rho_j(1+\rho_j)^{-1}}{\rho_j+(1+\rho_j)^{-1}}$$

Therefore

$$E[\mu(t+\Delta t)]=\frac{[\mu(t)\rho(t)+\mu(t)(1+\rho_j)^{-1}]}{[\rho(t)+(1+\rho_j)^{-1}]}=\frac{[\mu(t)\rho(t)(1+\rho_j)+\mu(t)]}{[\rho(t)(1+\rho_j)+1]}=\mu(t)$$

<u>Calculating Precision</u>

Starting with the original formulation

$$\mu(t+\Delta t)=\frac{[\mu(t)\rho(t)+(x_j-s_j\rho_j(1+\rho_j)^{-1})]}{[\rho(t)+(1+\rho_j)^{-1}]}$$

Calculating the variance for $\mu(t+\Delta t)$

$$\mathrm{Var}[\mu(t+\Delta t)]=\mathrm{Var}\left[\frac{x_j}{\rho(t)+(1+\rho_j)^{-1}}\right]=[\rho(t)+(1+\rho_j)^{-1}]^{-2}\,\mathrm{Var}[x_j]$$

Following Equation 4-5

$$\mathrm{Var}[\mu(t+\Delta t)] = [\rho(t) + (1+\rho_j)^{-1}]^{-2} \frac{[1+\rho(t)(1+\rho_j)]}{[\rho(t)+(1+\rho_j)^2]}$$

After simplifications

$$\mathrm{Var}[\mu(t+\Delta t)] = \frac{1}{[\rho(t)+\rho(t)^2(1+\rho_j)]}$$

And therefore precision $\mu(t+\Delta t)$ can be shown as

$$\rho(t)+\rho(t)^2(1+\rho_j)$$

APPENDIX E

SAS RESULTS-MULTINOMIAL REGRESSION FOR SPATIAL SURVEY

The LOGISTIC Procedure

Model Information

Data Set	WORK.MDATA
Response Variable	op
Number of Response Levels	3
Model	generalized logit
Optimization Technique	Newton-Raphson

Number of Observations Read	480
Number of Observations Used	480

Response Profile

Ordered Value	op	Total Frequency
1	0	116
2	1	185
3	2	179

Logits modeled use op=0 as the reference category.

Backward Elimination Procedure

Step 0. The following effects were entered:

Intercept rone rtwo rthree pd ai

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	1039.386	845.800
SC	1047.734	895.885
-2 Log L	1035.386	821.800

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	213.5860	10	<.0001
Score	179.1036	10	<.0001
Wald	128.6942	10	<.0001

Step 1. Effect rthree is removed:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	1039.386	843.436
SC	1047.734	885.174
-2 Log L	1035.386	823.436

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	211.9500	8	<.0001
Score	177.7735	8	<.0001
Wald	127.8362	8	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
1.6340	2	0.4418

Step 2. Effect rone is removed:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	1039.386	841.189
SC	1047.734	874.580
-2 Log L	1035.386	825.189

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	210.1965	6	<.0001
Score	176.5891	6	<.0001
Wald	127.2382	6	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
3.3829	4	0.4959

NOTE: No (additional) effects met the 0.05 significance level for removal from the model.

Summary of Backward Elimination

Step	Effect Removed	DF	Number In	Wald Chi-Square	Pr > ChiSq
1	rthree	2	4	1.6300	0.4426
2	rone	2	3	1.7438	0.4182

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
rtwo	2	7.5438	0.0230
pd	2	70.2201	<.0001
ai	2	98.1048	<.0001

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	op	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	1	2.0172	0.3552	32.2545	<.0001
Intercept	2	1	1.7657	0.3837	21.1784	<.0001
rtwo	1	1	-0.2456	0.0919	7.1375	0.0075
rtwo	2	1	-0.1363	0.1060	1.6557	0.1982
pd	1	1	1.1990	0.2826	18.0036	<.0001
pd	2	1	2.7347	0.3342	66.9698	<.0001
ai	1	1	-1.1070	0.1910	33.5981	<.0001
ai	2	1	-2.1986	0.2248	95.6897	<.0001

