Data-Driven Modeling of Evacuation Decision-Making in Extreme Weather Events

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Abstract. Data from surveys administered after Hurricane Sandy provide a wealth of information that can be used to develop models of evacuation decision-making. We use a model based on survey data for predicting whether or not a family will evacuate. The model uses 26 features for each household including its neighborhood characteristics. We augment a 1.7 million node household-level synthetic social network of Miami, Florida with public data for the requisite model features so that our population is consistent with the survey-based model. Results show that household features that drive hurricane evacuations dominate the effects of specifying large numbers of families as "early evacuators" in a contagion process, and also dominate effects of peer influence to evacuate. There is a strong network-based evacuation suppression effect from the fear of looting. We also study spatial factors affecting evacuation rates as well as policy interventions to encourage evacuation.

Keywords: hurricane survey data, survey-based modeling, evacuation decision-making, social networks, agent-based simulation

1 Introduction

1.1 Background and Motivation

Many factors affect the decision of whether to evacuate in the face of an oncoming hurricane. These include past evacuation/hurricane experience; risk perceptions (household and human safety, storm threat, concern for looting); storm characteristics such as wind speed, rainfall, and flooding; receiving an evacuation notice; traffic gridlock; presence of children, elderly, and infirm family members; pets; the household's education level; property protection and insurance; economic factors (household income, availability of resources); work duties; race; and having somewhere to stay [2, 4, 5, 12, 13, 16].

No modeling work on evacuation decision-making, during hurricanes, takes all of these factors into account. Most papers include only a few or handful of factors, e.g., [15, 17]. Some use conventional threshold models [10, 17], such as Granovetter's [3,6]. A few have used synthetic data (i.e., digital twin data [1]) to represent the population over which evacuation decisions are made [17]; most use stylized networks to some extent [8, 10, 12, 17]. Furthermore, most populations are relatively small, with at most on the order of 10,000 families [10, 15]; an exception is [17] with 35,064 families.

There is very limited data on actual behaviors, and complex factors are at play during disaster events. Therefore, the combination of data from surveys with agent based models provides a systematic approach for understanding evacuation behavior. In this paper, we take the first steps towards this goal by (*i*) using a statistical evacuation decision model with 26 features, including household and social network features; and (*ii*) using synthetic population data to augment a 1.7 million family-based representation of a Miami, FL social contact network. However, there are numerous modeling challenges in this process (e.g., the survey data are for the overall event, and not for daily decisions), and a better understanding of the phase space of the associated dynamical system (e.g., sensitivity analysis) can help in improving such models. In another paper in this conference [9], we undertake such a study using a stylized behavioral model, but a realistic contact network. Thus, these two works are complementary.

1.2 Our Contributions

First, we augment a synthetic population and social contact network of Miami, FL, developed in [9], where nodes are families and edges are communications between pairs of families. Specifically, we augment the 1.7 million families with additional properties from the American Community Survey (ACS) such as whether they have flood insurance, internet access, and household members that are elderly or disabled. These 26 features are required because our model of hurricane evacuation—originally presented in [12]—uses these parameter values to compute a family's daily probability of evacuation. The probability depends on both household characteristics and neighborhood (peer) effects.

Second, we perform agent-based simulations of hurricane evacuation decision-making for Miami, FL. These simulations include baseline behaviors and effects of model parameters and seeding conditions. To operationalize survey data showing that there are neighborhood effects in the social contact network on a family's evacuation decision, we introduce two thresholds c_u and c_d that control the fraction of neighbors evacuating at which peer-influence for evacuating and for looting, respectively, become important. These two phenomena have opposing effects: small c_u values enhance evacuation from peer influence and small c_d values suppress evacuation due to looting concerns. The probability of evacuation model includes two dominant contributions: (*i*) those from household characteristics (a term denoted g_{hh} below), such as education level of the head of household, whether elderly people are family members, and whether a family has home insurance, and (*ii*) those from network neighbor effects (denoted g_{net}

below). The model is detailed in Section 2. These factors interact. For example, an interesting result that comes from simulations is that the household term g_{hh} dominates the effect of seeding of randomly selected families as early evacuators and also dominates the effect of c_u. This is explained in Section 3 below. Geographically, we find that the evacuation rates across Miami are all non-zero, and vary spatially across the city, but that these variations are not extreme.

