Computational Simulation of Benefit Fraud and Community Resilience in the Wake of Disaster

Szu-Yun Lin, S.M.ASCE[1]; Sherif El-Tawil, F.ASCE[2]; and Benigno E. Aguirre[3]

Abstract: The monetary assistance provided for disaster relief creates opportunities for fraudulent behavior. Historical records have shown that the loss of recovery funds due to improper and fraudulent payments could reach hundreds of millions of dollars per event, siphoning support away from those who need it the most and potentially slowing down the economic resurgence of a disaster-stricken community. Focusing specifically on benefit fraud, a common type of postdisaster crime, an agent-based computational model based upon criminology theory is proposed to investigate how such behavior affects recovery during the postevent period. The simulation environment models a community facing a natural disaster, the presence of fraudsters and application inspectors, and the interactions between them. Data from the Hurricane Katrina and Rita disasters is used for calibration. The proposed model accounts for both microlevel disaster demands caused by building damage and meso-level social variables. It estimates the cost to communities associated with benefit fraud. Parametric studies quantify how reducing application review errors, decreasing disaster demands, and increasing oversight can help lessen the losses caused by benefit fraud. They demonstrate how computational simulation can be used to achieve a meaningful balance between the loss of fraudulent payments and the speed of distributing aid in order to improve the overall resilience performance of communities. **DOI: 10.1061/(ASCE)NH.1527-6996.0000407.**

Introduction and Motivation

The monetary assistance provided by the government and other organizations in the aftermath of large-scale disasters is enormous. While quick disbursement of this aid can reduce human suffering and enable rapid recovery, the abundance of resources combined with emergent conditions create opportunities for disaster-related fraud, which can reach millions of dollars per event. According to the US Government's Accountability Office (GAO 2006d), the amount of potentially fraudulent assistance in Hurricanes Katrina and Rita through FEMA's Individuals and Households Program (IHP) was estimated to be between \$600 million to \$1.4 billion, or 10% to 22% of the provided aid. For hurricane Sandy, the numbers are smaller, but still significant: \$39 million, or 3% of the provided monetary assistance (GAO 2014).

As discussed later on, a number of researchers have studied the influence of disasters and subsequent social conditions on the outcome of crime. However, these studies often addressed criminal behavior at the meso-scale, for example, the change in crime rate at the county level. They also examined the presumed emergence of social solidarity in a community that stopped the majority of crimes from happening, but most did not consider the temporal nature of the problem (Aguirre and Lane 2019). Importantly, from the perspective of this paper, the majority of existing studies did not consider postdisaster crime in the context of long-term community reconstruction and recovery.

Focusing specifically on benefit fraud, the objective of this paper is to address the identified gaps in the literature through computational simulation. Benefit fraud is a common type of postdisaster crime where individuals seek to enrich themselves by filing false damage claims. By explicitly considering the temporal nature of the problem and employing an agent-based methodology, this study models and investigates the mechanisms of benefit fraud, taking into account disaster demands and social variables at both the meso- (community) and micro (individual) levels. After calibration using data from the Hurricane Katrina and Rita events, the proposed model is used to conduct a parametric study to investigate the effects of key variables on the extent of and propensity for postdisaster benefit fraud.

Background

Disaster-related crime research is not a central research topic in the literature in disaster science. Zahran et al. (2009) considered baseline demographic variables (i.e., population and economic capital), social order variables (i.e., law enforcement and nonprofit density), and disaster variables (i.e., disaster frequency and presidential disaster declarations) for modeling crime outcomes in Florida. Prelog (2016) used disaster and social indicators, including disaster counts, property damage, crop damage, injuries, income inequality, racial heterogeneity, and ethnic heterogeneity to model the relationship between natural disasters and crime in the United States. Spencer (2017) considered the impact of unemployment and income when estimating the effect of hurricanes on criminal activities. Breetzke et al. (2018) examined the effect of socioeconomic deprivation, ethnic heterogeneity, residential mobility, and collective efficacy on crime variability in postearthquake Christchurch using 10 community-level measures [a systematic review of social vulnerability indicators in disasters can be found in Fatemi et al. (2017)]. The surveyed studies indicate that the current state-of-the-art seeks to estimate postimpact crime activities through statistical

[1]Graduate Student, Dept. of Civil and Environmental Engineering, Univ. of Michigan, Ann Arbor, MI 48109 (corresponding author). ORCID: https://orcid.org/0000-0001-5369-2571. Email: sylin@umich.edu

[2]Professor, Dept. of Civil and Environmental Engineering, Univ. of Michigan, Ann Arbor, MI 48109. Email: eltawil@umich.edu

[3]Emeritus Professor, Dept. of Sociology and Criminal Justice, Univ. of Delaware, Newark, DE 19716. ORCID: https://orcid.org/0000-0001-6924-794X. Email: aguirre@udel.edu

Note. This manuscript was submitted on November 27, 2019; approved on May 4, 2020; published online on July 17, 2020. Discussion period open until December 17, 2020; separate discussions must be submitted for individual papers. This paper is part of the ***Natural Hazards Review***, © ASCE, ISSN 1527-6988.

or equation-based methods that employ meso-level variables. This paper takes a different approach based on simulation.

Agent-based modeling (ABM) is selected as the primary computational tool in order to address the desired microlevel variables, i.e., individual-level parameters. ABM is a well-established computational method that has found broad applicability in social science (Epstein 2006; Fang et al. 2016a, b). The application of ABM in criminology arose in the early 2000s. Groff et al. (2019) provided a systematic review of studies that have used ABM to model urban crime, such as burglary (Johnson et al. 2007; Malleson et al. 2010), drug crime (Dray et al. 2008), and robbery (Groff 2007). ABM also has been applied to studying financial crimes, e.g., fraudulent activities in public service delivery programs (Kim et al. 2013) and tax evasion (Hokamp 2014). To the knowledge of the authors, no studies have used ABM to investigate crime in the wake of disasters as is done herein. By necessity, modeling postdisaster crime depends on modeling disaster demands, or the challenges posed by the effects of the disaster, which is another innovation in this paper that allows considering the effects of crime.

Methodology

The process of establishing an agent-based model is divided into the following steps. First, a conceptual model is formalized based on the observed phenomena and the knowledge acquired from previous disaster studies and existing theories in criminology. Second, a computational model, which includes the simulation environment, agents, and their behavior rules, is created for interpreting the conceptual model. After verifying that the constructed computational model adequately represents the properties of the conceptual model, the third step is to calibrate the computational model with empirical data. Finally, artificial experiments (parametric sensitivity analyses) are conducted to study the effects of various variables.

Linking Criminology Theories to the Conceptual Model

Before creating a computational model, it is necessary to formalize a conceptual model that adequately represents the situation of interest and captures the theoretical propositions to be explored. The proposed conceptual model builds upon established criminology theories. These theories are briefly reviewed next and key aspects are selected to explain social phenomena observed in disasters. The following discussion is only limited to the main ideas that underlie the proposed model. Additional details about the theories can be found in Schreck and Tewksbury (2011) and Tibbetts (2018).

The rational choice theory (Cornish and Clarke 1986) is a common theory used to explain criminal behavior. It proposes that the choice to commit crime is based upon the balance of risks, rewards, and efforts perceived by a potential criminal. As a subfield of the rational choice theory, the routine activity theory (Cohen and Felson 1979) is more focused on the available opportunity. In it, criminal activity is conditioned upon convergence of: (1) suitable targets, (2) motivated offenders, and (3) a dearth of guardians. It posits that the absence of any one of these conditions will likely prevent the occurrence of crime. The social disorganization theory (Shaw and McKay 1942) and the therapeutic community hypothesis (Fritz 1996) suggest that crime rate is a function of social conditions. The former suggests that certain ecological characteristics and criminal subcultures of the surrounding area, e.g., high unemployment and low law enforcement density, may increase the likelihood of individuals committing criminal activities. In contrast, the latter theory predicts that illegal activities will decrease in the aftermath of disasters because community cohesion and cooperation rise in the aftermath of disasters. Yet another theory, the social learning theory (Jeffery 1965), proposes that criminal behavior is learned and reinforced by previous actions, so that the propensity of being a repeat offender increases with prior fraud experience.

The most useful summary of these ideas is encapsulated in the routine activity theory. According to it, the roles involved in a criminal incident could be divided into three types: targets, offenders, and guardians. In the case of benefit fraud after disasters, the organizations distributing financial assistance are targets that may be scammed by fraudulent applicants (offenders). The government investigators who specialize in detecting fraud crimes are the guardians. Table 1 outlines the selected decision factors in a benefit fraud event as inspired by the preceding criminology theories and how those factors translate into implementation considerations within the proposed conceptual model.