Odds Ratio Estimates

Effect	op	Point Estimate	95% Wald Confidence Limits	
rtwo	1	0.782	0.653	0.937
rtwo	2	0.873	0.709	1.074
pd	1	3.317	1.906	5.771
pd	2	15.406	8.003	29.658
ai	1	0.331	0.227	0.481
ai	2	0.111	0.071	0.172

APPENDIX F

INSTRUCTIONS TO PLAYERS-ORGANIZATIONAL SURVEY

It is assumed that you as a car-owner have been involved in a car accident and your car has been totaled. You know that your car did not worth more than $10,000. This value is considered to be your Maximum Car Value or MCV. Now you are in the process of negotiation with your insurance company to maximize your payoff. The insurer on the other hand has an opposite goal which is to minimize its losses due to your claim. It is believed that the negotiation starts with insurer's offer to you. In these settings, you will have three options to choose from which are: 1) accept the insurer's offer, 2) reject and continue negotiation by offering the insurer your own price, and 3) reject and pursue your outside option which in this case will be the court. Similarly, the insurer has the option of either accepting or rejecting your offer.

For simplicity it is assumed that the negotiation process will be performed in two steps where step 1 is insurer's offer to you and step 2 is your offer to insurer. If at the end of the second step, no agreement is achieved, the case will be automatically referred to the court. The court is assumed to be the "fair" arbitrator.

Assumptions

1) The outcome of the court for you would be a random draw from the three following values: 0.7, 0.8, or 0.9 of the Current Value (CV) of your car.

2) Current Value (CV) of your car is the discounted value of your car for each step that an agreement is not achieved. CV is computed by applying a discount factor of 0.9 for each disagreement step.

3) You are supposed to pay a fixed cost of $500 for each step that the agreement is not achieved for your commuting expenses or CE. The table below shows the process in detail:

<table>
<tr><th colspan="2">STEP 1:
Insurer Offers
Bargaining over MCV</th><th colspan="2">Disagreement
You do not accept the offer</th><th colspan="2">STEP 2:
You Offer
Bargaining over CV= 0.9 * MCV</th><th colspan="2">Disagreement
Insurance does not accept the offer</th><th colspan="2">COURT
Bargaining over CV= 0.9*0.9 * MCV</th></tr>
<tr><td>Insurer</td><td>You</td><td>Insurer</td><td>You</td><td>Insurer</td><td>You</td><td>Insurer</td><td>You</td><td>Insurer</td><td>You</td></tr>
<tr><td>I(1)*</td><td>O(1)*</td><td>n/a</td><td>-CE*</td><td>I(2)</td><td>O(2)</td><td>n/a</td><td>-CE*</td><td rowspan="2">I(3)
I(4)
I(5)</td><td rowspan="2">O(3)
O(4)
O(5)</td></tr>
<tr><td colspan="8">*I(n)= Indicates insurer’s bargaining share in the nth round of the bargaining.
*O(n)= Indicates car-owner’s bargaining share in the nth round of the bargaining.
*CE= a fixed amount of $500 per every step that an agreement is not achieved.</td></tr>
</table>

Your Assigned Role

car-owner

Instructions

1) If you have been assigned the role of an car-owner then your insurer’s offer will be emailed to you. The email then asks for your decision regarding the insurer offer. This decision should either be 1) accept or 2) reject following your own offer, or 3) reject and refer it to the court. After receiving your insurer’s offer please make your decision from the options above and send it by email to me at: alinejat@tamu.edu.

2) If you have been selected as an insurer, you are supposed to indicate your offers to each of your customers (which are either 10 or 11) by completing the following table and email it back to me at: alinejat@tamu.edu. Your offers will be received by your clients and the results will be emailed back to you. If they did not accept your offer and

named their own offer, you are supposed to indicate whether you accept their offer or prefer to go to the court.