Third, we also conduct simulation-based intervention studies to address people's concerns over looting. We model police allaying these concerns by visiting residential areas to tell residents that law enforcement will monitor their homes while they are evacuated. We study this effect for different patterns of police visitations to different geographic regions and for different levels of effectiveness of these interactions. We find that geographic visitation patterns can increase evacuation fractions from 0.24 to 0.42 of families, a 75% increase. This is purely a network effect. Changing the effectiveness of visits can increase the fraction of evacuating families from 0.35 to 0.42.

2 Models and Results

2.1 Network Model

We perform simulations on a human social contact network of Miami, FL. We build this network using the procedures in [1]. Briefly, a collection of synthetic humans is generated that match distributions of age and gender in Miami, FL. These individuals are grouped into households (a household may contain one person). Households are assigned home locations with (lat, long), i.e., latitude and longitude, coordinates. Each person in each household is assigned a set of activities such as work and school. Each activity has a start/end time and an associated geolocation where it takes place. In this way, people can be co-located (i.e., at the same location with overlapping visit times). Two people (that are nodes in the human contact network) who are co-located have an edge between them in the network. See [1] for further details.

Because families choose to evacuate (or not), rather than individuals, we convert the individual-based social contact network into a family-based social network $G(V, E)$, with node set V and edge set E, as follows. Since we are concerned with communication that influences evacuation decisions, we consider only those persons between the ages of 18 and 70, inclusive, as decision-makers or having the ability to influence decision-makers. Nodes $v_i \in V$ are families. Suppose person h_i is a member of family v_i and person h_j is a member of family v_j. If h_i and h_j are colocated, then there is an edge between the respective families, i.e., $e_{ij} = \{v_i, v_j\} \in E$ of G. The graph is a simple graph, so there is at most one edge between two families. As part of this current work, we augment the network nodes (families in Miami) with attributes from the American Community Survey (ACS) to include the properties required for the evacuation model, as described in Section 2.2 and Table 1 below, so that simulations (Section 3) can use these properties with the model.

The resulting family-based network has 1,702,038 nodes and 42,789,880 edges. The average degree is 50.3 and the maximum degree is 760. The average clustering coefficient is 0.045 and the graph diameter is nine.

2.2 Family Behavior Model

Each family v_i in a network is either in state $s_i = 0$, the not-evacuating state, or state $s_i = 1$, the evacuating state. Once a family decides to evacuate, they stick with that decision. If a family is in state 0, then a model is needed to quantify under what conditions it transitions to state 1. We quantify this transition of state, $0 \rightarrow 1$, for a particular family v_i using a state transition evacuation probability $p_{i,evac}$, as described next.

Our behavioral model of hurricane evacuation was developed from survey data gathered for 1,212 respondents who experienced Hurricane Sandy in 2012 [7]. To build the model, variables that correlate with families' evacuation decisions were identified using a Binomial Logit model; the resulting variables are provided in Table 1. A logistic regression was performed to construct the probability $p_{i,evac}$ of family v_i evacuating, as a function of these variables, given by

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

with

$$g_{hh} = \Sigma_{i=1}^{n_i} c_i^{hh} \rho_i \quad \text{and} \quad g_{net} = \Sigma_{j=1}^{n_n} c_j^{net} \rho_j \ , \tag{2}$$

where g_{hh} represents the household-related (i.e., within-node) term whose variables ρ_i and coefficients c_i are given on the left in Table 1 and g_{net} represents the network (i.e., peer-effect) term whose variables ρ_j and coefficients c_j are given on the right in Table 1. For example, one summand of g_{hh} is $c_i^{hh} = -0.165$ for $\rho_i = k_{hh}$. Since male is the reference, $k_{hh} = 0$ if the head of household is male and $k_{hh} = 1$ if the head of household is female.