Table 1. Potential decision factors of benefit fraud and their consideration within the proposed conceptual model

Criminology theory	Decision factors	Implementation considerations in conceptual model
Rational choice theory	Financial demands attributed to the disaster	The repair cost attributed to the disaster. Also of importance is the elapsed time after the disaster without the arrival of assistance from outside the community
	Effort and skill needed to commit benefit fraud	Probability of an applicant completing a fraudulent application for financial assistance
	The perceived risks of crime	Number of applicants sanctioned and the extent of punishment for the crime
Routine activity theory	Availability of victims and their vulnerability	Insufficient oversight or weak application review process of victims (such as government or organizations providing aid)
	Guardian strength	Number and diligence of fraud investigators
Social disorganization theory	Extent of criminal subculture	The criminal subculture influences the propensity of applicants toward committing fraud, where people construct a normative and value consensus that makes criminal behavior appropriate
Therapeutic community hypothesis	Extent of community cohesion	Community cohesion influences the propensity of applicants toward committing fraud
Social learning theory	Repeat offending	Success in previous fraud efforts may increase the propensity of recommitting benefit fraud. It may also indicate the presence of a criminal career in the deviant, where repeat crime becomes an accepted way of doing things

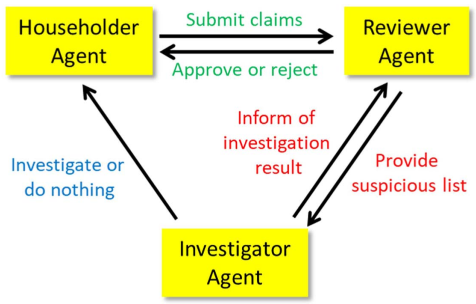

Fig. 1. Interactions between the agents.

Constructing the Computational Agent-Based Model

Scope and Assumptions

The proposed conceptual model addresses a situation in which benefit fraud may occur when the government or other organizations distribute monetary assistance to homeowners for house reconstruction or relocation after severe natural disasters. Potential claimants are the householders residing in the affected area, and benefit fraud refers to the householders obtaining or attempting to obtain financial assistance from the grantor but having no entitlement to do so, e.g., not having a covered loss as a direct result of the disaster, or duplicating the claims for supernumerary benefits. Benefit fraud committed by nonresidential criminals, organized groups, and identity thieves is not considered in this study and is left to future research that could include more types of agents.

The inventory of damaged residential buildings and demographic information of homeowners are assumed to be known at the beginning of a simulation. The temporal unit used to update an agent's activity and decision-making is one day. The simulation starts when the first aid application is accepted and ends when all applications have been reviewed and related investigations have concluded.

Agents and Interaction

The simulation of benefit fraud in a disaster is an abstract representation of a hypothesized dynamic relationship between 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, i.e., potential offenders, targets, and guardians, in a benefit fraud event. The interactions between the agents is illustrated in Fig. 1. The opportunity for benefit fraud is present during the interactions between householders and application reviewers. A householder agent decides whether to submit an application for financial assistance based on the disaster-caused loss and other social impact factors. The probability that a householder agent will submit duplicate/fraudulent applications represents the propensity toward committing fraud. The ability of reviewers to notice suspicious claims represents the vulnerability of the target. Investigator agents provide fraud deterrence and guardianship by investigating suspicious applicants. Claims by fraudulent agents are frozen once they are discovered by investigator agents.

The analysis procedure of the ABM simulation is shown in Fig. 2. The ecological characteristics of the community, e.g., community cohesion and criminal subcultures, and the householder's loss caused by the disaster are the initial inputs to the simulation scenario. This information can be collected by other government agencies in the aftermath of disasters, so investigator

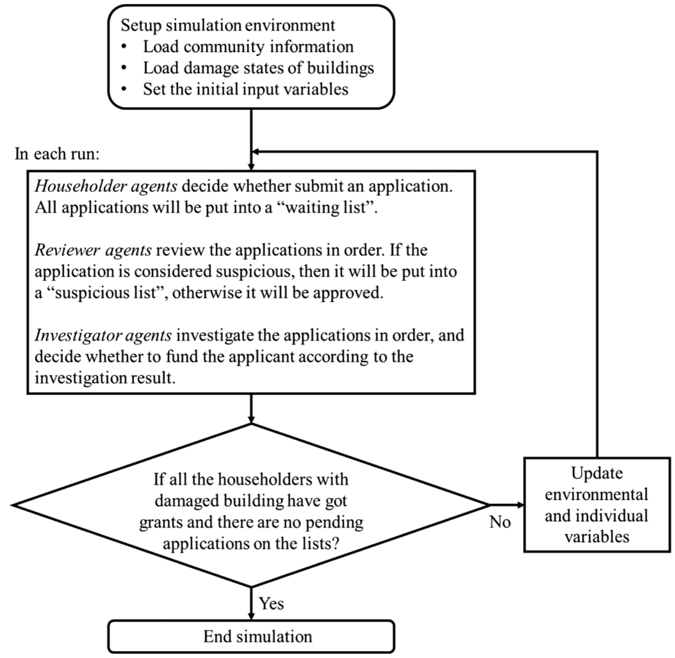

Fig. 2. Analysis procedure of the ABM simulation.

agents can make informed decisions about the likelihood that applications are justified or fraudulent. Applications may have four different results: (1) approved and paid with or without further investigations, (2) rejected as ineligible or incomplete without investigations, (3) approved and paid by the reviewers but determined as fraud by the investigators in the aftermath, and (4) seen as suspicious by the reviewers and determined as fraud by the investigators before payment is made.

Decision-Making Rules

The decision process for a householder agent is illustrated in Fig. 3. Each agent decides whether to submit an application at every step and may submit more than one application during a simulation, i.e., duplicate applications. In Fig. 3, the probability of a householder agent completing an application at specific time, P_c, characterizes the probability of householders submitting applications in different postdisaster phases. The probability of submitting duplicate/fraudulent applications, denoted as P_f, used to estimate the crime propensity, is described in the next section.

The behavior rules for a reviewer agent are shown in Fig. 4. Reviewers examine applications in the order of submission. Applications that are ineligible or incomplete are rejected and canceled. Eligible applications are either awarded directly or sent to investigators for further investigation. Two types of application review errors are considered here to represent the vulnerability of targets in the routine activity theory. Type I error, rv_error_{type1}, refers to judging a justified application to be suspicious, and Type II error, rv_error_{type2}, indicates the case of approving a fraudulent application without further investigations.

The decision rules for investigator agents are presented in Fig. 5. As with reviewer agents, there may be two types of errors in the investigation results, i.e., judge a justified application as a fraud (inv_error_{type1}) or approve a fraudulent application (inv_error_{type2}). In addition to the suspicious cases listed by the reviewers, investigators may investigate applications already approved by the reviewers. Investigators will provide the results of the investigation to the reviewers, and applicants seen as defrauders cannot submit

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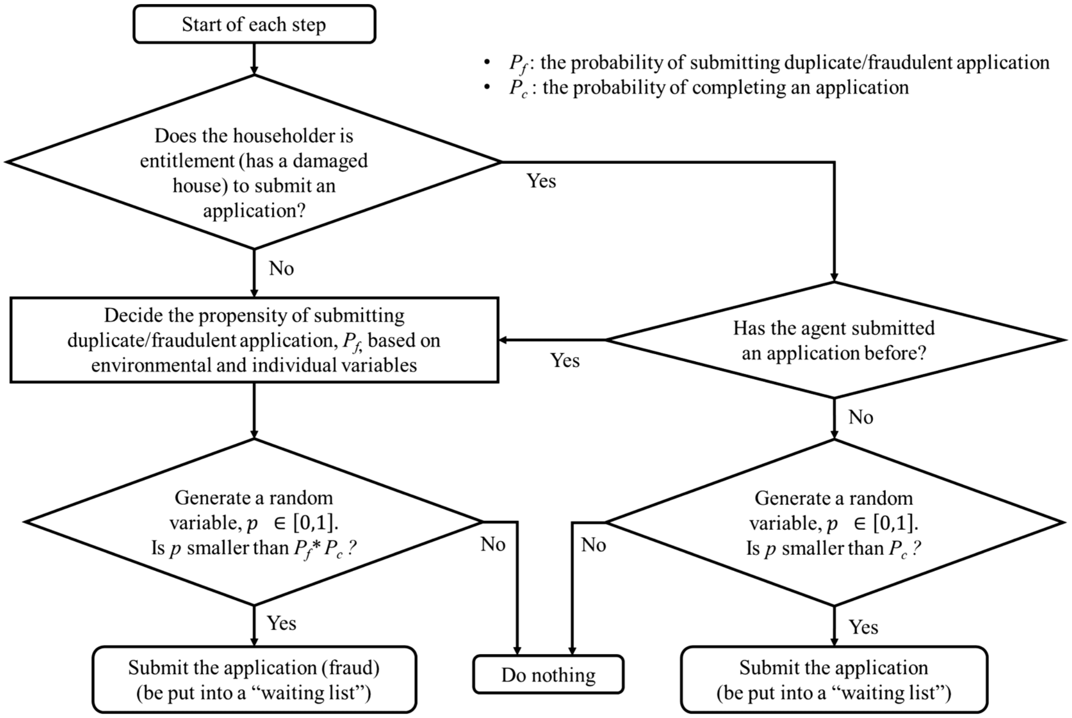

Fig. 3. Decision-making process of householder agents.

