Effect of Benefit Fraud on Community Resilience in the Wake of Disaster

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Abstract

Emergency financial assistance provided for disaster relief creates opportunities for fraudulent behavior. History has shown that the amount of recovery funds lost to improper and potentially fraudulent payments could research millions to billions of dollars per event. Reducing such cost and investing available resources more appropriately could help communities recover more rapidly from the impact of severe disasters. Unfortunately, research on the effects of fraud activity has been overlooked in resilience research. In this study, a conceptual model is formulated based on the observed phenomena and criminology theory. Then, an agent-based computational model, which includes a simulation environment of a community facing an earthquake disaster, fraudsters, and application inspectors is created to model benefit fraud behavior. The simulation considers the effect of both micro-level disaster demands due to building damages and meso-level social variables on benefit fraud, and estimates the cost to communities associated with these post-disaster crimes. Statistical data from the U.S. government reports in the aftermath of Hurricane Katrina and Rita is used for calibration. The results of simulation runs demonstrate that strengthening application review and lessening target vulnerability can help lessen the loss caused by benefit fraud, but it is important to find the balance between the loss of fraudulent payments and the speed of aid distribution in order to improve the overall resilience of communities.

Keywords: community resilience; benefit fraud; post-disaster crimes; social impact; financial assistance policy

1. Background and Objectives

History has shown that severe disasters may create opportunities for criminal activities [1]. Many research efforts have studied the influence of disasters and social conditions on crime activities by quantifying its effect at the meso level through statistical or equation-based methods, e.g., estimating crime rate in a county in the aftermath of disasters. Various quantization variables have been proposed to represent the impact of disasters and the vulnerability of exposed communities, such as disaster frequency, property damage, crop damage, injuries, population, economic capital, income inequality, unemployment, racial heterogeneity, and ethnic heterogeneity [2-5]. However, conventional statistical methods usually treat these meso-level impact factors as one-time initial inputs and take the statistical outcome of crimes as the simulation result. The variances of these social and disaster variables over time for different subunits of society have been overlooked in the models of crime in disaster. The dissimilar temporal patterns of the impact of disasters on the different social subsystems should be investigated, as discussed in [6].

Besides the impact of disasters on criminal behavior, the influence of criminal behavior on the recovery of communities after disasters is also of interest. This is an area that has been overlooked in most resilience studies. Records show that the loss of recovery funds due to fraudulent crimes could be millions to billions of dollars per event [7, 8]. Reducing such cost and investing available resources more appropriately could help communities recover more rapidly from the impact of disasters. Among five common types of fraud after disasters defined by the U.S. Department of Justice [9], i.e., fraudulent charities, identity theft, government- and private-sector benefit fraud, government-contract and procurement fraud, and public corruption, this study specifically focuses on ‘benefit fraud.’ This refers to individuals who obtain or attempt to obtain financial assistance or benefits to which they are not entitled [9]. The other types of post-disaster crime may also have impacts on community resilience and are left for future research.

To address the research gaps mentioned above, this study aims to develop a computational model to explore the dynamic process of benefit fraud activities, considering disaster demands and social characteristic at both meso (environment) and micro (individual) levels. For that purpose, agent-based modeling (ABM) is chosen to be the simulation technique used in this study because of its ability to capture the characteristic and behavior of individual entities in time and space. Unlike traditional statistical or equation based methods that operate in a top-down manner, ABM models operate from the bottom up, simulating the generative behaviors and interactions of heterogeneous individual entities for investigating macro-level output patterns. Although the validation of ABM could be a significant challenge, with the capability of systematically adjusting decision-making rules of agents and the parameters of modeling environment, ABM may be the most feasible approach to examine concept theories and uncover new phenomena when real data is lacking or a field trial is excessively expensive [10].

The objective of this study is to couple criminal models, specially focusing on benefit fraud, to disaster resilience simulations. An agent-based model that considers demands and social variables at both the meso- and micro-levels is employed to simulate the temporal nature of the problem. Data from U.S. government reports in the aftermath of Hurricane Katrina and Rita is used for calibration. After verifying that the proposed model is able to capture the key features of benefit fraud in the wake of disaster and produce reasonable results, sensitivity analyses are conducted to explore the effects of key variables on the extent of and propensity for post-disaster benefit fraud.

