The importance of neighborhood in hurricane evacuation

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Utility models rely on bounded rationality informed by very large numbers of transactions among large numbers of agents. Most people subject to a hurricane evacuation order, however, are making seldom-faced decision based on feelings about loved ones, possessions and well-being in the long run. This goal of this study is to develop an agent-based model (ABM) in which the agents are given demographic state variables and a set of decision rules drawn from survey data. The decision rules contribute to a single behavior: whether to evacuate in advance of a hurricane. This first paper describes the ABM framework and compares two candidate ex-ante evacuation decision rules. The ultimate goal of this research is for the ABM to serve as a non-linear regression model with the decision rules as explanatory variables and the weights of decision rules as the estimators. The distribution of decision weights may provide policy-makers with insights into developing effective evacuation strategies.

1 Background

Though developed separately, this work is effectively both an extension of and a departure from a hurricane-evacuation agent-based model (ABM) by Widener et al. (2012). The Widner, Horner, and Metcalf (WHM) approach is to regress survey data and from the significant parameters construct a utility function that is the decision rule for all agents in the ABM. From their survey data, the WHM econometric model of the evacuation decision finds three significant variables: a) whether the subject lives in the risk area, b)

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whether the subject owns a vehicle, and c) the subject's experience with previous hurricanes. In addition to the utility model, WHM develop network models in which agents are nodes in a network with one of three topologies, each with a fixed and constant degree n(numbers of connections) that is varied from one simulation to another. The topologies explored by WHM are: n random connections to agents within radius 800 meters; n-1small world(Watts and Strogatz, 1998) connections to agents within radius 800 meters plus one connection to a random distant agent; a random network of degree n without radius constraint. Network connections are not considered in the utility model, and utility is not considered in the network models.

In our model the agents have a propensity for evacuation based on regressed survey data. An agent makes the decision to evacuate based on a payoff function that includes the propensity and the influence of network neighbors who have already evacuated. Propensity is additive, resulting from linear probit regression, as compared with the WHM utility function, which is multiplicative, simulated by AnyLogic from survey data and tuned to produce an evacuation rate of 75 percent.

2 Modeling behavior explicitly

The WHM model is a unique use of agent-based modeling for hurricane evacuation, and an important first step. The limitations of this model are:

- 1. Utility is a product of behavior: it doesn't reveal component behaviors. Utility models rely on bounded rationality informed by very large numbers of transactions among large numbers of agents. A utility model may accurately capture the average behavior of a large number of people without providing any visibility of the actions of individuals. A utility model designed to capture the behavior of the majority who evacuate provides no insight into the why the others did not evacuate, which is the real question of interest to policy-makers. The decisions of those individuals are not necessarily rational or even transitive. Decision rules can capture this.
- 2. Agents are homogeneous in behavior space (identical utility function). Many agents may decide to evacuate based on a single criterion the other criteria are irrelevant. Other agents may have decision rules in which many considerations are weighed. The relevant subsets of criteria may be different between different groups of agents. Giving the agents the ability to switch between rules provides the capability to model these conditions.
- 3. Networks are fixed and constant, whereas networks vary from person to person, and people operate on multiple networks simultaneously. Real households exist within at least three concurrent networks: immediate neighbors (which is a proximity network), contacts through work or school (possibly a small-world network) and remote contacts (possibly power-law distributed).

The long-range goal of our study is to use survey and demographic data to calibrate a set of decision rules. In the full model, the decision rules will be given weights that will be adjusted until the behavioral attributes (number evacuated, time of evacuation, etc.) match historical data. The objective of this paper is to present the initial ABM and framework for incorporating survey and demographic data. In so doing, we present an initial set of simulations showing that this basic model qualitatively reproduces the known outcome. We also discuss the problem of inferring ex-ante decision rules from ex-post survey data, and compare two candidate ex-ante evacuation decision rules.

3 Survey data

In 2010 The Florida International University Metropolitan Center completed 1,099 telephone interviews from a random probability sample of households located in Harris and Galveston counties in Texas with a response rate of 36%. A geocoded zip code area stratified sampling frame was used to oversample areas of higher storm surge risk. More interviews were done proportionally in zip code areas that are lower elevation and near to the coast.