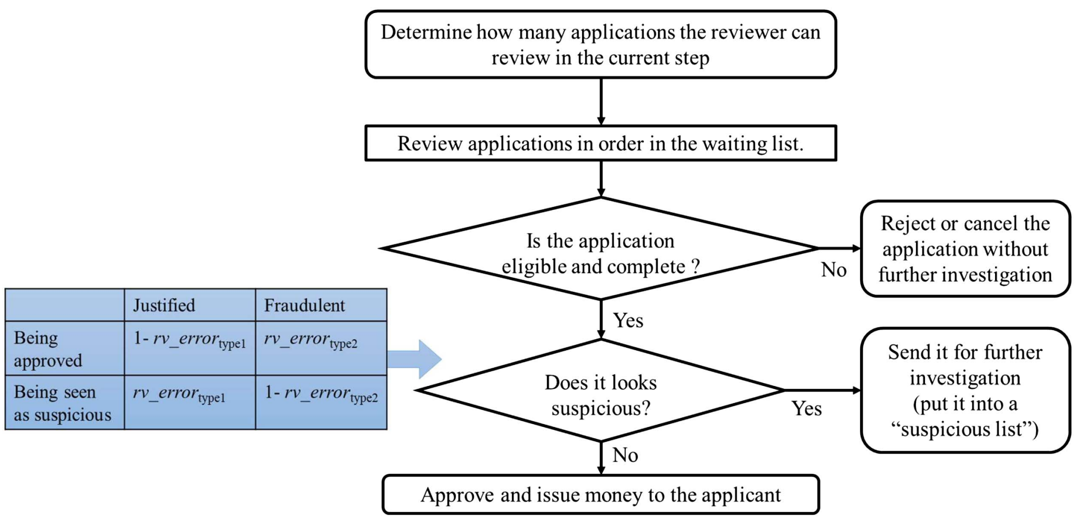

Fig. 4. Decision-making process of reviewer agents.

further applications. The speed and accuracy of investigations represent the guardian strength in the routine activity theory.

Propensity for Committing Fraud

The probability that a householder will submit duplicate/fraudulent applications is denoted P_f in Fig. 3. P_f is a direct function of the social and disaster-related variables at each time step of the analysis, specifically the environmental (meso) and individual (micro) level variables. The former pertains to the effect of the environment within which agents take actions and the latter to the individual characteristics of each householder agent. Based on the social disorganization theory and the therapeutic community hypothesis, two meso-level variables, CC and CS, are used to consider the effect of community cohesion and criminal subculture, respectively. The measures employed in this work for the quantification of these two variables are listed in Tables 2 and 3. The microlevel variables are disaster-caused demands (DD) and personal experience with fraud (E). DD represents the motivation of potential offenders to commit frauds in the wake of disaster (the rational choice theory and routine activity theory), and E characterizes the learning effect of the social learning theory.

The probability that a householder agent will submit a duplicate/fraudulent application at time t, $P_{f,t}$, is proposed to be an additive combination of these variables (weighted) as shown in Eq. (1)

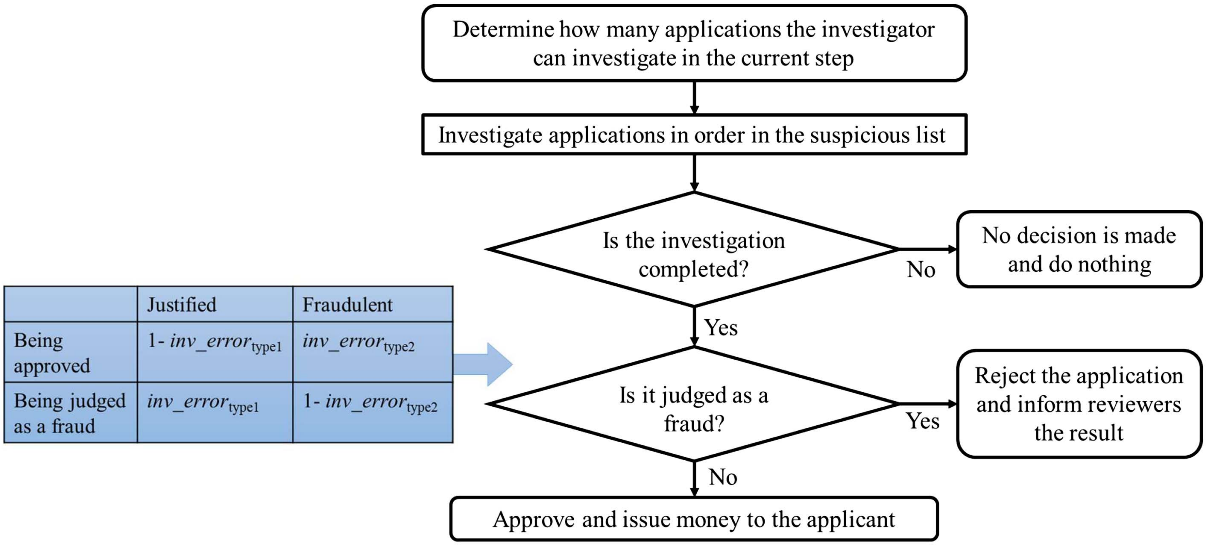

Fig. 5. Decision-making process of investigator agents.

Table 2. Meso-level community cohesion variables

Variables	Measures
Racial heterogeneity	Herfindahl index (Kwoka 1985): the sum of squared proportions of different *racial* categories
Ethnic heterogeneity	Herfindahl index (Kwoka 1985): the sum of squared proportions of different *ethnic* categories
Economic status	GDP per capita
Income inequality	Gini coefficient (Gini 1997)
Unemployment	Unemployment rates of population (15 years or older)
Nonprofit organization density	Total number of nonprofit organizations divided by the population size and then multiplied by 10,000
Religion-linked organization density	Total number of religion-linked organization divided by the population size and then multiplied by 10,000
Law enforcement density	Total number of law enforcement personnel divided by the population size and then multiplied by 10,000

Table 3. Meso-level criminal subculture variables

Variables	Measures
WCC loss	Average losses caused by white collar crime (WWC)
WCC rate	Percent of white collar crime over the total crime taking place
Percent repeat offenders	Percent of all arrestees who are repeat offenders
Percent WWC guardians	Percent of police force devoted to control white collar crime
Percent dangerous area	Percent city subunits as defined by US Census recognized by police as areas populated by criminals, i.e., dangerous places
Gang density	Total number of gangs divided by the population size and then multiplied by 10,000

$$
\begin{aligned}
P_{f,t} = P_i \cdot (\boldsymbol{w_{CC}} \cdot \boldsymbol{CC_t} + \boldsymbol{w_{CS}} \cdot \boldsymbol{CS_t} &+ \boldsymbol{w_{DD}} \cdot \boldsymbol{DD_t} + \boldsymbol{w_E} \cdot \boldsymbol{E_t}) \\
\text{s.t.} \qquad & 0 \le P_{f,t} \le 1 \\
& 0 \le P_i \le 1 \\
-1 \le CC_t, CS_t, &DD_t, E_t \le 1 \\
w_{CC}, w_{CS}, &w_{DD}, w_E \ge 0 \qquad (1)
\end{aligned}
$$

where P_i = given initial probability for a householder to submit a duplicate/fraudulent claim (input parameter); and CC_t, CS_t, DD_t, E_t = quantified values for the effects of community cohesion, criminal subculture, disaster-caused demands, and the agent's personal experience in committing benefit fraud at time t, respectively. The positive quantified values indicate the stimulative influences on the propensity of committing a crime, and the negative ones represent the debilitating effects. $w_{CC}, w_{CS}, w_{DD}, w_E$ = corresponding weights for each variable. Calibration of these variables is discussed later on in the paper. It is worth noting that there are no interaction terms in Eq. (1), i.e., no correlation is assumed between CC_t, CS_t, DD_t, E_t. However, different forms of the equation or model can be adopted in the future to estimate $P_{f,t}$ in the proposed ABM.

Calibration

The main purpose of this section is to show that the proposed agent-based model is able to capture the key features of benefit fraud in the wake of disaster and produce reasonable results. The procedure used here is empirical validation as defined by Groff (2014), where empirical knowledge and data is used to build and calibrate a model. The statistical data of the individuals and household disaster relief provided by FEMA for Hurricanes Katrina and Rita is used to calibrate the ABM model in a control experiment.

Case Study: Individuals and Households Program (IHP) for Hurricane Katrina and Rita

On August 29 and September 24, 2005, Hurricanes Katrina and Rita caused over 1,800 deaths and more than 1.2 million people were evacuated or displaced throughout the Gulf Coast region (NHC 2006). The Federal Emergency Management Agency's (FEMA) Individuals and Households Program (IHP) is one of the main disaster relief programs that provided financial assistance to the victims, including rental, repair, replacement, property, and expedited assistance. The information and data on the benefit fraud of FEMA's IHP assistance is obtained from the US Department of Justice Hurricane Katrina Fraud Task Force (DOJ 2005, 2006a, b, 2007, 2010, 2011), the US Department of Homeland Security Office of Inspector General (DHS 2006; DHS OIG 2006, 2011), and the US Government Accountability Office (GAO 2006c, d, e, f, 2007, 2014).

Distribution of Aid

After the hurricanes, FEMA IHP provided expedited assistance of $2,000. The program also offered rental assistance funds (based on area fair market rent) and additional housing assistance with repair and replacement assistance capped at $5,200 and $10,500, respectively. The combination of all forms of IHP financial assistance had a maximum cap of $26,200 (DHS OIG 2006). In 2006, the expedited assistance was adjusted to $500, and the other housing assistances were increased to $5,400, $10,900 and $27,200, respectively, to reflect increases in the Consumer Price Index (GAO 2006e).

According to DHS OIG (2006), by September 30, 2005, FEMA had received 1,557,937 registrations for IHP assistance from residents in all affected areas and awarded over $2.4 billion. By October 18, 2005, there were 1,645,784 total registrations. Among those, about 19% were cancelled due to ineligibility or flagged as potential duplicates (DHS OIG 2006). By November 16, 2005, the registrations increased to 1,680,516, of which 984,432 (or 59%) were eligible and worth approximately $3.5 billion in assistance (DHS OIG 2006). By mid-December 2005, mid-February 2006, and mid-May 2006, IHP payments totaled about $5.4 billion, $6.3 billion, and $6.7 billion, respectively (GAO 2006c, d). By August 2006, among the total 2.4 million applications for IHP, only 67% of household assistance and 41% of other needs assistance applications were found eligible and had been approved, and approximately 9% of applications were pending or appealing the assistance decision. Approximately $7 billion of IHP assistance was distributed by October 2006 (GAO 2006e, 2007).

