Increasing Evacuation During Disaster Events

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ABSTRACT

Timely evacuation is a standard recommendation by local agencies before disaster events such as hurricanes, which have enough advance notice. However, it has been observed in many recent disasters (e.g., Sandy), that only a small fraction of the population evacuates in time. Recent work by social scientists has examined the factors that influence household evacuation decisions; in addition to individual factors it has been found that peer effect plays a role in this decision but in two opposing ways. Specifically, households are motivated to evacuate if their neighbors evacuate. However, if too many neighbors leave then some households have concerns of looting and crime, and they choose not to evacuate. This makes the dynamics of evacuation very complex.

In this paper, we use a detailed agent based model to study the dynamics of evacuation in Virginia's coastal region. We use data from a large survey and social contagion and collective action theories to develop the model. We evaluate different strategies to increase evacuation.

KEYWORDS

Agent based models; social networks; contagion processes; disaster informatics; evacuation

1 INTRODUCTION

1.1 Background and Motivation

Households in coastal areas face the dilemma of evacuating during a hurricane event to avoid life threatening risk posed by intense wind and flood inundation versus staying put to safeguard their assets and belongings and avoid looting. The longer one waits, the more precise the information (about intensity and location of landfall) that may be available to provide guidance for the need and direction of evacuation. However, arranging related logistics with more waiting may become challenging. As time passes, finding a

place to stay may be more difficult, roads may be more congested, and risk of getting stranded may be higher. In reality, the decision to evacuate depends on a complex mix of sociodemographic factors, risk perceptions, access to transportation, prior experiences, storm intensity and peer behavior [21, 31, 35].

Many of these interacting factors coevolve as a hurricane approaches, and empirical agent-based models (ABM) powered with real observations can offer novel insights to represent and simulate human behavior in these contexts. There has been a large number of works on developing ABMs [12, 27, 29, 37]. Some of the prior ABM approaches use very limited to almost no observational data from natural hazards [12, 16, 27, 29, 34, 36]. Some of these ABMs [14, 16, 34, 36] use threshold functions to model peer effects, in which a household is more likely to evacuate when its neighbors evacuate. However, most prior studies miss an important component in evacuation behavior, namely concerns about looting and criminal activity, which social scientists have shown contribute to reduced evacuation [10, 20, 30]. Specifically, these concerns work in opposition to the above peer effects, and a household with such concerns might not evacuate if its neighbors leave [14]. These factors have not been taken into account in ABMs for evacuation behavior in a data-driven manner. Our paper is the first to do so.

There have been many studies in the literature on the topic of evacuation, some of which use statistical models [7, 23, 24], while others use parameterized methods [4, 9, 17] and ABMs [12, 16, 27, 29, 34, 36]. Some researchers have even identified criminal activity as a major issue in the evacuation decision [10, 20, 30, 32].

1.2 Contributions

1. Survey data and statistical analyses of evacuation. Survey results from 1,212 Hurricane Sandy respondents were analyzed to understand evacuation behavior of households. A detailed regression-based analysis identifies the intrinsic (household-specific) as well as exogenous factors (peer behavior) that significantly influence households' evacuation decision-making (see Section 2.3). Among the significant observations from hurricane surveys is that neighbors' evacuation (peer influence) can have two competing effects on a family: it can motivate a family to evacuate, and it can inhibit a family from evacuating because of fear of crime and looting. Ours is the first work to quantify these effects from surveys and then incorporate them in an agent-based model to study interactions between these effects with respect to evacuation behavior.

2. Evacuation Model. An ABM for evacuation decision (ABM_{ed}) is constructed from the statistical model and the social network. It

is a data- and theory-driven model: the data-driven model accounts for within-family factors and the theory-driven model accounts for exogenous factors that contribute to evacuation decisions. Specifically, the data-driven (survey-based) model accounts for a family's decision to evacuate, but does not account for the temporal effects during the lead-up to a hurricane's arrival. Also, the survey data shows that a family factors neighbors' evacuation decisions in its own decision to evacuate, but does not provide requisite detail on how neighborhood effects are incorporated. Thus, we use contagion and collective action theories [2, 6, 13, 25, 26] to introduce two parameters, $c_{i,lev}$ and $c_{i,rem}$, that characterize the minimum fraction (or number) of neighbors that have chosen to evacuate, in order for that family to consider neighborhood effects relevant. The first (respectively, second) parameter controls the neighborhood states that a family deems important when considering evacuation (respectively, remaining in place). The general modeling framework in Section 2.1 is customized for these hurricane evacuation phenomena in Section 2.4.

3. Dynamics of evacuation decisions, and interventions. We use ABM_{ed} on a realistic synthetic population of VA Beach, VA, constructed using the methods of [3, 5, 11]; see Section 2.2. We study the effects of two types of interventions: (a) seeding, which involves convincing a subset S of nodes to evacuate, and (b) providing security to a subset S' of nodes, which corresponds to setting $c_{i,rem} = 1$. Our main results on the dynamics of ABM_{ed} are: (*i*) We show that planning these interventions within a given budget, so that the expected number of evacuations is maximized within T steps, has a large inapproximability factor. For $T = 1$, we design an algorithm with a rigorous worst case guarantee, relative to the optimal. Due to its computational hardness for higher T, we instead design an algorithm to maximize the number of nodes which are provided security (so $c_{i,rem}$ becomes 1 for them), by a tour of cost bounded by a given budget. These results are in Section 3. (*ii*) In practice, we find through simulation that seeding does not make a big difference in the overall evacuation rate, and households can decide to evacuate based on intrinsic factors alone—*this is in contrast with the classic studies of contagion, where seeding must be done to achieve diffusion [13].* (*iii*) Network effects and incentives can be effective in increasing evacuation rates, based on our simulation results (Section 4.2). We model police going door-to-door to reduce families' concerns of crime and looting, which corresponds to increasing $c_{i,rem}$ in our model. We find that this has a significant effect on simulation results—the removal of fear of looting can increase the fraction of families evacuating by up to 50%. The effect of $c_{i,lev}$ (for controlling the neighborhood effect to encourage evacuation) is dwarfed by that of $c_{i,rem}$ (for controlling the influence of crime to remain in place).