To estimate network effects for the term g_{net}, additional statistical analyses were conducted to infer the parameters given on the right side of Table 1. For all families in Miami, an evacuation vector $\eta_{i,evac} = (0, \eta_{si}, \eta_i, \eta_{vi})$ and a looting vector $\ell_{i,loot} = (0, \ell_{si}, \ell_i, \ell_{vi})$ were determined by logistic regression, using a subset of independent variables on the left in Table 1. Details are omitted here for lack of space; see [12] for details.

Figure 1 contains representative plots of probability values $p_{i,evac}$ from the survey model of Equation 1, for different conditions. These data are illustrative, to give a sense of the probability magnitudes and their changes across conditions. For example, in Figure 1c, if looting is not important, then all of η_{si}, η_i, and η_{vi} are zero, but if looting is somewhat important, then $\eta_{si} = 1$ and the other two variables are zero for g_{net} in Equation 2. From the plot, when the fear of looting is somewhat important, $p_{i,evac} = 0.0778$, a decrease from 0.1379, when looting is not a concern (i.e., bar "all= 0").

Table 1: Logistic regression results: dependent variable $p_{i,evac}$. The variables ρ_i and ρ_j in Equation 2 are given in the tables on the left and right, respectively. Similarly, coefficients are the c_i^{hh} (left) and c_j^{net} (right) in Equation 2. p-values for parameters are given in [12]; variables significant at the 0.05 level are shown in italics.

Parameters and coefficients for household terms g_{hh}.

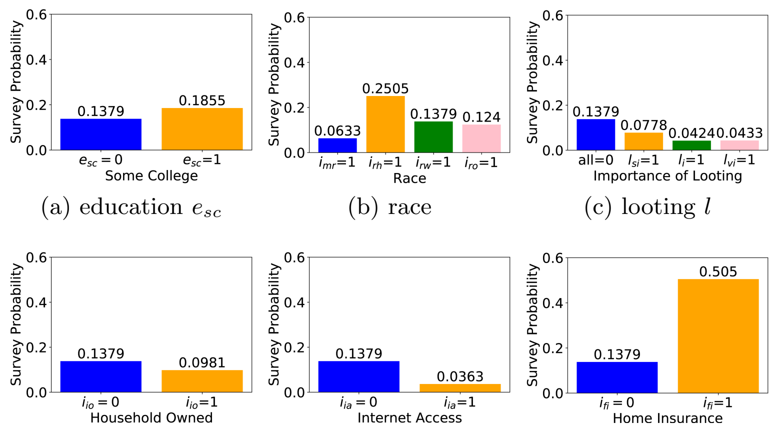
Independent Variable	**Coeff.**
Age (in years), a_{hoh}	-0.00017
Female (Ref: Male), k_{hh}	-0.165
Race (Ref: Black)	
White, i_{rw}	-0.301
Hispanic, i_{rh}	0.436
Other, i_{ro}	-0.423
Mixed, i_{mr}	-1.163
Education (Ref: High school or less)	
Some college, e_{sc}	0.353
Bachelor or higher, e_{alb}	0.397
Employment status, h_{mw}	0.073
Household size, i_{hs}	-0.231
No. of HH members who are disabled, i_{md}	0.066
No. of HH members who are elderly, i_{me}	0.279
Household is owned, i_{io}	-0.386
Living in a mobile home, i_{mh}	-0.0718
HH has access to the internet, i_{ia}	-1.446
HH Income, i_{hi}	0.015
No. of vehicles owned by HH, r_c	0.056
Age of house, a_{hhs}	-0.0025
HH has home insurance, i_{fi}	1.853

Parameters and coefficients for network terms g_{net}.