Client Number	Your Offer	Client's Response	Your Response
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			

APPENDIX G

SAS RESULTS-MULTINOMIAL REGRESSION FOR INSURER'S OFFER

The LOGISTIC Procedure

Model Information

Data Set	WORK.MDATA
Response Variable	act
Number of Response Levels	3
Model	generalized logit
Optimization Technique	Newton-Raphson

Number of Observations Read	68
Number of Observations Used	68

Response Profile

Ordered Value	act	Total Frequency
1	1	34
2	2	25
3	3	9

Logits modeled use act=1 as the reference category.

Backward Elimination Procedure

Step 0. The following effects were entered:

Intercept offer

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	137.567	133.807
SC	142.006	142.685
-2 Log L	133.567	125.807

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7.7599	2	0.0207
Score	7.1834	2	0.0276
Wald	6.1587	2	0.0460

NOTE: No (additional) effects met the 0.05 significance level for removal from the model.

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
offer	2	6.1587	0.0460

Analysis of Maximum Likelihood Estimates

Parameter	act	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	2	1	4.3344	2.0175	4.6156	0.0317
Intercept	3	1	3.5939	2.4773	2.1046	0.1469
offer	2	1	-0.00068	0.000290	5.4247	0.0199
offer	3	1	-0.00072	0.000365	3.8889	0.0486

Odds Ratio Estimates

Effect	act	Point Estimate	95% Wald Confidence Limits	
offer	2	0.999	0.999	1.000
offer	3	0.999	0.999	1.000