2. Proposed agent-based model

The proposed agent-based model consists of three types of agents: 1) householders in the disaster area, 2) application reviewers in the organizations that distribute financial assistance, and 3) government special investigators, corresponding to the three key components of the routine activity theory [11], i.e., potential offenders, targets, and guardians. A benefit fraud event in the wake of disaster is represented by the interactions between these three types of agents, as illustrated in Figure 1.

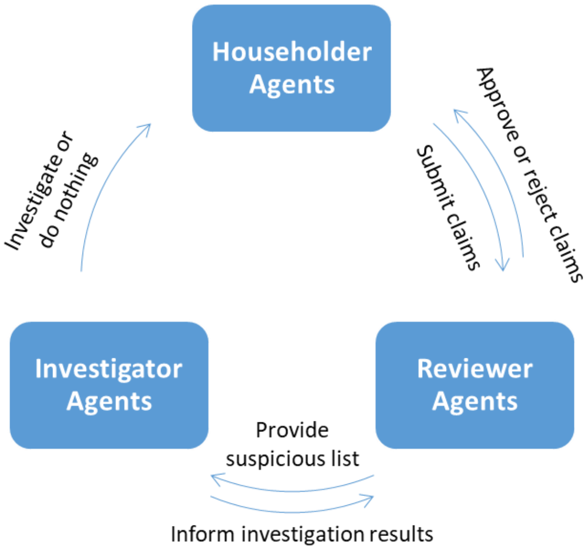

Fig. 1 – Interactions between three types of agents

In each run, each householder agent will decide whether to submit an application at every step, and a householder may submit more than one application during the whole simulation, i.e., duplicate applications. The probability of a householder agent to submit a duplicate/fraudulent application at time t, $P_{f,t}$, is calculated by Eq. (1).

$$P_{f,t} = P_i \cdot (w_{CC} \cdot CC_t + w_{CS} \cdot CS_t + w_{DD} \cdot DD_t + w_E \cdot E_t) \quad \text{s.t.} \quad 0 \leq P_{f,t} \leq 1, \quad 0 \leq P_i \leq 1, \quad -1 \leq CC_t, CS_t, DD_t, E_t \leq 1, \quad w_{CC}, w_{CS}, w_{DD}, w_E \geq 0 \tag{1}$$

where P_i is the given initial probability for householders to submit a duplicate/fraudulent. CC_t and CS_t are the quantified values for the effect of community cohesion and criminal subculture at time t. Normal random variables with the time-varying mean values in Fig. 2 and standard deviation of 0.25 are generated as the *CC* and *CS* indices for each householder agent to reflect the variation of community cohesion and criminal subculture impacts on distinct individuals. The positive quantified values indicate that the variables have a stimulative effects on the propensity of committing a crime, and the negative ones represent debilitating effects.

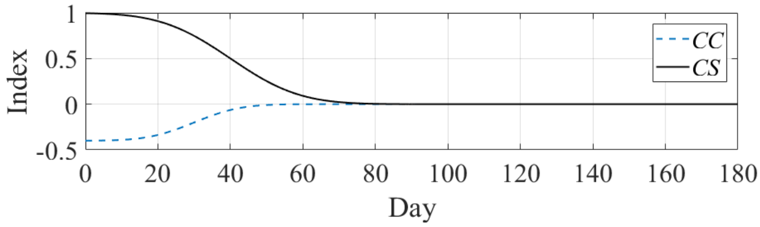

Fig. 2 – Simulation procedure of the proposed ABM

DD_t is the micro variable for the effect of disaster-caused demands, as defined in Eq. (2), where DL = 4, 3, 2, and 1 for destroyed, major, minor, and none damage levels of the householder agent's home, respectively; $T_{without\ support}$ is number of weeks after the disaster that the householder agent has not received monetary support.

$$DD_t = \frac{DL \times T_{without\ support}}{8} \quad \text{s.t.} \quad 0 \leq DD_t \leq 1 \tag{2}$$

E_t represents the effect of agent's personal experience, as computed in Eq. (3). w_{CC}, w_{CS}, w_{DD}, and w_E in Eq. (1) are the corresponding weights for each variable, and are all equal to one in the calibrated model and sensitivity analyses.