The approximate number of total registrations and awarded aid of IHP assistance for hurricanes Katrina and Rita are plotted in Figs. 6 and 7. About 65% of the registration were received in the first month, assuming that the total number of registrations by October 2006 is 100% (Fig. 6). Fig. 7 shows that about 50% of aid was awarded in the first three months, and over 90% was distributed in the first six months.

Improper and Potentially Fraudulent Payments

Although a considerable proportion of total registrations had been determined as ineligible applications and canceled before being paid, many improper and potentially fraudulent payments among the awarded applications were recognized, including duplicate registrations, invalid primary residences, and bogus damaged addresses. The GAO selected a random sample of 250 payments of the 2.6 million IHP payments made to hurricanes Katrina and Rita registrants by February 2006 for further examination (GAO 2006d). An estimated 16% of payments (95% confidence interval of 12% to 21% of payment or from $600 million to $1.4 billion) totaling approximately $1 billion were improper and potentially fraudulent due to invalid applications (GAO 2006d). On the other hand, using a different sampling and analysis method, DHS reported an estimated improper payment rate of 8.56% for an estimated improper payment amount of $450 million by March 1, 2006 (DHS 2006). FEMA reported that it had overpaid about $290 million to nearly 60,000 registrants but it had recollected only about $7 million by November 2006 through its own internal means (GAO 2006f). FEMA's recoupment activities were suspended from June 2007 through January 2011 due to a lawsuit and other challenges. As a result, even though more than $621.6 million of potentially improper IHP payments have been identified, much of this improper disaster assistance disbursed since Hurricane Katrina was uncollected for several years. This evidence shows the weakness of the benefit distribution process that exposed IHP assistance to fraud, and served to emphasize the importance of preventive controls (DHS OIG 2011).

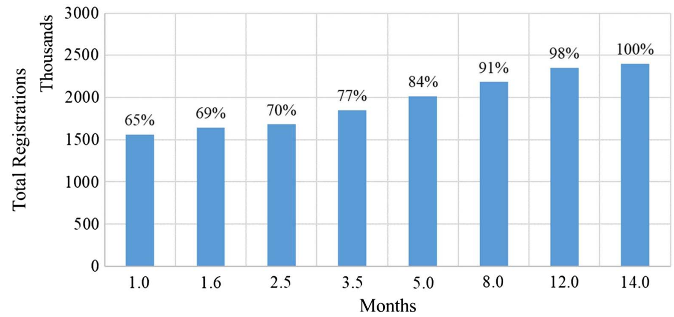

Fig. 6. Approximate number of registrations for IHP assistance.

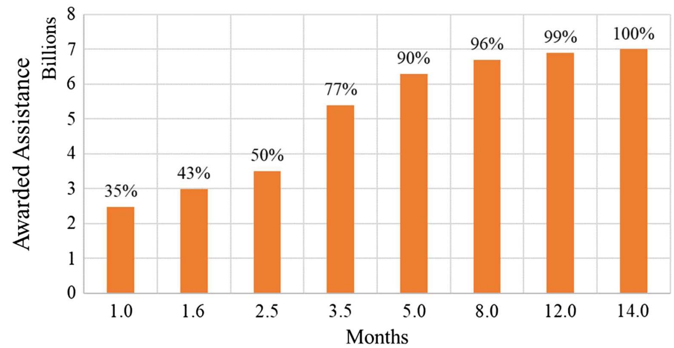

Fig. 7. Awarded assistance for IHP (USD).

Control Experiment

Model Environment and Parameters

In the control experiment, the number of householder agents is set to 1.3 million, the approximate number of victims of hurricanes Katrina and Rita. The distribution of home damage levels and the number of householder agents for each damage level are listed in Table 4, which is based on the estimated number of damaged houses in Mississippi after hurricanes Katrina and Rita (DHS OIG 2006). The damage level of houses are randomly assigned to the householder agents at the beginning of each simulation according to the distribution in Table 4. The definition of different damage levels and the corresponding eligible assistance are documented in DHS OIG (2006). It is assumed that the claimed and awarded

Table 4. Distribution of house damage states and corresponding eligible IHP assistance

Damage level	None	Minor	Major	Destroyed
Percentage	7.7%	81.0%	9.8%	1.5%
Number of householder agents in ABM	100,000	1,053,000	127,000	20,000
Eligible house assistance (USD/householder)	0	2,600	5,200	10,500
Eligible assistance for other needs (USD/householder)	2,000	2,000	2,000	2,000
Total eligible IHP assistance (USD/householder)	2,000	4,600	7,200	12,500

Table 5. Parameterization of the model for control experiment

Parameter	Value
Number of householders	1.3 million
Number of application reviewers	3,000
Number of special investigators	1,000
Number of applications reviewed per day by per reviewer, mean (standard deviation)	5 (1)
Number of applications investigated per day by per investigator, mean (standard deviation)	2.4 (0.5)
Probability of householder completing an application in a given day, P_c	30%[a], 25%[b], 8%[c]
Initial probability for householders to submit a fraudulent claim, P_i, mean (standard deviation)	1% (0.1%)
Probability of application being eligible and complete	95%[a], 75%[b], 60%[c]
Probability of Type I error of review (judging a justified claim to be suspicious)	0%[a], 2%[b], 5%[c]
Probability of Type II error of review (approving a fraud claim without further investigations)	100%[a], 80%[b], 60%[c]
Probability of Type I error of investigation (judging a justified claim as a fraud)	0%
Probability of Type II error of investigation (approving a fraud claim)	0%
The deadline of submitting applications (number of days after the disaster occurred)	426 days (14 months)

[a]Day 1–Day 14.
[b]Day 15–Day 45.
[c]After Day 46.

amounts are equal to the eligible assistance for the householder agent, as listed in Table 4, but householder agents may submit more than one claim in the overall simulation, i.e., duplicate/fraudulent applications.

The other parameters used in the control experiment are listed in Table 5, where the number of applications reviewed and investigated per day, and the initial probability for householders to submit a fraudulent claim are set to normal random variables to capture the uncertainty and variations among individuals. To cater to the fact that most of the registrations had been made in the first few months, the probability of a householder completing an application in a given day, P_c, varies in different postdisaster phases (Table 5). Also, it was often observed that very few ineligible and suspicious applications were detected due to the felt need for immediate support and the lack of inspection staff during the emergency phase right after the disaster. It is assumed that the vulnerability of targets being exposed to fraud will decrease with the recruitment of more staff and enhancing fraud-related training. Therefore, the eligible rate of applications and the errors of review vary with time to represent the changes in target vulnerability. To simplify the problem, it is assumed that neither type I error nor type II errors of investigation occurred in the control experiment.

Due to lack of pertinent records, the mean values of *CC* and *CS* are assumed to be time-dependent index functions as plotted in Fig. 8. The initial negative value of *CC* in the early stages of the disaster reflects the cooperative behavior of the community during the immediate postimpact period as predicted by the therapeutic community hypothesis. Eventually, as modeled by the index function, the helpful behavior disappears and returns to neutral. In accord with the social disorganization theory, the downhill trend of *CS* reflects the dearth of guardians and the negative effect of social disorganization during the postemergency phase. It is also a function of the enhanced defenses devoted to control benefit crime in the latter phase of disaster.

To consider the variation of community cohesion and criminal subculture impacts on individuals, normal random variables with the time-varying mean values in Fig. 8 and standard deviation of 0.25 are employed for the *CC* and *CS* indices for each householder agent at every time step. The values and trends indicated by Fig. 8 and discussed above are initial estimates that guided by relevant theories of criminology. These estimates can be refined in the future as better information becomes available.

Variable DD_t (at time t) is calculated for individual householder agent at each step as shown in Eq. (2). The equation models the effects of disaster-caused demands and the period of time experienced without financial support, where increases in both enhance the effects of the disaster demands and vice versa

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

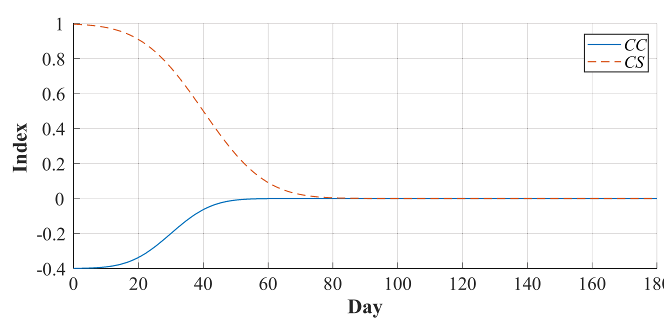

Fig. 8. Time varying community cohesion and criminal subculture effects as inspired by criminology theories.

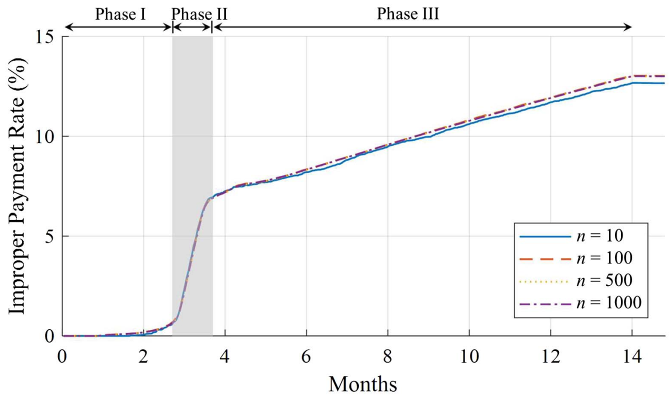

Fig. 9. Estimated improper payment rate obtained from Monte Carlo simulations with a different number of realizations.