Novelty of our work. Our paper is the first ABM for evacuation decisions that combines a detailed survey with a realistic population. Our model is the first to account for the evacuation-inhibiting effect of concerns over looting and other crime, with increasing numbers of evacuating neighbors.

Organization. Our model is presented in Section 2. Results on the complexity of intervention design problems are in Section 3, and simulation results are in Section 4. We conclude in Section 5.

2 MODELS

The graph dynamical systems (GDS) model [1, 22] provides a formal framework for specifying and reasoning about models of human behavior and the resulting dynamics of a system. GDS is presented in Section 2.1. This general model is applied to our particular case of hurricane evacuations, and the details of these modeling efforts are presented in the sections specified in Figure 1.
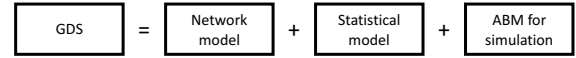
Figure 1: The GDS model of Section 2.1 is composed of the three elements on the RHS, which are represented below: Section 2.2 contains the network model, Section 2.3 contains the statistical model, and Section 2.4 contains the ABM.

2.1 A Graph Dynamical Systems Framework

Graph dynamical system description. We use the framework of *graph dynamical systems* (GDS) to abstract our agent based model, which is used to study evacuation behavior. Let V denote the set of agents. Each node $v_i \in V$ can be associated with a state $x_i(t) \in \{0, 1\}$ at time t, with $x_i(t) = 1$ (resp., 0) indicating that agent v_i has evacuated (resp., not evacuated). Let $\mathbf{x(t)} \in \{0, 1\}^n$ denote the vector of agent states at time t. A GDS $\mathcal{S}$ consists of two components: (1) an interaction network $G = (V, E)$, where V represents the set of agents (in our case, the households which are deciding whether or not to evacuate), and E represents a set of edges, with $e = \{v_i, v_j\} \in E$ if agents v_i and v_j can influence each other; and (2) a set $\mathcal{F} = \{f_i : v_i \in V\}$ of *local* functions $f_i : \{0, 1\}^{deg(v_i)} \to \{0, 1\}$ for each node $v_i \in V$, which determines the next state of node v_i in terms of the states of $N(i)$, the set of neighbors of v_i; $deg(v_i) = |N(i)|$. The model is a progressive model [18] in that the only state transition is $0 \to 1$; once a node is in state 1, it remains in state 1. (Once a family decides to evacuate, it does not then change its mind to remain in place.) Given a vector $\mathbf{x(t)}$ describing the states of all agents at time t, the vector $\mathbf{x(t + 1)}$ at the next time is obtained by updating $x_i(t + 1)$ using its local function $f_i(\cdot)$ for all $v_i \in V$.

The EvacThresh local functions: modeling evacuation behavior. The EvacThresh function $f_i(\cdot)$ is probabilistic, and depends on the *probability of evacuation* (the y-axis variable in Figure 2), in order to capture the qualitative aspects of the results of [15]. For each node v_i, we have parameters $a_i, b_i, c_{i,lev}, c_{i,rem}, p_i^{init}$, and p_i^{final}. Let $n_i(t) = \sum_{j \in N(i)} x_j(t)$ denote the number of neighbors of node v_i in state 1. At each time step t, we have

$$\Pr[x_i(t) = 1 | x_i(t-1) = 0] = \begin{cases} p_i^{init} = \frac{1}{1+exp(-a_i)}, & \text{if } n_i(t) < c_i \\ p_i^{final} = \frac{1}{1+exp(-a_i-b_i)}, & \text{if } n_i(t) \geq c_i \end{cases}$$

$$(1)$$

where c_i may represent $c_{i,lev}$ (Figure 2 (Left)) or $c_{i,rem}$ (Figure 2 (Middle)) or both (Figure 2 (Right)), and where we also denote the LHS above as $p_{i,evac}$ for node v_i. Definitions for $c_{i,rem}$ and $c_{i,lev}$ are given in Section 1.2, Contribution 2. The parameter b_i combines both peer effects, as well as concerns of looting. If node v_i has no looting concern, we have $b_i \leq 0$, and $p_i^{final} \geq p_i^{init}$; otherwise, we have $b_i \geq 0$, and $p_i^{final} < p_i^{init}$. This is illustrated in Figure 2.
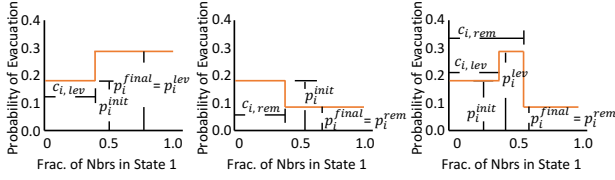
Figure 2: The EVACTHRESH model, for an arbitrary v_i, illustrating the probability of evacuation $p_{i,evac}$ (y-axis) vs the fraction $n_i(t)$ of neighbors who have already evacuated (x-axis), in three different cases. (Left) There is concern only for evacuating, and $p_i^{final} > p_i^{init}$. (Middle) There is concern for only looting, and $p_i^{final} < p_i^{init}$. (Right) There is concern for both evacuating and looting, and $p_i^{final} < p_i^{init}$.

Interventions. We consider two kinds of interventions, both of which involve selecting a subset $S \subset V$ of nodes: (1) *Seeding*, in which the nodes in S are convinced to evacuate, i.e., $x_i(0) = 1$ for all $v_i \in S$. (2) *Providing security*, in which the neighborhoods where nodes in S live are provided security, so that the local function $f_i(\cdot)$ for each $v_i \in S$ is as in Figure 2(Left). We use $c_1(S)$ and $c_2(S)$ to denote the costs of set S in these two cases. In general, the costs are sub-additive, since they typically involve logistical costs. For instance, in case (2), a law enforcement official has to come to the location where v stays, so we model $c_1(S)$ as the cost of the minimum tour connecting the nodes in S.