$$E_t = 0.2\, N_{approved}, \qquad \text{s.t.} \quad 0 \leq E_t \leq 1 \tag{3}$$

3. Calibration: Individuals and Households Program for Hurricanes Katrina and Rita

The Individuals and Households Program (IHP) is adopted for the calibration. IHP is one of the financial assistance programs for disaster relief provided by the U.S. Federal Emergency Management Agency (FEMA) in the aftermath of 2005 Hurricanes Katrina and Rita. The number of householder agents in the simulation is set to 1.3 million, which is the approximate number of people who were evacuated or displaced after Hurricanes Katrina and Rita [12]. The number of application reviewers and special investigators is assumed to be 3,000 and 1,000, respectively. Table 1 provides the estimated number of damaged houses in

Mississippi and the eligible IHP assistance for different damage levels after hurricanes Katrina and Rita [13]. The same distribution is used to randomly assign home damage levels to householder agents at the beginning of the simulation.

Table 2 lists the other parameters used in the calibrated model, and the independent variables to be adjusted in the sensitivity analyses are indicated in bold. To consider uncertainty, the number of applications reviewed per day by per reviewer, N_{rv}, the number of applications investigated per day by per investigator, N_{inv}, and the initial probability for householders to submit a fraudulent claim, P_i are assumed to be Gaussian random variables, which are indicated by mean and standard deviation in Table 2. To represent the fact that most of the applications had been submitted in the first few months, the probability of a householder completing an application, P_c, and the probability of application being eligible and complete, P_e, decreases over time.

Two types of application review errors are considered here to represent the vulnerability of targets. Type I error, $error_{type1}$, represents the case of judging a justified application to be suspicious; Type II error, $error_{type2}$, refers to the case of approving a fraudulent application without further investigation. Both errors are set to vary with time to represent the fact that the application review is usually less strict during the emergency phase. It is assumed that are no error in the investigation results in this article to simplify the simulation. The deadline of submitting applications is 426 days after the disaster occurred.

Table 1 – Analysis procedure of the ABM simulation

Damage level	**None**	**Minor**	**Major**	**Destroyed**	**Total**
Percentage	7.7%	81.0%	9.8%	1.5%	**100%**
Number of householder agents	100,000	1,053,000	127,000	20,000	**1,300,000**
Eligible IHP assistance (USD)	2,000 per household	4,600 per household	7,200 per household	12,500 per household	**6,028,200,000**

Table 2 – Parameterization of the calibrated model and independent variables for sensitivity analyses

Parameter	**Value**
N_{rv}, mean (standard deviation)	**3(1)**, **4(1)**, 5 (1)
N_{inv}, mean (standard deviation)	2.4 (0.5)
P_i , mean (standard deviation)	1% (0.1%)
P_c	30% [a], 25% [b], 8% [c]
P_e	95% [a], 75% [b], 60% [c]
$error_{type1}$	0% [a], 2% [b], 5% [c]
$error_{type2}$	100% [a], 80% [b], 60% [c] (E1) **75% [a], 60% [b], 45% [c] (E2)** **50% [a], 40% [b], 30% [c] (E3)**

Note: [a] Day 1 – Day 14; [b] Day 15 – Day 45; [c] After Day 46 -;

Monte Carlo simulations are conducted to capture the uncertainty of the parameters. Based on the result of a convergence analyses, which is not shown here due to the limited space, the mean value and standard deviation of one thousand Monte Carlo realizations are used to present the results of the calibrated model and sensitivity analyses.

Fig. 3 shows the comparison between the results of the calibrated ABM and the reported data derived from the government reports, where the shaded area represents the range between standard deviations, i.e., $\pm\sigma$. According to the report of the U.S. Government Accountability Office [7], the amount of potentially fraudulent assistance in Hurricane Katrina and Rita through FEMA's IHP was estimated to be between $600 million to $1.4 billion, or 10 to 22 percent. The other statistical data, e.g. number of applications and amount of distributed assistance, are derived from the U.S. Department of Justice Hurricane Katrina Fraud Task Force [9, 14-18], the U.S. Department of Homeland Security Office of Inspector General [13, 19, 20], and the U.S. Government Accountability Office [7, 8, 21-24]. Clearly, the calibrated results match the trends reasonably.