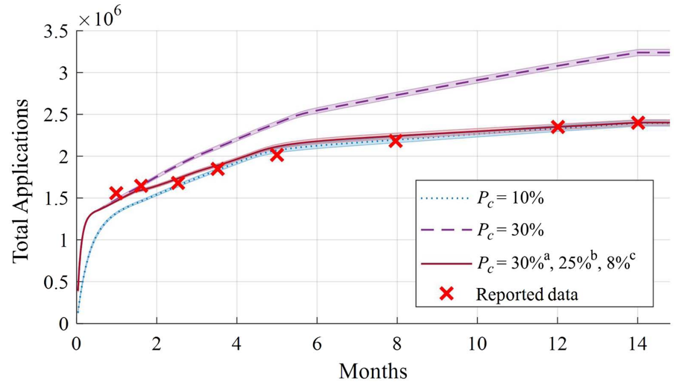

Fig. 10. Number of received applications in the control experiment: (a) Day 1–Day 14; (b) Day 15–Day 45; and (c) after Day 46.

where $DL = 4$, 3, 2, and 1 for destroyed, major, minor, and none damage levels of the householder agent's home, respectively; $T_{without\,support}$ = number of weeks after the disaster that the householder agent has not received monetary support; and DD_t is capped to 1.0. For a householder agent with a destroyed home, DD_t equals 1 if their $T_{without\,support}$ is longer than two weeks.

Based on the social learning theory, the success in previous applications may increase the propensity of recommitting benefit fraud. Therefore, the fourth meso-level variable, E_t, is used to represent the effect of an agent's personal experience. E_t is assumed to be 0.2 times the number of approved applications $N_{approved}$, submitted by the agent, with an upper bound of 1.0, as expressed in Eq. (3). The corresponding weights w_{CC}, w_{CS}, w_{DD}, w_E in Eq. (1) are all equal to one. As with CC and CS, these weights are assumed values at present that can eventually be refined as more information becomes available in the future

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

Monte Carlo simulations are conducted to capture the effects of variability in the main parameters. The estimated improper payment rate obtained from a different number of Monte Carlo realizations, i.e., n, are compared in Fig. 9. It is clear that the results converge when the number of realizations is more than 500. Therefore, the mean value and standard deviation of one thousand Monte Carlo realizations ($n = 1{,}000$) are used in the following calibration and parametric studies.

Fig. 9 shows that the crime response of the community occurs in three distinct phases. In Phase I, there is an initial gentle increase in fraud for the first two months. Phase II, which spans about a month, sees a sharp rise in improper payments at the beginning of the third month. In Phase III, the crime rate ameliorates. These distinct phases fit the observation in Aguirre and Lane (2019) that crime level exhibits distinct phases in the aftermath of disasters.

Adjustment of Parameters

One of the main strengths of ABM is the ability to model the desired meso-level phenomena by properly adjusting individual-level parameters. Fig. 10 shows how the probability of a householder completing an application, P_c, affects the average number of received applications during the first 14 months, where the shaded area represents the range between standard deviations, i.e., $\pm\sigma$. The actual data from the Hurricane Katrina and Rita case study is represented as circles. With P_c constant at 10% and the other parameters kept the same as shown in Table 5, the figure shows that the number of applications after the third month matches well with the actual data, but the results in the first two months are fewer than the reported data (dotted line in Fig. 10). Increasing P_c to 30% (dashed line in Fig. 10) makes the number of applications rise faster in the beginning, but causes significant deviations at later times. Therefore, to represent the fact that most of the registrations had been made in the first few months and became much fewer later, P_c is made to vary from 30% to 8% with the postdisaster phase as shown in Table 5 (solid line in Fig. 10).

Using the distribution of P_c in Table 5, Fig. 11 shows the change in the amount of assistance granted versus the number of application reviewers. Clearly, the results of the case with 3,000 reviewers match the actual data well, lending some credence to the selected parameters. Fig. 12 shows the improper payments rate over time as a function of P_i, the initial probability that a householder will submit a fraudulent claim. The estimated final improper payment rates are approximately 8.3%, 13.0%, and 18.3% when P_i equals 0.6%, 1.0%, and 1.5% (with 0.1% standard deviation), respectively. The numbers compare favorably to the estimates provided in GAO (12% to 21%) (GAO 2006d) and DHS (8.56%) (DHS 2006). It is observed from Fig. 12 that the improper payment rate had a shaper rise during the third month in the control experiment, which is a direct function of the selected parameters and trends. Judging the veracity of this prediction is not feasible because the collected statistics are not available at the given time intervals (only the final numbers are available). Nevertheless, Fig. 12 indicates that the parameters and trends can be broadly tuned by changing the initial agents' propensity toward committing frauds, P_i, and the other parameters.

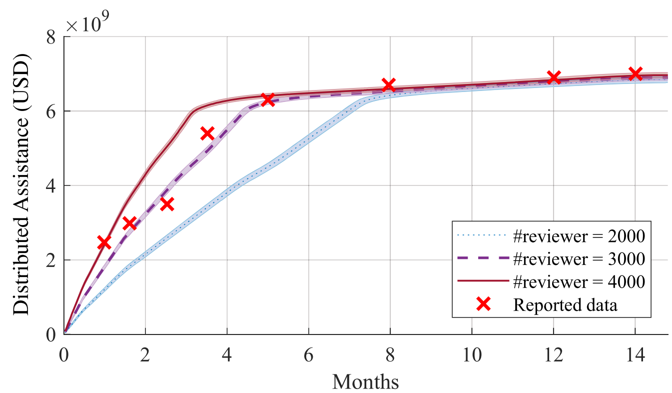

Fig. 11. Distributed assistance in the control experiment.

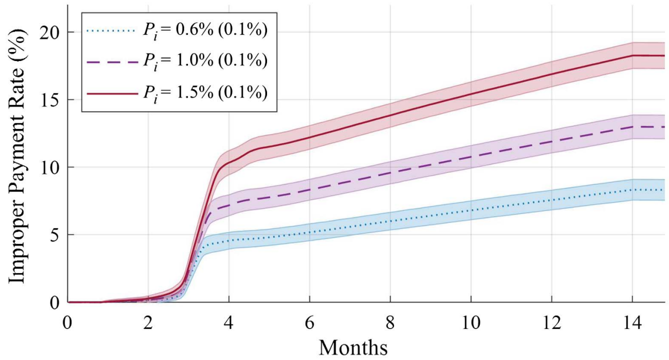

Fig. 12. Improper payment rate.

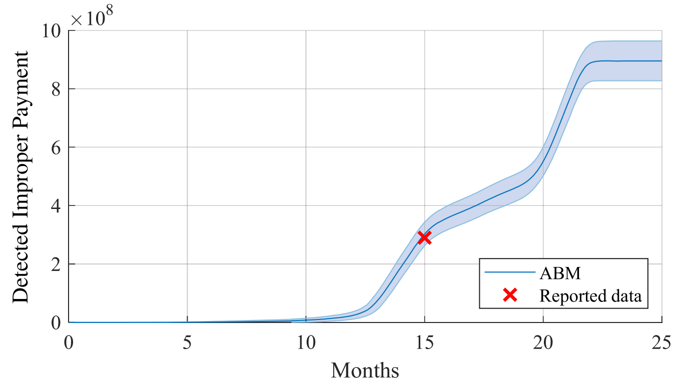

Fig. 14. Detected improper payments.

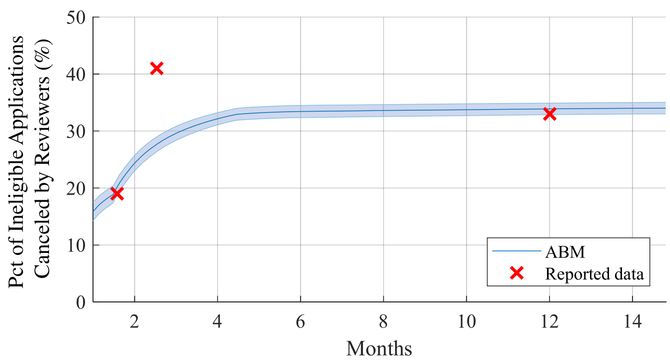

Fig. 13. Ineligible applications canceled by reviewers.

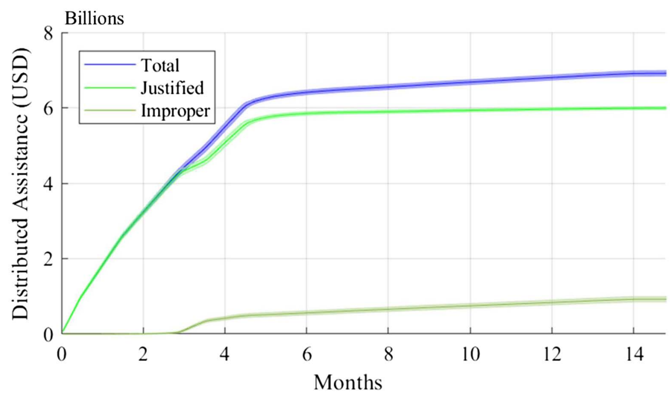

Fig. 15. Comparison of justified and improper payments.