Problems of interest. For a GDS abstraction $\mathcal{S}_{evac}$, and interventions S_1, S_2, we define evac($\mathcal{S}_{evac}, S_1, S_2, T$) as the expected number of nodes who choose to evacuate, for interventions S_1, S_2, during T time steps. We study the following questions:
(1) What are the dynamics of evacuation? How many and what kind of people end up evacuating?
(2) MAXEVAC problem: given a budget B, design interventions S_1, S_2, such that $c(S_1) + c(S_2) \leq B$, and evac($\mathcal{S}_{evac}, S_1, S_2, T$) is maximized.
(3) MINCOSTEVAC problem (complement of MAXEVAC): given a target evacuation factor s, choose an intervention S_1, S_2, such that evac($\mathcal{S}_{evac}, S_1, S_2, T$) $\geq s|V|$, and $c(S_1) + c(S_2)$ is minimized.
Example. Figure 3 shows an example of a GDS $\mathcal{S}_{evac}$ with local functions as in Figure 2. For node 3, we have $p_3^{final} < p_3^{init}$ because of looting concern, but for all the remaining nodes, we have $p_i^{final} > p_i^{init}$. As shown in the figure, the probability of the transition $\mathbf{x}(1) \rightarrow \mathbf{x}(2)$ is 0.189. There are 8 possible configurations to which the system can transition in one step from $\mathbf{x}(1)$, each corresponding to a subset of the three nodes 2, 3, 4 switching to state 1 (including the configuration in which none of them switches to 1). Starting from the configuration $\mathbf{x}(1)$, and with $S_1 = \{1, 5\}$ as the seed set, it is easy to verify that the expected number of nodes which evacuate, i.e, switch to state 1, is 2.7 (this includes the nodes 1 and 5, which are already in state 1), i.e., evac($\mathcal{S}_{evac}, S_1 = \{1, 5\}, S_2 = \emptyset$) = 2.7.

2.2 Synthetic Population and Social Networks

Synthetic population. We develop a synthetic population for the Virginia Beach region of Virginia that was impacted by Hurricane
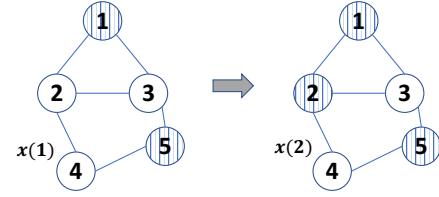
Figure 3: An example showing the transitions in a $\mathcal{S}_{evac}$ model on a graph with five nodes, and EVACTHRESH local functions, with parameters $\theta_i = 0.5$ and $p_i^{init} = 0.2$ for all v_i, $p_2^{final} = p_4^{final} = p_5^{final} = 0.3$, and $p_3^{final} = 0.1$. The system starts in configuration $\mathbf{x}(1)$ with $\mathbf{x}_1(1) = \mathbf{x}_5(1) = 1$ (they are colored blue), and $\mathbf{x}_i(1) = 0$ for all $v_i = 2, 3, 4$ (they are colored white). The probability of transition $\mathbf{x}(1) \rightarrow \mathbf{x}(2)$ (i.e., the probability that the system state at left at time $t = 1$ will transition to the state shown at right at $t = 2$) is $p_2^{final}(1 - p_3^{final})(1 - p_4^{final}) = 0.3 \cdot (1 - 0.1) \cdot (1 - 0.3) = 0.189$. In this calculation, a node v_i that does not change state remains in its current state with probability $(1 - p_i^{final})$. See Section 2.1 for definitions of $\mathbf{x}(t)$ [vector of agent states] and $x_i(t)$ [an agent v_i's state].

Sandy. This region has a population of over 450,000 that is distributed over 167,722 households. Households (i.e., families) are nodes in our social networks and agents in our ABM. Our synthetic representation of this population is statistically indistinguishable from the Census data for this region, at a block group level. Additionally, it is geographically situated based on land-use data, with a real geo-location which invokes the concept of neighbors and long range connections [3]. For each family, we generate attributes such as its geographic (longitude, latitude) house structure coordinates, household income, household size, and whether a family has internet access. We also use individual characteristics (most often, those of head of household) such as race, gender, and age. (The statistical analysis, Section 2.3, has more detail.) Hence, the households are heterogeneous.

Social networks and their structures. We add edges between households based on the Kleinberg small world (KSW) model [19]. In particular, we specify the short-range distance d_{sr} over which local interactions take place among neighbors (resulting in bi-directed edges), and the number q of long-range directed edges incoming to each v_i, that represent work-related interactions of adults. See Table 1. Hence, we generate and study a family of networks.

In the absence of long-range edges (i.e., $q = 0$), there are thousands of strongly and weakly connected components in the networks: as d_{sr} increases, the number of connected components decreases from 19487 to 1235, while the size of the largest weakly connected component (WCC) increases from 381 families to 51006. When q increases to 2, there is a one WCC in every graph. Average degrees for all d_{sr} and q can be computed from the degrees for $q = 0$ in Table 1, based on the graph construction process.

Here, our work is confined to face-to-face interactions, although interactions of other types are candidates for future work. This might include other network models. For example, communication networks for social media are often scale free networks.

Table 1: Kleinberg small world (KSW) networks [19] used in our experiments. The exponent $\alpha = 2.5$ in the KSW model is for computing the probabilities of selecting particular long-range nodes with which to form long-range edges with each node $v_i \in V$. The value of q can be added to the average in-degree in the table to get average in-degree for different q. There are five graph instances for each (d_{sr}, q) combination.

No. Nodes	Short-Range Distances (km)	No. Long-Range Edges	Avg. In- & Out-Deg Per d_{sr}, for $q = 0$
167722	0.04, 0.07, 0.10	0, 2, 4, 8, 16, 32	9.58, 22.68, 40.96

2.3 Statistical Model of Evacuation Behavior

2.3.1 Survey. An internet-based survey was conducted by GfK (formerly known as Knowledge Networks) using its unique panel of respondents (KnowledgePanel®), to assess factors driving evacuation decisions [24]. It was implemented in counties affected by Hurricane Sandy which hit northeastern U.S. in October 2012.

With the statistical control applied to the sample selection, GfK ensures the representativeness of KnowledgePanel survey samples as measured by their proximity to population benchmarks. The survey was posted online on July 7, 2013 and was closed two weeks later on July 22. A total of 1,212 individuals completed the survey with a response rate of 61.93%. Altogether the survey had 48 questions on issues related to hurricane risk, coastal vulnerability and demographics, and on average, took about 15 minutes to complete.