The survey questionnaire asked about behaviors adopted to minimize the risk of being affected by a hurricane in 2008 and specifically to deal with Ike once that hurricane hit the coast of Texas. Respondents who evacuated due to Ike were asked to report their evacuation expenditures (i.e. expenditures on transportation, food, and lodging). Alternatively, those respondents who did not evacuate were asked to state how much they would have spent if they had decided to evacuate. Stated evacuation expenditures can be treated as additional data points to increase sample size and thus improve the efficiency of estimates. The hypothetical nature of stated evacuation expenditures can be a concern. Hence, it is necessary to identify the hypothetical bias in stated data and subtract it from predicted evacuation expenditures. We explain our approach to deal with potential hypothetical biases in the next section.

The survey also gathered information on covariates of evacuation expenditures. All respondents were asked whether their housing unit was raised to deal with storm surge and about preparations implemented previous to the hurricane season such as having material to protect their windows. The questionnaire also asked respondents whether an order of evacuation was issued for their neighborhoods, and about the type of evacuation order they received (i.e. voluntary or mandatory). In addition, respondents reported how important hurricane effects (e.g. surge), crime, and pets were for them in deciding whether to evacuate or stay at home when facing a hurricane like Ike. Finally, the survey garnered information about socioeconomic characteristics of respondents.

Of the households surveyed, 1,093 households responded to a question about the decision to evacuate, with 551 responding that they evacuated. Of those, however, on a subsequent question on timing, 41 responded "do not remember" or "did not evacuate". The cumulative distribution function (CDF) in Figure 1 is calculated from the 46.6 percent of the responses



Figure 1: Cumulative distribution (CDF) as a function of time for evacuating households from a survey of 1093 households. Although 551 said they evacuated, on a subsequent question on timing, 41 of those responded "do not remember" or "did not evacuate". Thus, this represents evacuation by 46.6 percent of the respondents. A widespread evacuation order was issued early Thursday morning and the hurricane struck late Friday night.

that included an evacuation day and period (AM or PM). A widespread evacuation order was issued early Thursday morning and more than fifty percent of the respondents had not evacuated by the time the hurricane struck late Friday night.

One potential source of behavioral heterogeneity is the perception of risk. Figure 2 shows the number of respondents as a function of their perception of the risk of damage. To some extent this response shows variability in interpretation of the questions. This is especially evident in Figure 3, where a number of respondents expressed no concern for the hurricane striking their county yet high concern for the hurricane striking their home. Table 1 breaks down the level of concern into groups that either did or did not evacuate.



Figure 2: Likelihood of damage. Circle diameter represents the number of responses, solid circles are responses from those who chose to evacuate, while open circles are those who did not.



Figure 3: Concern mismatch. This is the arithmetic difference between concern that the hurricane would strike the county and concern that the hurricane would strike the respondent's home. The peak at zero shows that most respondents did not distinguish between the two outcomes. The bars to the left of zero are respondents for whom there was greater concern that the hurricane would strike their home than would strike the county. The bars to the right of zero are respondents for whom the concern that the hurricane would strike the county was greater than the concern that the hurricane would strike the county was greater than the concern that the hurricane would strike their home.

Likelihood of damage greater than one-third of home value	Evacuated	No order	Voluntary order	Mandatory order	Don't know / no response
None	yes	19	29	46	18
	no	122	39	15	9
Low	yes	30	25	49	14
	no	126	41	15	8
Medium	yes	16	20	37	10
wedum	no	38	13	4	3
High	yes	8	39	90	13
0	no	$2\overline{6}$	15	5	1

Table 1: Evacuation based on likelihood of damage and evacuation order.

Descriptive statistics of the survey results are shown in Figure 4. Only 56% provided income info, and 22% of those selected, out of eleven categories, the highest - annual income greater than 100,000 dollars. Neither income group nor any subgrouping of income was significant in any regression. The only address information in the survey is zip code, which is insufficient to tie participants to a particular census tract. It is possible, however, to collate the survey data with census data aggregated to the zip code level. Although zip code areas tend to encompass a great deal of economic diversity, there is distinct variability in income by zip code area. Figure 5 shows mean income and Gini index for each zip code collated with previous hurricane experience and with the decision to evacuate. The markers indicate whether that household was subject to an evacuation order. Although there is no obvious trend here, there is a distinct correlation between income and Gini index. Furthermore, the small number of respondents with high incomes in zip codes with Gini indices above 0.55 makes regression on these economic data problematic.