Results of Control Experiment

The parameters of the model used in the control experiment are listed in Table 5. Fig. 13 shows the proportion of ineligible applications canceled by reviewers before payment as a percentage of total reviewed applications over time. According to DHS OIG (2006), 19% of the registrations were cancelled or flagged as potential duplicates by October 18, 2005, and only about 59% were eligible by November 16, 2005 (41% were found ineligible). By August 2006, only 67% of household assistance were discovered eligible, i.e., 33% were ineligible, (GAO 2006e, p. 18). The reported data is not enough for calibration, but it can be tuned as needed or when detailed information becomes available by adjusting the probability of applications being eligible and complete, P_e, as listed in Table 5.

The FEMA investigation detected about \$290 million in overpayments by November 2006, about 15 months after the hurricane (GAO 2006f, p. 4). The simulation shows that the average improper payment rate by the 15th months is \$312 million, which matches well with the given data, as shown in Fig. 14. It should be noted that, in the actual scenario, it took about 23 months to detect all improper payments, but the rate of detection is not known. Fig. 15 shows the proportion of justified and improper payments of total distributed assistance estimated in the control experiment.

Limitations of the Calibrated Model

It is commonly accepted that validation of ABMs is challenging due to the complexity and uncertainty of modeling human behavior and limitations in obtaining meaningful calibration data. Even if more calibration data were available, the resulting calibrated model will still only be valid within the range of parameters for which it was calibrated. Moreover, while any specific favorable comparison to experimental or observed data strengthens confidence in the model, the high-dimensional nature of the research problem suggests that the model will not necessarily yield correct answers under all conditions. The control experiment conducted above shows that the proposed model can reasonably capture the general characteristics of postdisaster benefit fraud in a manner that is consistent with well-known theories of criminology. Most importantly, it clearly points to areas that need additional data and provides motivation for researchers to collect this type of information during future events.

Parametric Sensitivity Analyses

The agent-based model described and calibrated in the previous section is used to conduct a parametric sensitivity analysis to gain deeper insight into the benefit fraud problem. Two key dependent variables are considered here. 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, which is taken as the time required for 95% of victims with disaster-caused loss to receive the grants, $T_{95\%}$.

Setting of Simulation Experiment

An artificial environment is designed to represent a community of 1 million households that is subjected to disasters with varying intensity levels. Three different distributions of house damage

Table 6. Percentage distribution of house damage state for designed disaster scenarios

Damage state	None (%)	Slight (%)	Moderate (%)	Extensive (%)	Complete (%)	Total (%)
Level 1	50	34	13	3	0	100
Level 2	25	27	31	13	4	100
Level 3	0	11	34	40	15	100

states are adopted to represent different level of the disaster impact, as shown in Table 6 and Fig. 16. The replacement cost of a residential building is assumed \$253,728, which corresponds to the replacement cost of an average class, two story, single family dwelling model with a typical size of 148.64 m^2 (1,600 square feet) (FEMA 2003). The repair cost ratios of residential buildings, including structural and nonstructural components, for five damage states (none, slight, moderate, extensive, and complete) are defined as 0%, 2%, 10%, 50%, and 100% of building replacement cost, respectively (FEMA 2003). To capture the uncertainty of house damages, the repair cost of each damage state is set to a log-normal random variable with μ (mean of logarithmic values) equal to the logarithm of repair cost ratio times replacement cost, i.e., $\log(\text{repair cost ratio} \times \text{replacement cost})$ and σ (standard deviation of logarithmic values) equal to 0.35. It is assumed that the amount of grants claimed by householder agents and approved by reviewer agents equal to a quarter of the repair cost, with cap of \$34,900, which is the maximum amount for IHP declared by FEMA on October 1, 2018 (FEMA 2018). For criminals with undamaged houses, the requested amount is randomly assigned according to the distribution of building damage states in the whole community, exclusive of nondamaged houses. Table 7 lists the other parameters of the base model, and the independent variables to be adjusted in the parametric studies are indicated in bold.

The effect of disaster-caused demands is quantified considering the damage state of the housing stock and the length of time experienced after the impact without financial support, as expressed by Eq. (2), where DL = 4, 3, 2, and 1 for complete, extensive, moderate, and slight damage levels of the householder agent's home, respectively. The damage state of houses are randomly assigned based on the distributions in Table 6 at the beginning of each Monte Carlo realization. Namely, the damage state of the housing stock is known at the beginning of each realization, and the spatial correlation which exists due to the geo-clustering effect or the intensity of disasters is ignored in the case studies. The effect of the agent's personal experience is expressed by Eq. (3). The corresponding weights w_{DD}, w_{CC}, w_{CS}, w_E in Eq. (1) are all set to unity, if no values are specified.

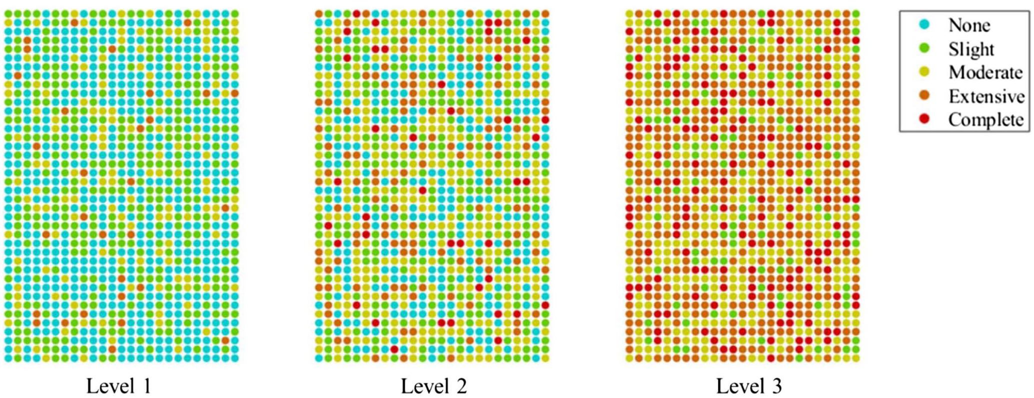

Fig. 16. Visual representation of house damage states of the disaster scenarios listed in Table 6.

Table 7. Parameterization of the model for sensitivity analysis

Parameter	Value
Number of householders	1 million
Number of application reviewers	3,000
Number of special investigators	**2,000**, 3,000, **4,000**
Number of applications reviewed per day by per reviewer, mean (standard deviation)	**2(1), 3 (1)**, **4(1),** 5 (1)
Number of applications investigated per day by per investigator	1
Probability of householder completing an application in that day, P_c	30%[a], 25%[b], 8%[c]
Initial probability for householders to submit a fraudulent claim, P_i, mean (standard deviation)	1% (0.1%)
Probability of application being eligible and complete	95%[a], 75%[b], 60%[c]
Probability of Type I error of review (judging a justified claim to be suspicious)	0%[a], 2%[b], 5%[c]
Probability of Type II error of review (approving a fraud claim without further investigation)	100%[a], 80%[b], 60%[c] (E1) **75%[a], 60%[b], 45%[c] (E2)** **50%[a], 40%[b], 30%[c] (E3)** **25%[a], 20%[b], 15%[c] (E4)**
Probability of Type I error of investigation (judging a justified claim as a fraud)	0%
Probability of Type II error of investigation (approving a fraud claim)	0%
The deadline of submitting applications (number of days after the disaster occurred)	426 days (14 months)

Note: The independent variables to be adjusted in the parametric studies are indicated in bold.
[a]Day 1–Day 14.
[b]Day 15–Day 45.
[c]After Day 46.

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Table 8. Combination of weights used in Eq. (1)

Combination	w_{DD}	w_{CC}	w_{CS}	w_E
W_{Base}	1	1	1	1
W1	1	0	0	0
W2	1	0	0	1
W3	1	1	0	0
W4	1	0	1	0

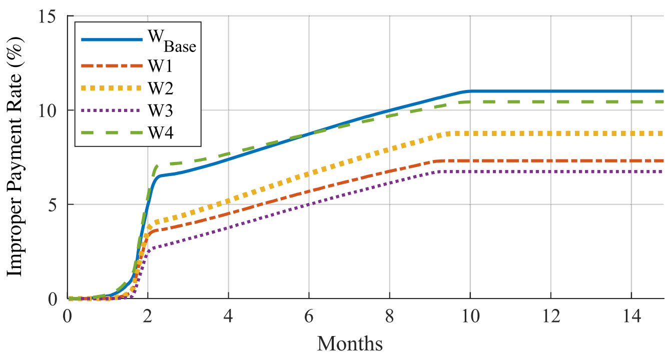

Fig. 17. Effect of weight values for the key meso- and microvariables.

Effect of Meso-/Microimpact Factors on Crime Propensity

The influence of the four meso-/microvariables is investigated by adopting five different combinations of weights in Eq. (1): the base case, W_{Base}, and four other cases (W1 to W4), as listed in Table 8. Consider the base model subjected to a Level 2 disaster scenario. Fig. 17 shows the improper payment rate over time for cases with different weights. By comparing the results of case W1 with the ones for case W2 in Eq. (1), the effect of an agent's personal experience (E) increases with time as more applications are reviewed. Secondly, by comparing the results of W1 with W3 and W4, community cohesion (CC) reduces the fraud rate while the criminal subculture (CS) has an opposite effect, matching the therapeutic community hypothesis and the social disorganization theory theories, respectively, used to formulate the model. While influential, varying the weights results in a variation in fraudulent applications that is somewhat modest, i.e., between 6.9% and 10.9% (Fig. 17).