2.3.2 Analysis and correlations of neighbors' evacuation. Using a Binomial Logit model, we tested for the factors associated with households' evacuation behavior, i.e., we tested in order to identify which variables in the survey are important in predicting evacuation behavior. We estimated the following equation:

$$Y_i^* = \beta' Z_i + \mu_i \, , \tag{2}$$

where Y_i^* is the log odds of evacuation, all β values in the equations of this section are binomial logit regression model parameters, Z_i are the explanatory variables, and μ is the error term. Y_i is 1 if the log-odds of evacuation $Y_i^* > 0$, and 0 elsewhere. And

$$\beta' Z_i = \beta_0 + \Sigma_{k=1}^{K} \beta_{Hk} H_{ki} \, , \tag{3}$$

where H denotes a vector of explanatory factors. We considered a variety of explanatory variables including respondent's age, gender, race, highest level of education completed; employment status; the importance of neighbors' evacuation decisions in respondent's own decision to evacuate; the importance of concerns of crime or looting in the neighborhood in respondent's own decision to evacuate; household size; number of elderly members in the households; number of disabled members in the household; household ownership; living in a mobile home; household has access to the internet; income; number of vehicles owned; the age of the housing structure; and whether household has a home insurance. We estimated the equation using a Binomial Logit model, as appropriate for the level of measurement for the dependent variable, with robust standard errors.

Our results indicated that respondent's employment status; consideration of neighbors' evacuation behavior; concerns about neighborhood criminal activities or looting; having access to the internet

in the house; age of the house; and having home insurance, each played a significant role in a respondent's decision to evacuate during hurricane Sandy. The effect sizes were modest, nonetheless. The estimated model is shown in Table 2.

Table 2: Logistic Regression results: dependent variable is if the respondent evacuated or not during Hurricane Sandy. (*) symbol next to p-value shows the variable is significant.

Independent Variable	Odds Ratio	p-Value
Age (in years), a_{hoh}	1.000	0.991
Female (Ref: Male), k_{hh}	0.848	0.451
Race (Ref: Black)		
White, i_{rw}	0.740	0.540
Other, i_{ro}	0.655	0.620
Hispanic, i_{rh}	1.548	0.657
Mixed, i_{mr}	0.312	0.000*
Education (Ref: High school or less)		
Some college, e_{sc}	1.423	0.146
Bachelor or higher, e_{alb}	1.488	0.264
Employment status, h_{mw}	1.076	0.004*
Evacuation decision made by neighbors etc. (Ref: not important)		
Somewhat important, η_{si}	1.134	0.550
Important, η_i	1.688	0.027*
Very important, η_{vi}	1.614	0.423
Concerns about crime such as looting (Ref: not important at all)		
Somewhat important, ℓ_{si}	0.527	0.042*
Important, ℓ_i	0.277	0.085*
Very important, ℓ_{vi}	0.283	0.051*
Interaction (neighbor and looting), β_{el}	1.055	0.500
Household size, i_{hs}	0.794	0.354
No. of HH members who are disabled, i_{md}	1.068	0.671
No. of HH members who are elderly, i_{me}	1.322	0.225
Household is owned, i_{io}	0.680	0.428
Living in a mobile home, i_{mh}	0.931	0.709
HH has access to the internet, i_{ia}	0.235	0.028*
HH Income, i_{hi}	1.015	0.770
No. of vehicles owned by HH, r_c	1.057	0.810
Age of house, a_{hhs}	0.997	0.074*
HH has home insurance, i_{fi}	6.379	0.000*
constant	0.434	0.479

Respondent's age, gender or race did not influence her decision to evacuate. The same pattern was evident for household size, the number of elderly, and disabled members living in the household. None of the economic status indicators such as income, household ownership, living in a mobile home, or number of vehicles was associated with evacuation decisions. Education was marginally associated. No meaningful difference existed in evacuation behavior between respondents who completed high school or attended high school or a lower schooling level, and those with a bachelor's degree. Further, respondents living in an older housing structure had a higher likelihood of evacuation during Hurricane Sandy.

2.3.3 Estimating importance of neighbors' evacuation and concerns about crime and looting. To estimate the probability of evacuation for each household in the synthetic population, we need data on each of the explanatory variables used in the binary logit equation. Since the synthetic population's attributes are derived from the census data, the demographic features for each household are readily available. However the behavioral features, such as the importance of neighbors evacuation decisions (which motivates a family to evacuate) and concerns about crime (which motivates a family to stay) must be estimated from the survey data separately.

For each of these two features, an ordered logistic regression model was separately built based on the survey data. The ordered

logistic was used to handle the 4-level response in the survey data, i.e., *not important* (*index* = 0), *somewhat important* (*index* = 1), *important* (*index* = 2), and *very important* (*index* = 3). These models were then applied to the synthetic population to estimate their corresponding features, which in turn were used to estimate the probability of evacuation. In both "neighbor" and "looting" models, we found age, gender, race, education level, family size and household income to be significant in estimating the importance.

2.3.4 Estimating the probability of evacuation. With important variables identified in Section 2.3.2, and the additional analysis results in Section 2.3.3, a logistic regression was performed with the explanatory variables of Table 2 to calculate the probability $p_{i,evac}$ of a family v_i evacuating, given by:

$$p_{i,evac} = 1/(1 + [1/\exp(-0.835045 + g_{hh} + g_{net})]) \qquad (4)$$

where g_{hh} represents the ***intrinsic*** (i.e., household-related) terms

$$\begin{aligned} g_{hh} = &- 0.00017\, a_{hoh} - 0.165\, k_{hh} - 0.301\, i_{rw} \\ &+ 0.436\, i_{rh} - 0.423\, i_{ro} - 1.163\, i_{mr} \\ &0.353\, e_{sc} + 0.397\, e_{alb} + 0.073\, h_{mw} \\ &- 1.446\, i_{ia} - 0.0025\, a_{hhs} + 1.853\, i_{fi} \\ &- 0.231\, i_{hs} + 0.015\, i_{hi} + 0.066\, i_{md} + 0.279\, i_{me} \\ &- 0.386\, i_{io} - 0.0718\, i_{mh} + 0.056\, r_c \end{aligned} \qquad (5)$$

and g_{net} represents the ***network*** (i.e., exogeneous) terms

$$\begin{aligned} g_{net} = &0.125\, \eta_{si} + 0.523\, \eta_i + 0.478\, \eta_{vi} + 0.053\, \beta_{el} \\ &- 0.640\, \ell_{si} - 1.284\, \ell_i - 1.263\, \ell_{vi}\,. \end{aligned} \qquad (6)$$