Independent Variable	**Coeff.**
Evacuation decision made by neighbors $\eta_{i,evac}$ (Ref: not important)	
Somewhat important, η_{si}	0.125
Important, η_i	0.523
Very important, η_{vi}	0.478
Concerns about crime such as looting $\ell_{i,loot}$ (Ref: not important)	
Somewhat important, ℓ_{si}	-0.640
Important, ℓ_i	-1.284
Very important, ℓ_{vi}	-1.263
Interaction (neighbor and looting), β_{el}	0.053

2.3 Agent-Based Model for Simulation

To produce a temporal agent-based model (ABM) for agent-based simulation (ABS) of evacuation behavior, modifications are required of Equation 1. First, $p_{i,evac}$ from survey data is a single probability over the entire hurricane event. For ABS, we seek a daily probability to simulate temporal decision making by families in Miami, FL. The daily probability $p_{i,evac}^{daily}$ uses the geometric mean given by $p_{i,evac}^{daily} = 1 - (1 - p_{i,evac})^{1/t_{max}}$, where $t_{max} = 10$ days because we simulate the evacuation behavior ten days before (i.e., leading up to) hurricane arrival, as shown in Section 3.



(a) education e_{sc} (b) race (c) looting l

(d) home ownership i_{io} (e) internet access i_{ia} (f) home insurance i_{fi}

Fig. 1: Probabilities of evacuation, over the entire duration of a hurricane event, from the model of Equation 1 for education (e_{sc}), race, looting (l), house-owned (i_{io}), internet-access (i_{ia}), and home-insurance (i_{fi}) in Table 1.

Second, the peer (network) effects of evacuating and looting in the right of Table 1 require further model constructs. This is because the vectors $\eta_{i,evac}$ and $\ell_{i,loot}$, which are also derived from the survey data, cannot be operationalized. For example, if for some family, neighbor influence is "important," then the question naturally arises in how to quantify this effect (i.e., discriminate this effect) if the family has two, or eight, or 12 neighboring families evacuating. To address this ambiguity, we introduce two new parameters c_u and c_d, which are thresholds, with meanings as follows. If for family v_i, the fraction of neighbors evacuated is $\geq c_u$, then evacuation effects are activated, meaning that the appropriate term from the vector $\eta_{i,evac}$ is included in Equation 2 for g_{net}; otherwise the "not important" variable is used. Similarly, if for family v_i, the fraction of neighbors evacuated is $\geq c_d$, then looting effects are activated, meaning that the appropriate term from the vector $\ell_{i,loot}$ is included in Equation 2 for g_{net}; otherwise the "not important" variable is used. Parameters c_u and c_d are studied in the simulations.

3 Simulations and Results

3.1 Simulation Description and Parameters

A **simulation instance** consists of a set of **seed nodes** v_j that are in state $s_j(t) = 1$ at time $t = 0$. Time progresses forward in integer time steps (each representing one day), and at each time, each node (family) v_i in state $s_i(t) = 0$ computes $p_{i,evac}^{daily}$ per Section 2 and performs a Bernoulli trial, in parallel, to determine its next state, i.e., $s_i(t+1)$. If $s_i(t) = 1$, then $s_i(t+1) = 1$ for all

t. Simulations are run in the interval $t \in [0..9]$ to produce $s_i(1)$ through $s_i(10)$ for all $1 \leq i \leq n$. A **simulation** consists of a group of simulation instances or replicates; here, we run 100 replicates, each having a different seed node set but otherwise the replicates are identical. All results are reported based on the mean and standard deviation of the 100 replicates at each t. Simulation parameters are listed in Table 2.

Table 2: Summary of the parameters and their values used in the simulations.

Parameter	**Description**
Network	Miami, FL.
Number of seed nodes, n_s.	Values are 0 and 10 to 10^5, by powers of 10. Seed nodes are chosen uniformly at random.
Family characteristics	Vary by family in family social contact network. See Table 1.
Peer effect values c_u, c_d.	Each varies from 0 to 1, in increments of 0.2.
Subregions of Miami.	Miami is discretized into 24 equi-sized blocks for intervention studies.