Effect of Disaster-Caused Demand

The effects of disaster intensity (Table 6 and Fig. 16) are shown in Fig. 18, which depicts the progress of payment distribution and the improper payment rate over time as a function of disaster demand. It is intuitive that the more severe the disaster, the more loss caused and the more financial assistance will be needed. However, what is not obvious is that it takes longer to distribute the aid [Figs. 18(a and b)] and that the total amount of improper payment and the overall improper payment rate become higher [Figs. 18(c and d)] as a disaster becomes more severe. This is directly attributed to limitations in staffing, which directly correlate with a reduction in oversight (guardianship) as well as the desire to expedite the distribution of aid.

Fig. 18 shows that the timing of the increase in the improper payment rate is slightly different for different levels of disaster. As can be seen in Fig. 18(d), the rise of the fraudulent rate in the Level 1 case is earlier than the other two. That is because the effect of CS is greater than DD in the Level 1 case, and the used CS index (Fig. 8) is higher in the first few weeks. This demonstrates that, with properly calibrated parameters, the proposed model can be used not only to assess the overall fraudulent results, but also to investigate the timing of the increase of improper payments.

Figs. 18(c and d) reproduce the three distinct phases observed in Fig. 9, although the span for each phase changes with the level of disaster demand. The model suggests that an increasing disaster

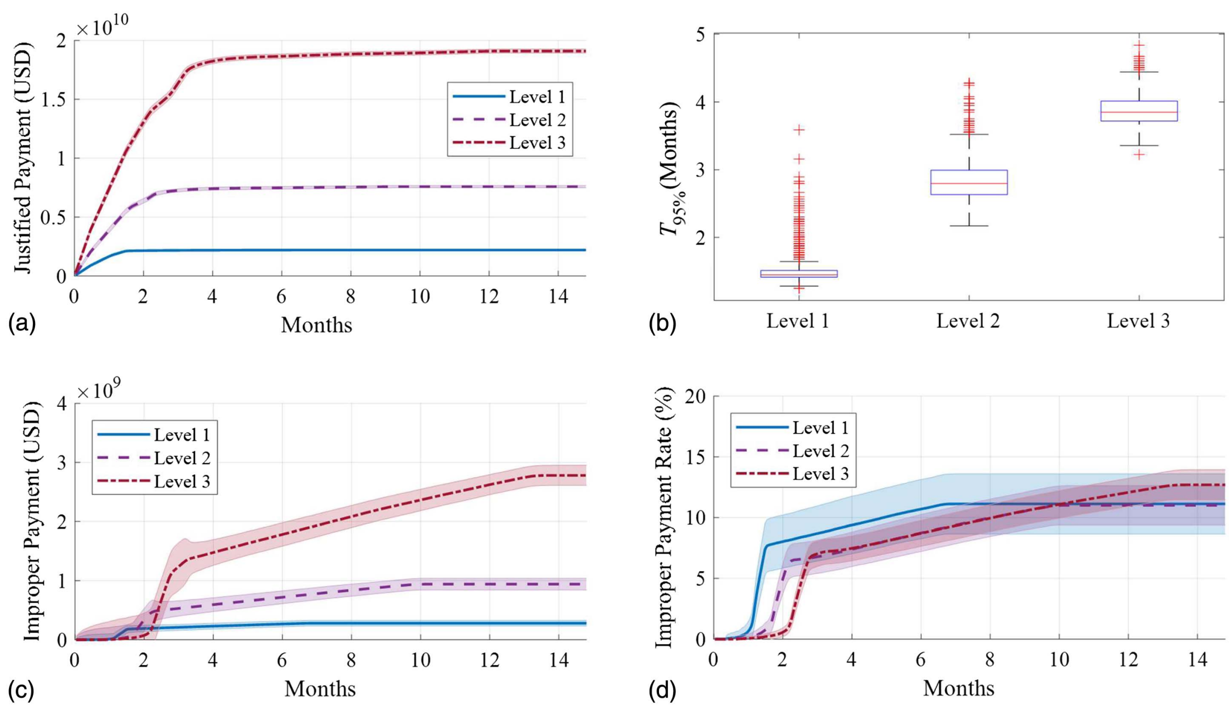

Fig. 18. Effect of disaster-caused demand: (a) justified payment; (b) $T_{95\%}$; (c) improper payment; and (d) improper payment rate.

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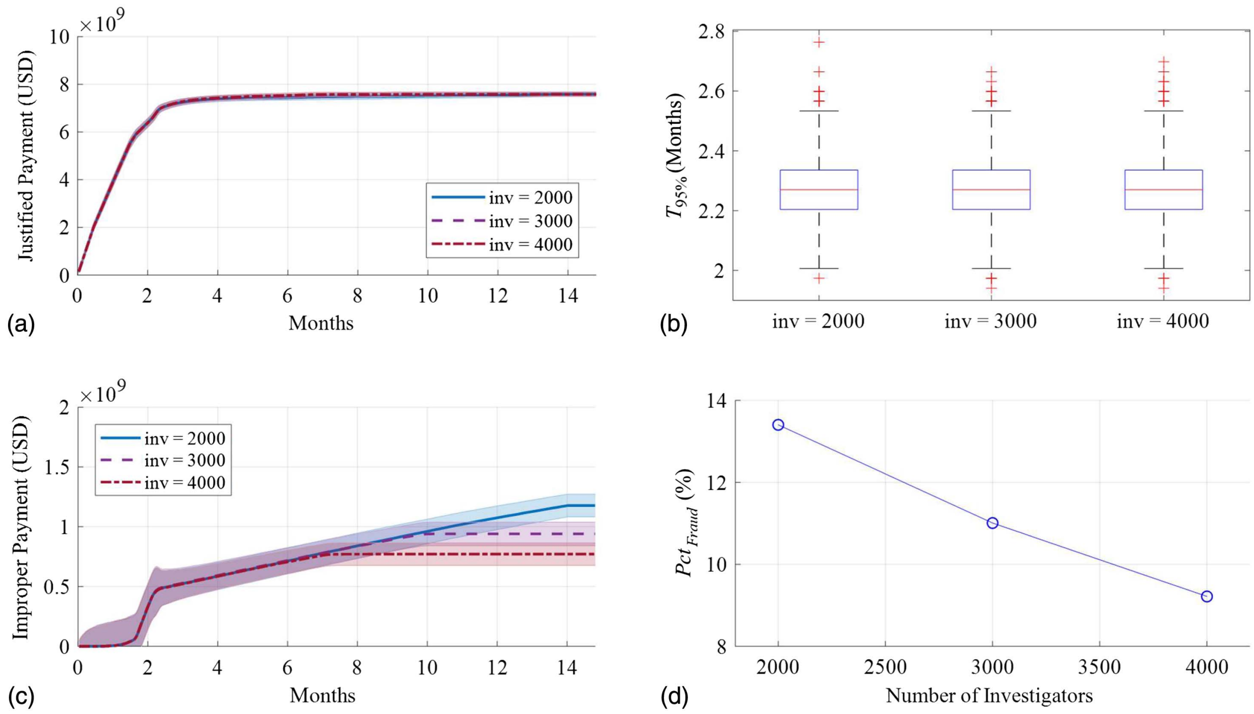

Fig. 19. Effect of guardian strength: (a) justified payment; (b) $T_{95\%}$; (c) improper payment; and (d) Pct_{Fraud}.

demand pushes the crime spike later on in time. Those most motivated to seek benefits due to their dire situation apply early. Influenced by the strong community cohesion right after the disaster, the so-called Gemeinschaft feelings, these applications are mostly legitimate and represent Phase I of the process. When the disaster demand is high, Phase I will take longer than when the disaster demand is low because the review speed is assumed constant. As the opportunity for fraud becomes more broadly recognized and as the Gemeinschaft feelings abate, fraudulent applications for undamaged houses or duplicate claims after a first successful claim start coming in, pushing the fraud sharply upwards (Phase II). The rate then flattens out as the guardianship efforts kicks in (Phase III).

Effect of Guardian Strength

The effect of using more government special investigators (2,000, 3,000, and 4,000) is investigated to determine the influence of guardian strength in a Level 2 disaster scenario. The distribution of payment and the estimated improper payment rate are plotted in Fig. 19 for this example. Because the number of investigators does not affect the speed of application review, the progress and time required for distributing the justified aid is barely affected, as shown in Figs. 19(a and b). From Fig. 19(c), the increase in the amount of improper payments can be slowed down if the fraudulent behaviors are detected earlier. The final improper payment rate can also be reduced, as shown in Fig. 19(d).

Effect of Target Vulnerability

The effect of target vulnerability is evaluated by considering different probabilities of Type II review error, i.e., E1, E2, E3, and E4 listed in Table 7, where E1 indicates the highest probability of review errors and E4 is the lowest. As can be seen in Figs. 20(a and b), because the speed of review and the other parameters are kept unchanged, the progress and the time required for all justified assistance being paid are close for these four cases. However, the improper payment rate is significantly reduced with the decrease of review error, as shown in Figs. 20(c and d). Reducing the vulnerability of targets is an effective way to decrease the chance of success of fraudulent behaviors, but it might not be easy to achieve. For example, in order to decrease the review error, additional specialized training of reviewers must be completed and a more comprehensive standard reviewing procedure has to be established. Moreover, this is a first order sensitivity analysis, and only one independent variable is adjusted in the experiment. The interactions between different parameters are not considered, e.g., a stricter review of an application could reduce the errors, but it may take more time to review the same application.