APPENDIX H

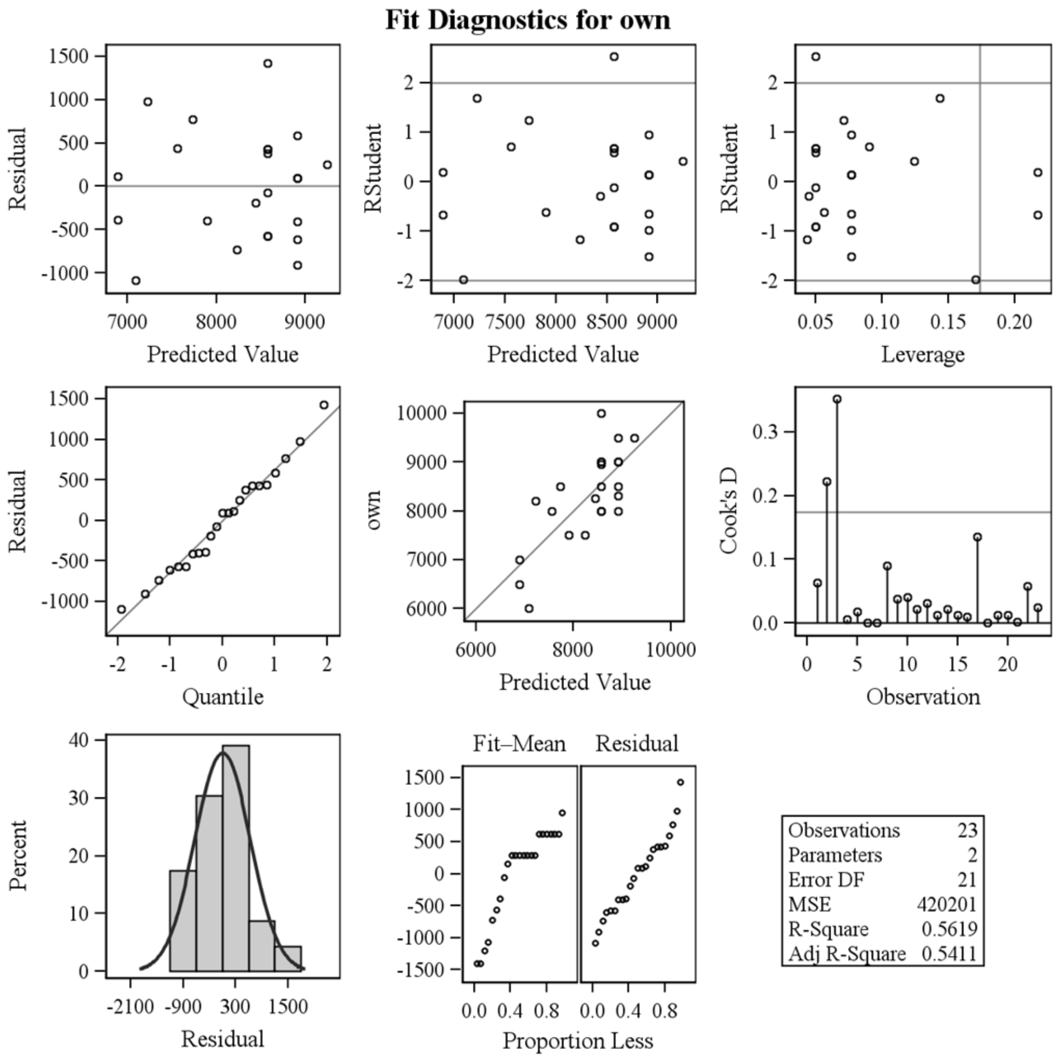
SAS RESULTS-LINEAR REGRESSION FOR OWNER'S COUNTEROFFER

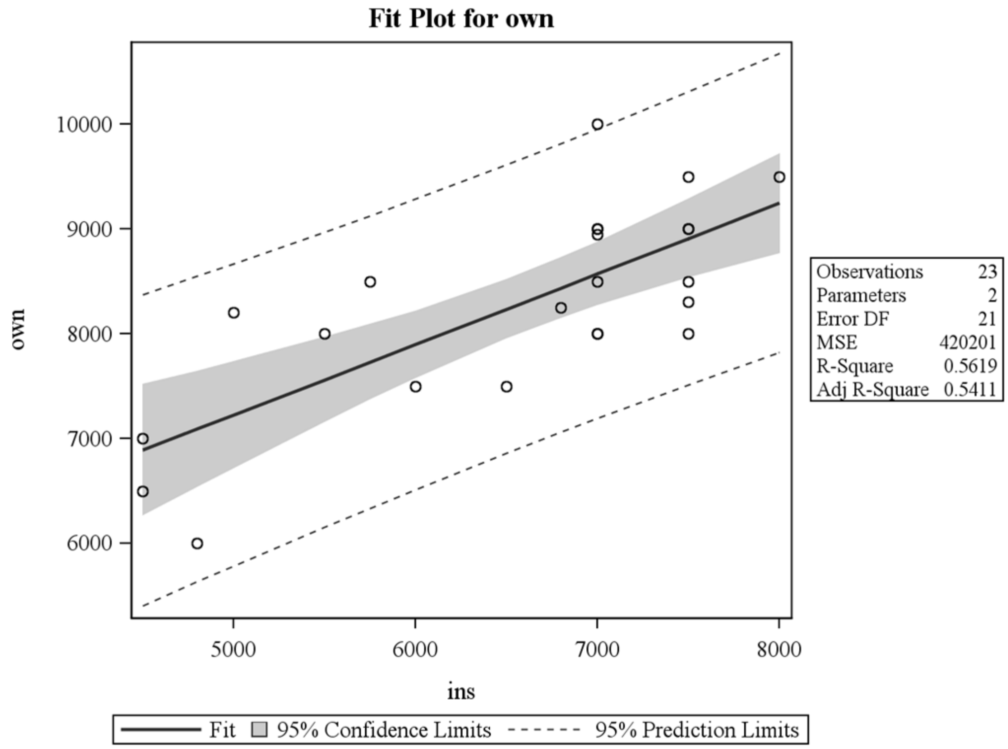
Number of Observations Read	23
Number of Observations Used	23