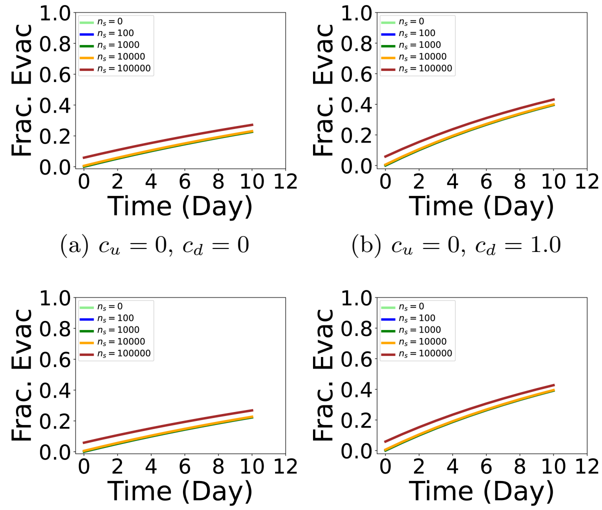
3.2 Simulation Results

Cumulative evacuation time history results. Figure 2 provides time histories for the fraction of families evacuating (Frac. Evac) as a function of time, for the ten days leading up to hurricane arrival (hurricane impact is on day 10). The results show a nonlinear evacuation fraction in time.

Effect of seeding. Each plot in Figure 2 has numbers n_s of seed nodes ranging from 0 to 10^5 families. For $n_s \leq 10^4$, the effect of seeding is insignificant. A pronounced effect of n_s is only realized when $n_s = 10^5$, which is approximately 6% of nodes. This is because our model is not a pure social influence model, akin to those of Granovetter and others [3,6,14] that rely on contagion spreading from seeded nodes. In our model, families can transition to the evacuating state on their own accord, without social influence, owing to family features (see left of Table 1). This is not to say that social influence is not a factor, as we address below.

Effect of peer influence thresholds c_u and c_d. The four plots in Figure 2 show results for different combinations of (c_u, c_d), each taking values of 0 and 1. These values are applied uniformly to all families. Figure 2a is the reference case where $c_u = c_d = 0$. These conditions mean that families account for peer effects in both evacuating and in concern for looting, for those families where peer evacuation and peer looting effects are somewhat important, important, or very important in the right of Table 1. That is, influence for each v_i to evacuate exists for all fractions η_1 of neighbors evacuating that are $\eta_1 \geq c_u = 0$. Similarly, influence for each v_i to remain behind (i.e., not evacuate) exists for all fractions η_1 of neighbors evacuating that are $\eta_1 \geq c_d = 0$.

In Figure 2b, c_d is increased to 1.0. This means that looting does not become a concern for each family until all of its neighbors (i.e., a fraction of neighbors



(a) $c_u = 0$, $c_d = 0$ (b) $c_u = 0$, $c_d = 1.0$

(c) $c_u = 1.0$, $c_d = 0$ (d) $c_u = 1.0$, $c_d = 1.0$

Fig. 2: Simulation results of the fraction of evacuating families in Miami, FL (Frac. Evac.) as a function of time leading up to the hurricane arrival. We are always modeling the 10 days leading up to the arrival of a hurricane. Day 10 is the arrival of the hurricane. Time zero is the start of the simulation, which is ten days prior to hurricane landfall. In the plots, c_u, and c_d values are either 0 or 1.0.

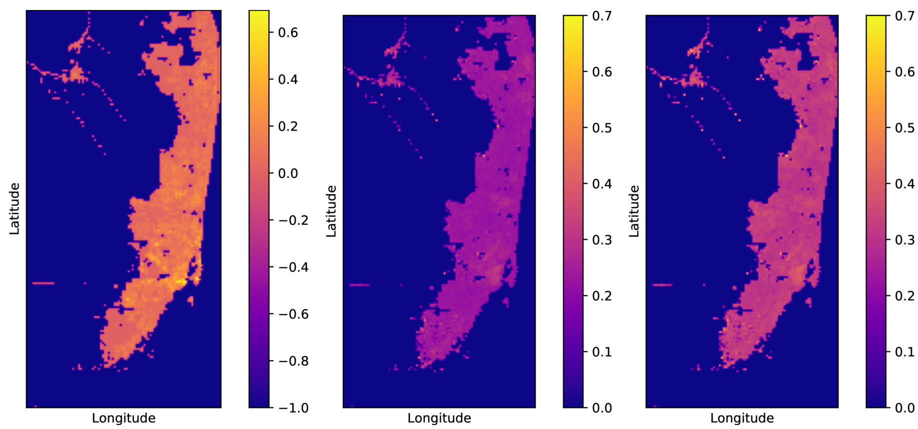
equal to $c_d = 1$) are evacuating. Since looting is not a concern, more families evacuate in Figure 2b than in Figure 2a.