Variables in Equations (5) and (6) are provided in Table 2 and the coefficients are determined from the logistic regression. In Equation (6), we note that an increase in probability from evacuating being operative (η_i coefficient) is lesser in magnitude than each of the three remaining terms for remaining in place (not evacuating). Thus, we see that when both effects are operative, the remaining behind (i.e., looting) term dominates (only one of the three terms is operative for a v_i), so the behavior is as shown in Figure 2(Right). Figure 2(Left) applies when only the evacuating influence is operative. Figure 2(Middle) applies when only the looting influence is operative.

The term g_{hh} is a data-driven model, while g_{net} is a data-plus-theory-driven model. Both are time-independent models, but g_{net} is augmented in the agent model (Section 2.4) to become time-dependent, accounting for the changing states of a node's neighbors. Theory enters through contagion theory [2, 6] and peer influence collective action theory [13, 25, 26]. Thus, g_{hh} in Equation (4) provides heterogeneity across families and g_{net} (when augmented) provides heterogeneity and time dependence in the dynamics of hurricane evacuation decision making.

Equations (4) through (6) represent the particular local function $f_i(\cdot)$ for family v_i that was presented in general terms by Equation (1) of the GDS description in Section 2.1.

2.3.5 Model based estimates of missing data on home insurance. In VA Beach 55,014 households out of a total of 167,722 households, had missing information about home insurance. To estimate this missing information we trained a regression model on all the 112,708 households for which home insurance data was available.

The response variable in the regression was whether the household had home insurance or not and the independent variables were demographic variables: household size, household income, age of the house, age of the head of the household, employment status, and marital status. Once this model was learned, it was applied to the households for which home insurance data was missing, to obtain an estimated probability of having home insurance.

2.4 Agent Model of Behavior

2.4.1 Overview of model development. The survey data are a collection of individual responses to questions that focus on respondents' and their families' demographics, and the end result of whether the family evacuated prior to the arrival of Hurricane Sandy. In this sense, the survey data are static, end-of-event information: for example, a respondent states that she and her family either evacuated or did not (not the day that they decided to evacuate nor the evacuation decisions of their neighbors). Consistent with the GDS framework in Section 2.1 and consistent with the neighborhood effects found in the survey data and analyses of Section 2.3, our goal is to develop a model that accounts for (*i*) time evolution of evacuation decisions, and for (*ii*) neighborhood effects. That is, the survey data did not have a temporal aspect: respondents state whether they evacuated or did not, and not *when*, if they did evacuate. Since our model considers temporal evacuation decisions, which enables interventions that would not otherwise be possible to explore, we convert the probability from the logistic model to a daily probability. We address these in the next two subsections and then in the third subsection, we put these results together to produce an algorithm for the probability of a family deciding to evacuate at each time step.

2.4.2 Predicting neighbor influence on evacuation and sheltering in-place. Section 2.3.3 describes the procedure for estimating the influence of neighbors for evacuating and for crime (i.e., remaining) on a family's evacuation decision. The covariates in these binary logit models are time-independent quantities and hence are computed once for each family. For each household v_i, for each of the two effects (evacuating and remaining), we compute probabilities for each of the four levels. To calculate the probability of evacuation as shown in Equation (6), the following parameters are required: ℓ_{si}, the indicator variable for the remaining (i.e., not evacuating) category of *somewhat important*; ℓ_i, the indicator variable for the remaining category of *important*; ℓ_{vi}, the indicator variable for the remaining category of *very important*; and the analogous three variables from Table 2 for the categories of evacuating. With these variables, we form two vectors for each v_i: $\eta_{i,evac} = (0, \eta_{si}, \eta_i, \eta_{vi})$ for evacuating and $\ell_{i,loot} = (0, \ell_{si}, \ell_i, \ell_{vi})$ for remaining. In each of these two vectors, at most one element will be 1: that is the element corresponding to the category with the greatest probability from the analyses of Section 2.3.3.

2.4.3 Network peer effects. Peer (i.e., distance-1 neighbor) effects from v_i's social network are incorporated into the evacuation model for family v_i, using the following motivating scenario. Through the regressions of Section 2.3.3, it is determined that a family v_i considers the influence of its distance-1 neighbors to be important in motivating them to evacuate, and very important in motivating

them to remain in place (due to looting concerns). Suppose at some time t, v_i has no neighbors that are evacuating, and the family is deciding to evacuate. Even though peer effects are important, there are no neighbors that are evacuating to provide these evacuating and remaining influences. So the contribution of peer influence to v_i in this situation is ambiguous.

We resolved this ambiguity in the following way. We specify critical fractions (or counts) of neighbors in state 1 for motivating evacuation $c_{i,lev}$ and for motivating remaining in place $c_{i,rem}$. That is, if at least a fraction (or count) $c_{i,lev}$ (respectively, $c_{i,rem}$) of v_i's neighbors is in state 1, then v_i considers these neighbors to be compelling in motivating v_i to leave (respectively, remain); otherwise, v_i ignores this neighborhood condition as not persuasive.

In this way, the driving force for changing v_i's probability of evacuation is dynamic: it changes in time according to the fraction (or count) of neighbors in state 1, and $c_{i,lev}$ and $c_{i,rem}$. The remaining terms in the probability of evacuation (Equation (4)) are assumed static for a simulation; these include age, gender, and education attainment.