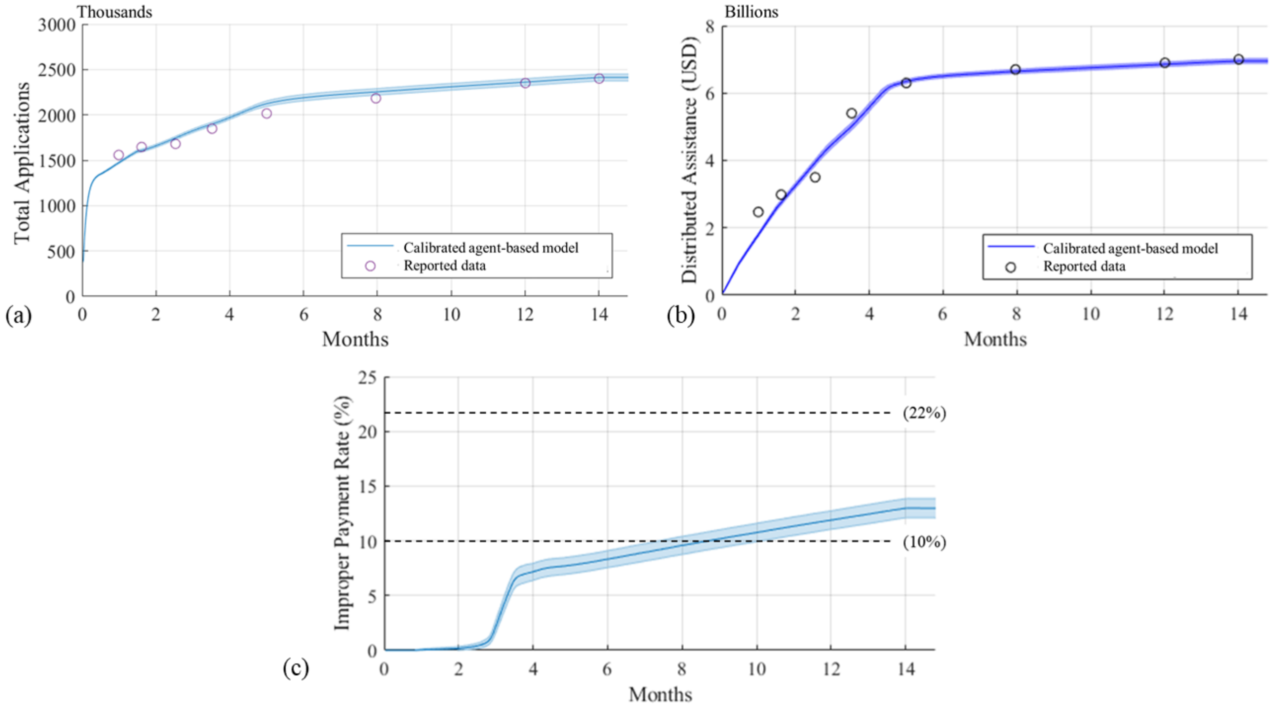

Fig. 3 – Comparison of the results of calibrated ABM and the reported data: (a) number of total applications, (b) distributed assistance, (c) improper payment rate

4. Sensitivity Analyses

Two key dependent variables are investigated through a sensitivity analysis. The first is the percentage of overall improper payments, Pct_{Fraud}, which indicates the proportion of funding that could be used more effectively. The second dependent variable is the speed of distributing financial assistance, and the time required for 95% of victims with disaster-caused loss to receive the grants, $T_{95\%}$, is adopted here. Both dependent variables are important and should be evaluated at the same time. The independent variables investigated in this article include average number of applications reviewed per day per reviewer, N_{rv}, and the type II error of application review, $error_{type2}$. There are multiple other parameters that were studied including the degree of disaster-caused demands and number of applications investigated per day, per investigator, but those are not presented here.

Firstly, N_{rv} is adjusted to 3, 4 and 5 (with standard deviation = 1), and the other parameters remain unchanged. Fig. 4 shows the effect of review speed on the estimated fraudulent rate and the distribution of payment over time. It is found that the faster the review speed, the faster the grants are distributed in the first few months. However, the sharp rise in improper payments occurs earlier. Nevertheless, the overall improper payment rate remains somewhat steady.

Sensitivity analyses of N_{rv} and $error_{type2}$ are presented in Fig. 5. In these analyses, only one independent variable is adjusted at a time, and the other parameter kept the same as shown in Table 2. From Fig. 5 (a), it is observed that speeding up the application review can greatly decrease $T_{95\%}$ to let victims get aid faster, but the overall improper payment rate increases slightly at the same time. Fig. 5 (b) shows that enhancing the accuracy of the application review can reduce the improper payments effectively but there is no significant effect on $T_{95\%}$.