Figure 2c is an initially surprising case. Based on the previous reasoning, one might conclude that fewer families evacuate than in the reference case (Figure 2a) because the influence to evacuate is essentially non-existent because $c_u = 1$. However, families generate their own driving force to evacuate through the g_{hh} term in Equation 2, so reference evacuation rates are maintained.

Figure 2d is consistent with the reasoning for the other three cases. The larger $c_d = 1$ means that fear of looting is suppressed, irrespective of what a family's neighbors choose to do, and hence evacuation rates increase.

Spatial evacuation rates. Figure 3 shows three heatmaps. In all maps, there are 98 cells in the horizontal direction and 200 cells in the vertical direction, producing 19,600 grid cells over Miami. (Only about 1/3 of these cells contain landmass in Miami, owing to the spatial extent of the city.) Figure 3a shows population spatial density. Since all families have home geo-locations, each family is mapped to one grid cell. Families are counted in each cell, and the logarithm (base 10) is applied to these counts, to make density variations more distinctive.

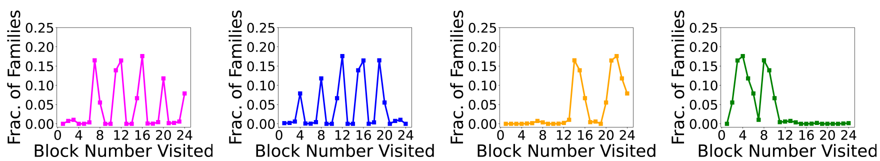
Figures 3b and 3c show the probabilities of evacuation at the end of days 6 and 10. They are generated as follows. Each simulation is composed of 100 simulation instances. For each family, we determine the fraction of these 100 instances in which it evacuates. The families within each grid cell are collected, and these fractions are averaged to obtain an average evacuation probability for that cell. These averages are plotted. Results indicate that while there is spatial variation in evacuation rates, these variations are not large.



(a) population density (b) end day 6 (c) end day 10

Fig. 3: Heatmaps for Miami, FL. The gradation is 98×200 cells in the horizontal and vertical directions, for a total of 19,600 grid cells. (a) Population density per cell (log base 10 scale). (b) Evacuation rates at the end of day 6. (c) Evacuation rates at the end of day 10. For (b) and (c), the simulation inputs are $c_u = c_d = 0.2$ and $n_s = 500$ families.

Policy-based interventions. A simulation-based intervention is executed as follows. The map of Miami is overlaid with a 6×4 grid of equal-sized blocks so that there are 24 grid cells or blocks. The police are sent to each block, in turn, to alleviate citizens' concerns over looting (e.g., by telling families of regular patrols of their residential areas by police). This is modeled as an increase in c_d, i.e., families' concerns over looting only materialize when a larger fraction of their neighbors evacuate. The police blanket the city in each of four different ways: (i) group 1: start at northwest-most block and traverse west to east across the first of the six rows, then go south to the next row of blocks and travel west to east again, and so on for each row. (ii) group 2: start at southwest-most block and traverse west to east across the first of the six rows, then go north to the next row of blocks and travel west to east again, and so on for each row. (iii) group 3: start at northwest-most block and traverse north to south down the first of the four columns, then go east to the top of the next column of blocks and travel south again, and so on for each column. (*iv*) group 4: start at northeast-most block and traverse north to south down the first of the four columns, then go west to the top of the next column of blocks and travel south again, and so on for each column. Figure 4 shows the fraction of Miami families visited per block by the police in visiting the total of 24 blocks. Note that Figures 4a and 4a are essentially mirror images and that Figures 4c and 4d are essentially mirror images. The order of visitation of high population density regions clearly changes with group number.