2.4.4 Probability of evacuation. Algorithm 1 describes the process of determining whether a family v_i evacuates at time $(t + 1)$, based on the system at time t. Inputs to the algorithm include the modeling results of this Section 2.4, and the rest of Section 2. The duration of the simulation is t^*. Algorithm 1 is the local function for each v_i. If a family is in state 1 at time $\hat{t}$, then it is evacuating at all time $t \geq \hat{t}$ (step 1). If not (i.e., v_i is in state 0), then the state of v_i is determined. First, the fraction (or count) of v_i's neighbors that are in state 1 is determined (step 3). Then, steps 4 and 5 determine whether peer influence for evacuating should be incorporated, and if so, the value. Next, steps 6 and 7 determine whether peer influence for remaining in place should be incorporated, and if so, the value. Steps 8 through 11 compute the probability of evacuation, convert it to a daily value, and perform a Bernoulli trial to determine whether v_i transitions to the evacuating state 1.

3 COMPLEXITY OF MAXEVAC AND MINCOSTEVAC

These problems turn out to be very hard even for the simplest case of $T = 1$, even if there is no concern of looting, so that $p_v^{final} > p_v^{init}$ for all nodes $v \in V$.

THEOREM 3.1. *Even if $p_v^{init} = 0$ and $p_v^{final} = 1$ for all v, $T = 1$, and no nodes have looting concerns, the MAXEVAC and MINCOSTEVAC problems are NP-complete; further, in this setting, the MINCOSTEVAC problem cannot be approximated within a factor of $O(n^{\frac{1}{2(\log \log n)^c}})$ for some c.*

We show an approximation algorithm for MINCOSTEVAC when $T = 1$, building on the result of [28].

THEOREM 3.2. *Suppose there is a solution S^* to MINCOSTEVAC for instances with $T = 1$ and no looting concern, such that $\text{evac}(\mathcal{S}_{evac}, S^*, \emptyset, T = 1) \geq q^*n$. Let $r_{max} = \max_v \theta_v deg(v)$. Then, it is possible to get a solution S with $|S| = O(|S^*| r_{max} \log^2 n(1 + \ln \frac{1}{\epsilon} + \frac{1}{\epsilon q^*}))$, such that $\text{evac}(\mathcal{S}_{evac}, S, \emptyset, 1) \geq (1 - \epsilon)q^*n$.*

PROOF. (Sketch) We reduce the MINCOSTEVAC problem to the partial set multi-cover problem. If no node i has looting concern,

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Algorithm 1: LOCAL FUNCTION COMPUTATION for vertex v_i at time t in a simulation.

1 **Input:** t, v_i, $\mathbf{x}(t)$, $n_i(t)$, $t^* = 10$ days, $c_{i,lev}$, $c_{i,rem}$, β_{el}, a_{hoh}, $\eta_{i,evac} = (0, \eta_{si}, \eta_i, \eta_{vi})$, $\ell_{i,loot} = (0, \ell_{si}, \ell_i, \ell_{vi})$, k_{hh}, i_{rw}, i_{rh}, i_{ro}, i_{mr}, h_{mw}, i_{ia}, a_{hhs}, i_{fi}, e_{sc}, e_{alb}, i_{hs}, i_{hi} i_{md}, i_{me}, i_{io}, i_{mh}, r_c. See Table 2 for symbol meanings.

2 **Output:** For family v_i at time $t + 1$, the next state $x_i(t + 1)$.

3 **Steps:**
- (1) **if** $x_i(t) == 1$ **do**
  - i. Return $x_i(t + 1) = 1$. // Family is already evacuating.
- (2) Set $x_i(t + 1) = 0$. // Family v_i's next state is initialized to 0.
- (3) Determine the fraction (or count) n_i of v_i's neighbors that are evacuating (i.e., in state 1).
- (4) Set vector $\eta = (0, 0, 0, 0)$. // v_i does not consider its neighbors leaving to be important in motivating v_i to leave; the effect is inoperative.
- (5) **if** $n_i \geq c_{i,lev}$ **do**
  - i. Make vector assignment $\eta = \eta_{i,evac}$ // Makes neighborhood influence to evacuate operative.
- (6) Set vector $\ell = (0, 0, 0, 0)$. // v_i does not consider its neighbors leaving to be important in motivating v_i to leave; the effect is inoperative.
- (7) **if** $n_i \geq c_{i,rem}$ **do**
  - i. Make vector assignment $\ell = \ell_{i,loot}$ // Makes neighborhood influence to remain operative.
- (8) Compute Equation (4) and convert to daily probability $p_{i,evac,daily} = 1 - (1 - p_{i,evac})^{(1/t^*)}$.
- (9) Generate a number $n_{random} \in [0, 1]$ uniformly.
- (10) **if** $(n_{random} \leq p_{i,evac,daily})$ **do**
  - i. Set $x_i(t + 1) = 1$. // Family v_i has transitioned to the evacuating state.
- (11) Return $x_i(t + 1)$.

---

it evacuates with probability p_i^{final}, if $r_i = \theta_i deg(i)$ neighbors have evacuated. Since $T = 1$, this corresponds to having at least r_i neighbors of i in the seed set S. We use the algorithm of [28] to find a subset S that maximizes the number of such nodes. □

Maximizing the evac($\cdot$) objective for larger T is a much harder problem. Further, our experiments suggest that in practice, seeding has limited impact on evacuation. Therefore, we consider the problem of finding a subset S of homes to visit, so that $c_2(S) \leq B$, where B is a given budget, and $\sum_v p_v^{final}$ is maximized. Here, we consider the sum of p_v^{final}'s, instead of $|S|$, since this corresponds to the maximum expected number of nodes that might directly evacuate within the set. We reduce this problem to the *orienteering* problem studied in [8] in the following manner. We consider a root node s from where the tours start, a cost w_{ij} of going from node i to node j, and a reward p_i^{final} for each node i. Next, for each possible $t \in V$, we use the algorithm of [8] to find a tour on a subset S_t with $c_2(S_t) \leq B$, and return the one with the maximum reward.

THEOREM 3.3. *For a given budget B, the above algorithm returns a set S with $c_2(S) \leq B$, and $\sum_{i \in S} p_i^{final}$ within an $O(1)$ factor of the optimum.*

The detailed proofs of the theorems are omitted here due to lack of space but will be available in the journal version of the paper.