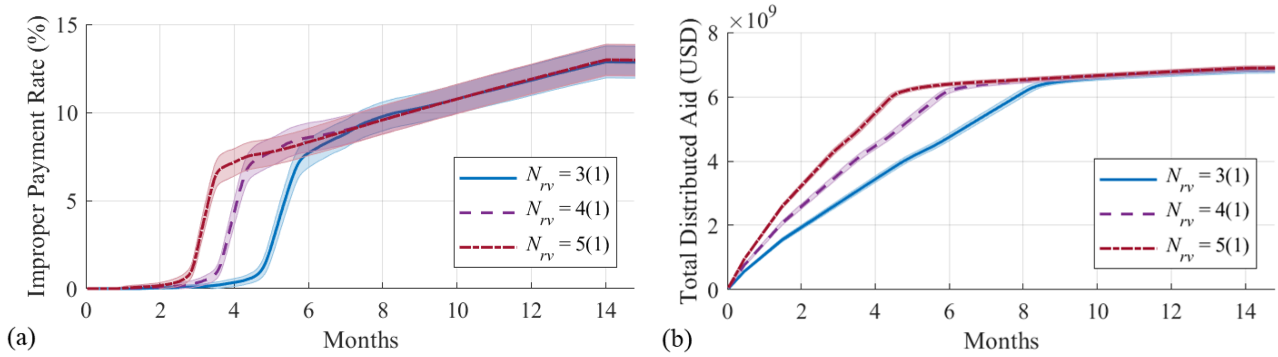

Fig. 4 – Effect of review speed: (a) overall improper payment, (b) total distributed assistance

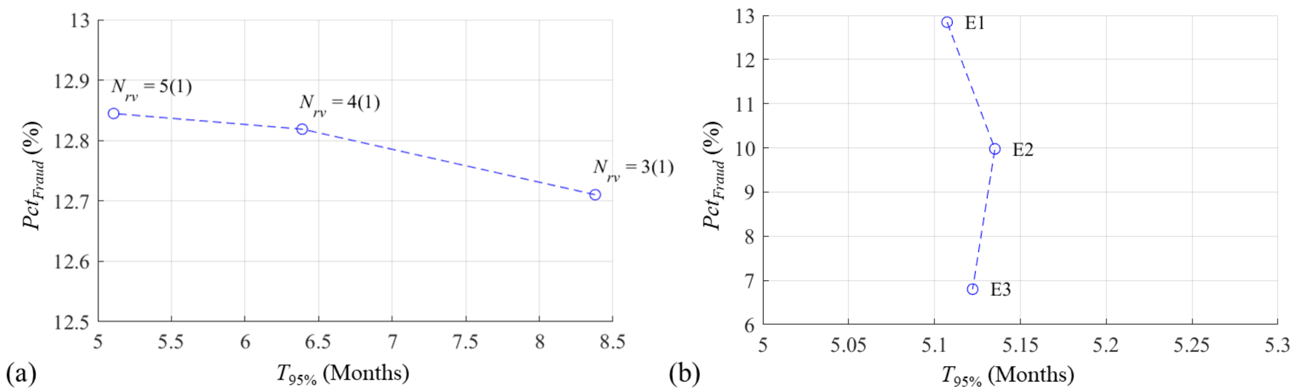

Fig. 5 – Sensitivity analyses with independent variables: (a) N_{rv}, (b) $error_{type2}$

5. Conclusions

This study has made an effort to integrate the effect of fraudulent activity in resilience simulations. A computational agent-based model is proposed to simulate the time pattern of benefit fraud activities considering disaster demands and social characteristic at both micro- and meso-levels. Data from the government reports of the U.S. FEMA's Individuals and Households Program (IHP) for Hurricane Katrina and Rita was used for the calibration. The result showed that the proposed model can capture the basic features of benefit fraud that arise after severe disasters and produce sensible results through calibration. Sensitivity analyses were conducted to study the effects of review speed and target vulnerability. It can be found that improving the accuracy of review can help reduce the loss caused by post-disaster benefit fraud. However, that will lead to an increase in review time, i.e. there is a trade-off between different objectives, quantified in this research. A higher-order sensitivity analysis is needed in future studies to find the optimal balance between the loss of fraudulent payments and the speed of aid distribution for improving the overall resilience of communities.

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