A group of survey questions asked respondents to rate, in terms of making the decision to evacuate, the issues listed in Table 3. Although 75 percent of the respondents answered these questions (see Figure 6), the responses are difficult to interpret because the majority of respondents rated all issues as extremely important or very important, and the relative rankings of the issues is consistent irrespective of whether the household evacuated, and whether or not they were subject to an evacuation order (Figure 7). Interpretation not withstanding, the responses to a few of these issues are significant in one or more of the regressions: TIMELEFT, FLOODING, LOOTING, TOGETHER, PETS.

Variable	Obs	Mean	Std. Dev.	Min	Max
	1002	F0 411 51		0	
EVACUATD	1093	.5041171	.5002119	0	1
HOUSKITA	1065	.8525822	.3546885	0	1
DILINGG	1048	.5133588	.5000601	0	1
PILINGS	1037	.2102218	.4076627	0	1
NOINFO	1082	.0018484	.0429735	0	1
BTVINFO	1082	.6072089	.4885969	0	1
RADINFO	1082	.2319778	.4222901	0	1
CTVINFO	1082	.4408503	.4967186	0	1
BTVONLY	1082	0	0	0	0
RADONLY	1082	0	0	0	0
CTVONLY	1082	0	0	0	0
NEIGINFL	1059	.1293673	.3357646	0	1
VOLUEVAC	979	.2533197	.4351347	0	1
MANDEVAC	979	.3003064	.4586255	0	1
CNCRNCNTY	1070	4.485047	1.532089	1	6
CNCRNHOME	1067	4.175258	1.65058	1	6
LOWDMGLK	952	38.63761	32.84261	0	100
HIDMGLK	943	30.21421	32.72122	0	100
SNGFAM	1047	.8825215	.3221435	0	1
DUPLEX	1047	.0066858	.0815317	0	1
CONDO	1047	.0219675	.1466475	0	1
APRTMNT	1047	.069723	.2548014	0	1
MOBLHOME	1047	.0191022	.1369497	0	1
OWNER	1049	.8798856	.3252503	0	1
RENTER	1049	.1201144	$.\ 3\ 2\ 5\ 2\ 5\ 0\ 3$	0	1
NUMBINHH	1054	2 649905	1 5622	1	
HHUND12	1091	.3033914	.8005603	0	6
HH12TO18	1089	.2745638	.6564901	0	4
НН121013	1093	1.362306	1.229419	0	6
HH65OLDR	1081	.6244218	. 8 2 3	0	7
SOMEHSCH	1011	0583581	2345353	 N	
HIGHSCHL	1011	2047478	4037169	0	1
SOMECOLL	1011	20185055	413408	0	1 1
COLLDEGR	1011	2908012	4543567	0	1 1
GRADDEGR	1011	.1889219	.3916403	0	1
	1000	1510701	2502020	0	
AFRIAMER	1020	.1010/21	.3082938 1519191	U	1
ASIAN	1020	.UZƏJY18 7004492	.1012181	U	1
	1020	1666667	.40/10/1	0	1
	1020 615	. 1000007 6 081301	. J / Z O U U O 3 5 1 5 0 7 0	0	11
THOOMGINE	010	0.201301	9.010313	1	11

Figure 4: Descriptive statistics of variables used in regression of decision to evacuate.