4 SIMULATIONS AND RESULTS

4.1 Simulation Process and Parameters

Simulation process. *Simulation instances* are performed by incrementing time at 1-day intervals, for $t^* = 10$ days (the tenth day is hurricane arrival). At each day (time t), $0 \leq t \leq t^* - 1$, all agents $v_i \in V$, $1 \leq i \leq n$, of the social network $G(V, E)$ are iterated over and Algorithm 1 is executed to determine each agent v_i's next state $x_i(t+1)$. A simulation is composed of 100 simulation instances, and results are averaged across the instances, and presented below. In all simulations, the set V of families is the same, and $n = |V| = 167722$. It is the connectivity (in terms of numbers of short- and long-range edges) that changes across networks.

**Parameters studied.** Input variables and their values used in simulations are provided in Table 3.

Table 3: Summary of parameters and values in simulations.

| Parameter	Description
Networks.	Vary d_{sr} and q in the networks of Table 1.
Num. random seeds, n_s.	Number of seed nodes (nodes evacuating at $t = 0$) specified per run (chosen uniformly at random). Values are 0, 50, 500, 5000, and 50000.
Neighborhood effect critical values, c_{lev}, c_{rem}.	Values of c_{lev} and c_{rem} are 0 to 1, in increments of 0.2 or finer, when these values are fractions of neighbors of a node v_i. Values of 0, 1, and 2 are used when these values are counts.
Geographic subregions of the population, k_{blk}.	The bounding box (rectangle) that circumscribes the VA Beach, VA population (roughly 46 km × 29 km) is partitioned into 25 equi-sized blocks. The kth block is k_{blk}. $1 \leq k_{blk} \leq 25$.

4.2 Simulation Results

Effect of network structure (d_{sr} and q). Figure 4 provides the average cumulative fraction s of nodes evacuating from the population at each day leading up to hurricane arrival. Figure 4a shows the effect of distances d_{sr} for introducing short-range edges in the social networks, and Figure 4b shows the effect of number q of long range incoming edges per node. First, the plots show that there are very small effects of numbers of short-range edges and long-range edges on the fraction of the population evacuating. These results are for the particular case where $c_{lev} = c_{rem} = 0.2$. Later, we will demonstrate that varying c_{lev} and c_{rem}, along with network structure, reveals significant interaction effects. Second, variances among the data in each curve are very small (there are vertical variance bars for each curve at each day on the x-axis, and they are non-visible, indicating that variances are very small among the 100 simulation instances). We therefore ignore variances in the following results.

Basic character of dynamics and effects of seeding. Continuing with Figure 4, the curves in the plots are concave downward. In epidemics, for example, the initial stages of an outbreak are concave upward as a virus takes hold in a population, and the latter stages are concave downward as the number of available agents
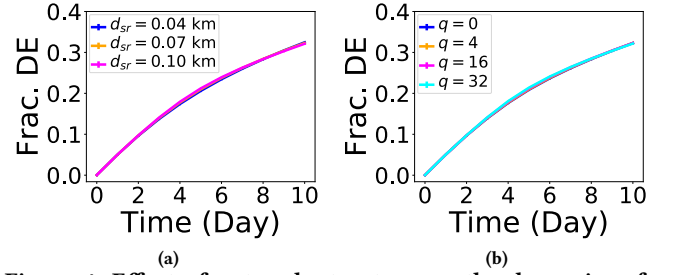
Figure 4: Effect of network structure on the dynamics of evacuation decision making. Dynamics are shown as the time history of the cumulative average fraction of the population that has decided to evacuate (Frac. DE). Other fixed conditions: $c_{lev} = c_{rem} = 0.2$, and $n_s = 50$ random seeds. (a) Curves for three short-range radii d_{sr} for short-range edges and fixed $q = 4$ random, long-range incoming edges per node. (b) Curves for four values of number q of long-range incoming edges for fixed $d_{sr} = 0.07$ km.
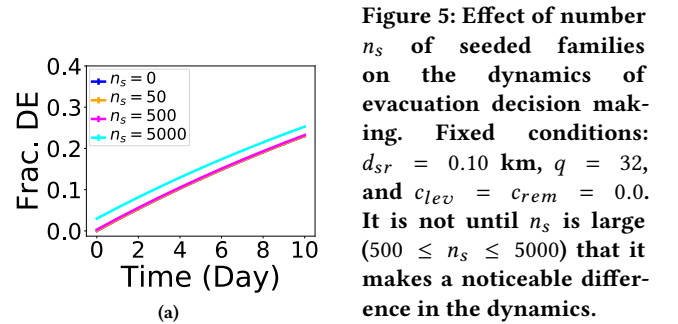
Figure 5: Effect of number n_s of seeded families on the dynamics of evacuation decision making. Fixed conditions: $d_{sr} = 0.10$ km, $q = 32$, and $c_{lev} = c_{rem} = 0.0$. It is not until n_s is large ($500 \leq n_s \leq 5000$) that it makes a noticeable difference in the dynamics.

for infection decreases, resulting in a sigmoidal curve. Here, because of the influence of family's intrinsic factors in Equation (4) on the probability of evacuation, a family may decide to evacuate without any external (network) influence. As a result, seeding the population with families that are evacuating is not required, as is the case with a Granovetter type [6, 13, 33] of contagion, where the driving force to change state to 1 (i.e., to become active, in a general sense), is provided solely by exogenous (peer) influence. This is also illustrated in Figure 5, where the effect of seeding is explicitly shown. The results indicate that the dynamics are not influenced appreciably until the number n_s of seed nodes is about 5000. It is also interesting that this set of input parameters yields approximately linear behavior in time, because a hallmark of complex systems is nonlinear behavior. This effect of seeding is pervasive across conditions.

Effects of c_{lev} and c_{rem}, coupled with network structure. Recall that Figure 4 illustrates that for fixed $c_{lev} = c_{rem} = 0.2$, the fraction of the population deciding to evacuate (Frac. DE) was not dependent on network structure. Figure 6 depicts how Frac. DE changes with c_{rem} and network structure (d_{sr}, and q). Here now, c_{rem} is the minimum *count* of v_i's neighbors in state 1 that makes neighbors compelling such that the dampening effect of looting on the probability of evacuation becomes operative.