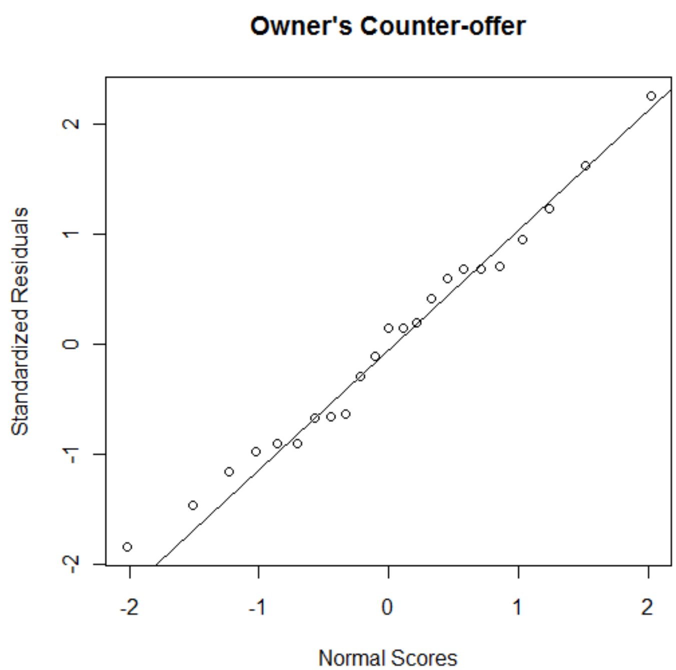
Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	11319039	11319039	26.94	<.0001
Error	21	8824222	420201		
Corrected Total	22	20143261			

Root MSE	648.22915	R-Square	0.5619
Dependent Mean	8291.30435	Adj R-Sq	0.5411
Coeff Var	7.81818		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	3854.04634	865.56428	4.45	0.0002
ins	1	0.67431	0.12992	5.19	<.0001


Fit Diagnostics for own
Residual
Predicted Value
RStudent
Leverage
Quantile
own
Cook's D
Observation
Percent
Fit–Mean
Residual
Proportion Less
Observations 23
Parameters 2
Error DF 21
MSE 420201
R-Square 0.5619
Adj R-Square 0.5411


Fit Plot for own
own
10000
9000
8000
7000
6000
5000
6000
7000
8000
ins
Observations 23
Parameters 2
Error DF 21
MSE 420201
R-Square 0.5619
Adj R-Square 0.5411
Fit
95% Confidence Limits
95% Prediction Limits


Owner's Counter-offer
Standardized Residuals
2
1
0
-1
-2
-2
-1
0
1
2
Normal Scores

APPENDIX I

R RESULTS-BINOMIAL REGRESSION FOR INSURER'S RESPONSE

```
Start:  AIC=26.74
bd ~ val

       Df Deviance    AIC
<none>      20.385 26.741
- val   1   31.755 34.933
> summary(m1)

Call:
glm(formula = bd ~ val, family = binomial(link = "logit"), data = mydata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7429  -0.4922   0.3592   0.7030   1.9387

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.565e+01  7.427e+00  -2.107   0.0352 *
val          1.990e-03  9.089e-04   2.190   0.0285 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 31.755  on 23  degrees of freedom
Residual deviance: 20.385  on 22  degrees of freedom
AIC: 24.385

Number of Fisher Scoring iterations: 6
```

VITA

Name: Ali Nejat

Address: Zachry Department of Civil Engineering
Texas A&M University
3136 TAMU
College Station, TX 77843-3136

Email Address: nejat.ali@gmail.com

Education: B.S., Civil Engineering, Zanjan University
Zanjan, Iran, 2000

M.S., Civil Engineering, Islamic Azad University
Tehran, Iran, 2003

Ph.D., Civil Engineering, Texas A&M University
College Station, Texas, 2011