Effect of Review Speed

The effect of review speed (number of applications reviewed by a single reviewer) is investigated via the base model subjected to a Level 2 disaster. The number of applications handled by a single person is considered to be 2, 3, 4, and 5 with a standard deviation of 1. The other parameters are kept the same as the base model shown in Table 7. Fig. 21 shows the distribution of payment and the estimated fraudulent rate over time. It is clear that the faster the applications are reviewed the more payments could be made in the first few months, but the overall improper payment increases slightly with the increase in the review speed, as shown in Figs. 21(c and d). This implies that distributing the financial assistance to the affected people faster will help the community recover faster, but it must be balanced with the anticipated increase in the cost associated with improper payments. Figs. 21(c and d) also suggest that a faster review speed contributes to shorter Phase I and more pronounced Phase II. This is because the opportunity for fraudulent duplicate applications occurs earlier as fraudsters, encouraged by the quick release of funds, submit more duplicate applications.

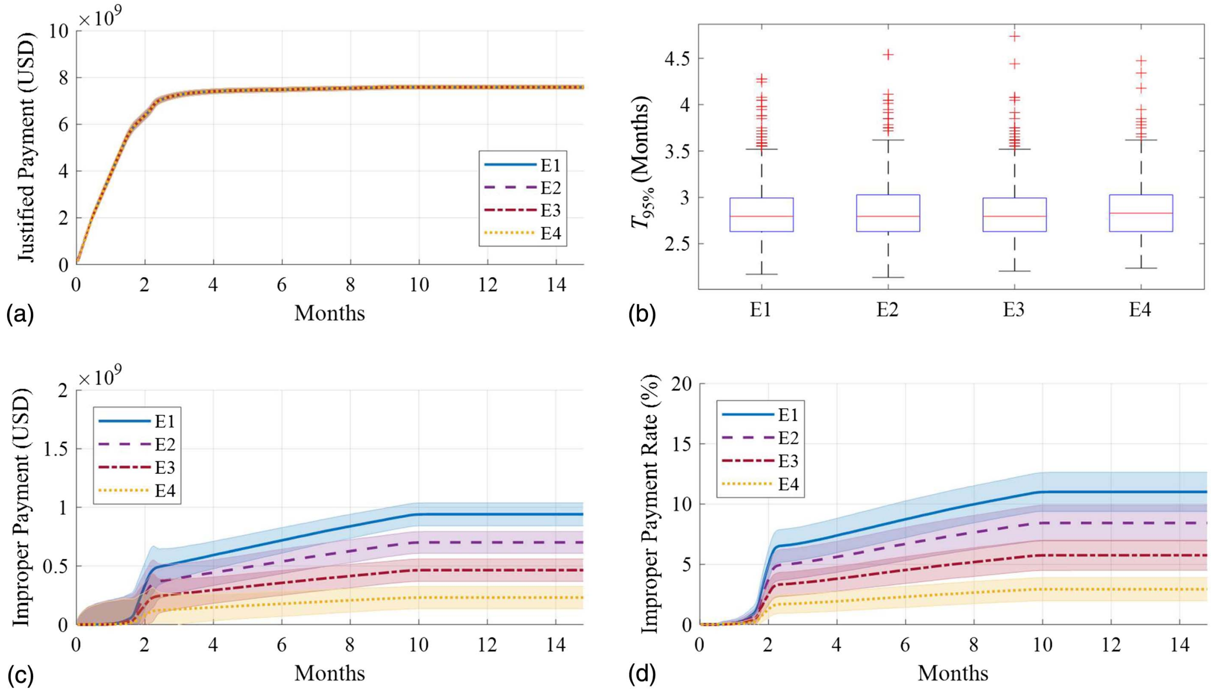

Fig. 20. Effect of target vulnerability: (a) justified payment; (b) $T_{95\%}$; (c) improper payment; and (d) improper payment rate.

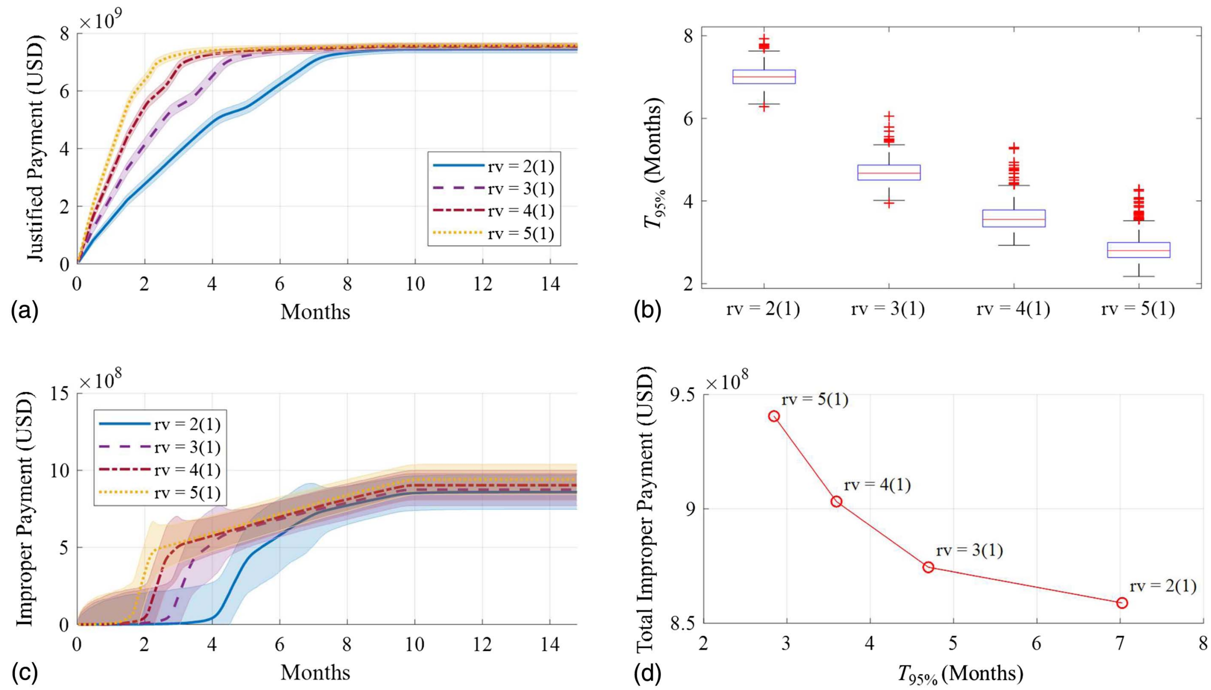

Fig. 21. Effect of review speed: (a) justified payment; (b) $T_{95\%}$; (c) improper payment; and (d) overall improper payment versus $T_{95\%}$.

Summary and Conclusions

A computational tool was proposed to simulate the dynamic process of criminal activities, specifically benefit fraud, in the wake of disasters. The formulation, which uses an agent-based simulation, considers observed phenomena, relies on established criminological theories, and addresses disaster demands and social characteristic at both the micro and meso-levels. Statistical data from FEMA's Individuals and Households Program (IHP) for Hurricanes Katrina and Rita was used to calibrate the simulation model and to show that it can capture the basic features of benefit fraud while producing sensible results.

The computational results show that fraudulent activity occurs in three distinct phases. In Phase I, where most of the applications come from people who are in a dire situation and the so-called Gemeinschaft feelings are still strong, the rate of fraudulent applications is small and increases gently. As the opportunity for fraud become more broadly recognized and encouraged by the release of an initial round of funding, fraudsters become more active, leading to a sharp spike in the improper payment rate in Phase II. In Phase III, the guardianship mechanisms kick in and the improper payment rate plateaus out. The observed phases match in spirit observations in actual disasters. The effects of community cohesion, criminal subculture, disaster demands, and a criminal's personal experience on crime propensity are examined in light of extensive parametric simulations. The results of the analysis show that increasing the accuracy of review, decreasing disaster demands, and enhancing guardian strength can help lessen the loss due to postdisaster benefit fraud. However, the organizations distributing the aid must seek a balance between losses to fraudulent payments and the speed of aid distribution in order to optimize the recovery performance of communities.

This study addresses an existing research gap regarding postdisaster benefit frauds in the context of long-term community reconstruction and recovery. The proposed agent-based methodology provides the ability to model postdisaster crime in great detail. For example, as shown in this paper, it is possible to model the spatial and temporal nature of the criminal process and its interactions with the unfolding disaster and subsequent recovery efforts. While experience with previous disasters and addressing logical gaps in the process can help improve in the aid-disbursement process, simulations of the sort presented here offer another systematic and powerful way to achieve this.

Due to lack of information about a number of key variables, which were assumed out of necessity, the simulation results are not truly predictive. As such, one of the key aspects of this study is that it provides insights into the type of information and its level of detail that should be sought by researchers and aid officials in future disasters. In the current multiagent model, benefit fraud is only captured in terms of repeatedly submitting applications or submitting applications when the property is not damaged. Future research should strive to include different behavioral patterns of benefit fraud, e.g., inflating damaged property, fraud committed by criminals outside of the affected areas, identity theft, or syndicated criminal activities, for better understanding the mechanisms of benefit fraud in the aftermath of disasters.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published article.

Acknowledgments

This research was supported by the University of Michigan and the US National Science Foundation (NSF) through grant ACI-1638186.

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