In Figure 6a, the largest variation in the *final* (i.e., $t = 10$) fraction s of families evacuating occurs for $d_{sr} = 0.04$ km, and this variation

decreases with increasing d_{sr}. This is because for $d_{sr} = 0.04$ km (0.10 km), the average in-degree of a node is 10 (40), so the in-degree of a node is changed more appreciably for lesser d_{sr} values when 32 long-range edges are added per node.

At $d_{sr} = 0.04$ km, $c_{rem} = 0$ means that the inhibiting effect of concerns about looting are always operative, even if no neighbors of family v_i are evacuating (blue and orange curves lay on top of each other). Incorporating looting decreases the probability of evacuation, and this results in the least values of s, regardless of q. As c_{rem} increases from 0, the final fraction of evacuating families increases, because increasing c_{rem} inhibits the activation of the looting effect. For a given $c_{rem} > 0$, the curve for $q = 0$ is greater than that for $q = 32$ because as the number q of long range edges increases, there are more paths over which the evacuation decision can propagate. Figure 6b illustrates how increasing c_{rem} (plotted on x-axis) from 0 to 1, which dampens looting concerns and thus makes evacuation more likely, indeed increases s by 50%.
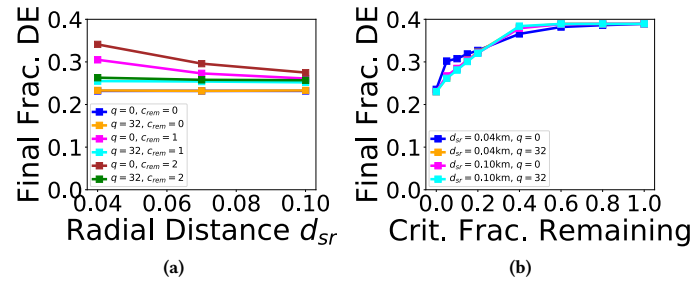

(a)   (b)

Figure 6: (a) Plot of the *final* fraction of the population that decides to evacuate (Final Frac. DE, s) as a function of d_{sr}, q, and c_{rem}. Fixed values are $c_{lev} = 0$, $n_s = 0$. c_{rem} is a count (not a fraction) of the minimum number of neighbors that must be in state 1 for a family to be concerned with looting. These results demonstrate that for some regions of the input space, network structure can have a significant effect of evacuation dynamics. (b) Plot of the final fraction of nodes in state 1 as a function of c_{rem} (the fraction of neighbors in state 1, for making operative concerns over looting), which varies from 0 to 1. Fixed conditions are $c_{lev} = c_{rem}$, $n_s = 0$. As c_{rem} increases from 0 to 1, s increases by 50%.

Interventions in the form of police reassuring citizens that their property will be protected against looting. Previous researchers have shown that targeting monitoring of homes and property by law enforcement agencies in hurricane affected areas can be effective in controlling criminal activities and hence in motivating people to leave [20, 30, 32]. Based on our results above, we conclude that (*i*) seeding families as evacuating has little impact on the overall evacuation fraction, for reasonable levels of seeding, and (*ii*) increasing c_{rem} can be effective in increasing the amount of evacuation. The latter result was obtained by methodically increasing c_{rem} globally (i.e., for the entire population) in Figure 6b. Here, we take a local approach and study a systematic targeting of successively larger geospatial zones by police in reassuring people in those zones of police property protection. Our base case in this study is the spread fraction s of evacuation when $c_{lev} = c_{rem} = 0$.

VA Beach, VA is circumscribed by a roughly 46 km × 29 km geographic region (a "bounding box"). We partition this region into

25 equi-sized rectangular blocks, and run a set of 25 simulations. The baseline condition is that $c_{rem} = 0$, i.e., that the families are always concerned about looting, no matter how many neighbors have evacuated. In a first simulation, the police visit households in block 1 to reassure them, resulting in an increase in c_{rem} to 0.2 for all families whose homes reside in block 1. In the kth simulation, police reassure all homes residing in blocks 1 through k, inclusive. Note that because of varying population density, there is not an equal number of households in each block; see Figure 7a.

Figure 7b shows the results. First, the stair-stepped nature of the results is caused by differences in population density, underscoring the need for realistic populations. Second, the effect of changing d_{sr} is small, but increases with increasing c_{rem}. The effect of c_{rem} is greater. Third, these effects are *solely* due to network and peer effects. That is, household-related variables are all held constant in this intervention study.

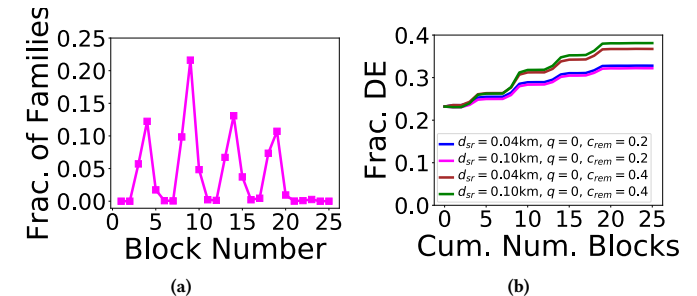(a)   (b)

Figure 7: (a) Fraction of households in each of 25 equi-sized zones within the bounding box of VA Beach, Va. The shape of the curve is the consequence of the greater population density in the northern part of the city. (b) Final fraction s of population evacuating as a function of the cumulative number of blocks visited by police to reassure families that they will monitor property to dissuade looting. Police visit the blocks in the order given in (a). Households that have been reassured have c_{rem} increased to 0.2 (or 0.4), from the baseline condition of 0. The steps in the plot correspond to police entering blocks (zones) with greater population density. Increasing c_{rem} dampens a family's concern over looting. Note that these results are *solely a network effect*. This intervention generates up to a 50% increase in the fraction of the population evacuating.

5 SUMMARY AND FUTURE WORK

We use a combination of hurricane survey data, synthetic populations, statistical models and ABM to understand the effects of network structure, seeding, human behavior, and interventions on the evacuation response to a hurricane. Our results show that network effects and incentives can help in increasing the evacuation rates. In future work, we plan to include the impact of utility disruptions and risk perceptions on evacuation behavior.

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