(a) Group 1 (b) Group 2 (c) Group 3 (d) Group 4

Fig. 4: Fractions of households in each of 24 equi-sized zones within the bounding box of Miami, FL. The different curves represent different traversals of the blocks by police in assuaging people's fears of looting. Households that have been reassured by police have c_d increased to 0.2 (or 0.4), from the baseline condition of 0; increasing c_d dampens a family's concern over looting. Police traversals: (a) group 1, (b) group 2, (c) group 3, and (d) group 4.

Figure 5 shows the effect of the police allaying people's concerns over looting. Each plot shows curves for the final fraction of families evacuating (i.e., at day 10), for each of the four traversal groups. The plots from left to right have increasing values of c_d, from 0.2 to 0.4. First, evacuation rates increase as c_d increases, as expected. Second, there are two large steps for the curves in Figure 5 for groups 3 and 4, corresponding to the two broader peaks in the family density plots of Figures 4c and 4d. But the green curves rise faster than the orange curves because the large population blocks are visited earlier in the traversal group 4. Third, by comparison, the traversal groups 1 and 2 are less steep (i.e., are more spread out) because the higher density zones in Figures 4a and 4b are more spread out. Nonetheless, the stair-stepped nature of the curves is still apparent. Fourth, the curves in Figure 5 for groups 1 and 2 are closer because the family density plots are more similar.

The point of this case study is to demonstrate that we can quantitatively evaluate the effects of different visitation strategies. Since the order of blocks visited on the x-axis of these plots is a proxy for time, this case study shows that the group 4 visitation strategy results in more people evacuating sooner. This is one example of how counterfactual analyses may be simulated to assist policy makers in their planning.

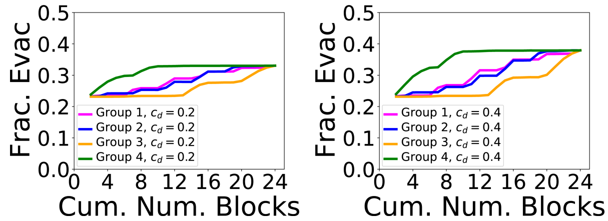


Fig. 5: Final fractions of the Miami, FL population evacuating as a function of the cumulative number of blocks visited by police to reassure families that they will monitor property to dissuade looting. Police visit the blocks in the orders dictated by the groups in Figure 4. The visits result in families' c_d values increasing from 0 to: (a) $c_d = 0.2$ and (b) $c_d = 0.4$. In both plots, $c_u = 0$ and $n_s = 100$ seeds.

3.3 Policy Implications of Results

We examine policy implications from the standpoint of encouraging more evacuations to better safeguard human life. We highlight two issues. First, in Figure 1, home insurance is an important factor in evacuations, which is also seen with the large positive coefficient at the bottom left in Table 1. This suggests, not surprisingly, that financial issues are important to families. Hence, governments might offer vouchers to offset expenses of evacuating or consider providing incentives to home owners for better insurance coverage. Second, allaying citizens' fears about looting, for example through greater police patrolling before, during, and after hurricanes, or through crowd-sourced citizen watches, might increase evacuations. Our experiments illustrate issues and parameters that are important and relevant for designing interventions.

4 CONCLUSIONS

We motivated our problem in Section 1.1, and our contributions are summarized in Section 1.2. Selected policy implications are in Section 3.3. This study also illustrates how survey data can be used to model scenarios that are beyond the conditions of a particular hurricane. A limitation of our work is that we only address human contact networks, and do not include the effects of social media, or virtual connections. This effect is hard to predict without computations: on one hand, spreading should be faster because there are more types of pathways (face-to-face and virtual), but this model uses *relative* thresholds so the increased node degrees will inhibit contagion transmission. Also, we do not include storm-specific variables, such as hurricane path, wind speed, storm surge, etc. which may produce spatially heterogeneous evacuation rates. Future work also includes model validation. Based on the parameters and process we study, we believe these results are also applicable to other disaster events such as evacuations caused by wildfires and chemical spills [11].

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