Variable	Description
EVACUATD	One if household evacuated
HOUSRITA	One if household in the Houston area for hurricane Rita
WINDPREP	One if the home had storm-proof windows before hurricane Ike
PILINGS	One if the home was raised on pilings before hurricane Ike
NOINFO	One if the respondent selected no sources of storm information
BTVINFO	One if the respondent got storm information from broadcast television
RADINFO	One if the respondent got storm information from radio
CTVINFO	One if the respondent got storm information from cable television
BTVONLY	One if the respondent got storm information from broadcast television exclusively
RADONLY	One if the respondent got storm information from radio exclusively
CTVONLY	One if the respondent got storm information from cable television exclusively
NEIGINFL	One if neighbors influenced the respondent's decision to evacuate
VOLUEVAC	One if the household was subject to a voluntary evacuation notice
MANDEVAC	One if the household was subject to a mandatory evacuation notice
CNCRNCNTY	Level of concern (1 to 6) that hurricane Ike would strike the county
CNCRNHOME	Level of concern (1 to 6) that hurricane Ike would strike the respondent's home
LOWDMGLK	Likelihood $(0 \text{ to } 100)$ that the home would sustain damage of one-third value or less
HIDMGLK	Likelihood (0 to 100) that the home would sustain damage of more than one-third value
SNGFAM	One if the dwelling is a single family home
DUPLEX	One if the dwelling is a duplex
CONDO	One if the dwelling is a condo
APRTMNT	One if the dwelling is an apartment
MOBLHOME	One if the dwelling is a mobile home
OWNER	One if the respondent is the owner of the dwelling
RENTER	One if the respondent is a renter of the dwelling
NUMBINHH	Number of people in the household
HHUND12	Number of household members under 12 years of age
HH12T018	Number of household between 12 and 18 years of age
HH19T064	Number of household between 19 and 64 years of age
HH650LDR	Number of household 65 years of age or older
SOMEHSCH	One if the respondent has attended school but not finished high school
HIGHSCHL	One if the respondent has finished high school and gone no further
SOMECOLL	One if the respondent has attended college or university but not completed a degree
COLLDEGR	One if the respondent has completed an undergraduate degree but no more
GRADDEGR	One if the respondent has completed an graduate degree
AFRIAMER	One if the respondent self-identifies as Black or African American
ASIAN	One if the respondent self-identifies as Asian
WHITE	One if the respondent self-identifies as White
HISPANIC	One if the respondent self-identifies as Hispanic
INCOMGRP	Household income (in groups of \$10k, from less than \$10k to more than \$100k - 11 groups)

Table 2: Survey data variable descriptions



Figure 5: The decision to evacuate by income and Gini index based on zip code. Income is on the horizontal axis: Hisplanics on the left, non-Hispanics on the right. Gini index is on the vertical axis: those who evacuated on the bottom and those who did not at the top. Those subject to either a voluntary or mandatory evacuation order shown as solid circles and those who were not as open circles.

Variable	Obs	Mean	Std. Dev.	Min	Max
TRAFFIC	812	1.745074	.8912718	1	4
TIMELEFT	809	1.840544	.8677601	1	4
EVORDERED	812	2.038177	.9955614	1	4
READINESS	805	1.921739	.8639185	1	4
FLOODING	816	2.102941	1.079282	1	4
RETURN	815	1.880982	.9282988	1	4
LOOTING	815	1.948466	1.00968	1	4
TOGETHER	807	1.693928	.9031241	1	4
MEDICAL	813	2.061501	1.085578	1	4
PETS	738	2.197832	1.158484	1	4
1					

Figure 6: Descriptive statistics of the issue variables.

The possibility of traffic delays

The amount of time left before the hurricane arrives

Evacuation orders given by government

How ready your home is to withstand hurricane winds

Possibility of flooding or storm surge

Being able to return to your home right away after the hurricane

Being able to protect your home from crime and looting

Being able to keep family members together after the hurricane

Medical or other needs of you or other household members

The needs of pets or animals

Figure 7: Importance (see legend in next figure).

Column headings

	\bigcap	Evacuation	Evacuation	No evacuation	No evacuation
Survey question	All	order	order	order	order
	respondents	Evacuated	Did not	Evacuated	Did not
			evacuate		evacuate

The possibility of traffic					
delays	819	308	135	62	254
The amount of time left					
before the hurricane	820	309	135	62	254
arrives					
Evacuation orders given	010	200	125	60	DE 4
by government	819	308	135	02	254
How ready your home is					
to withstand hurricane	820	309	135	62	254
winds					
Possibility of flooding or	000	200	105	C 2	25.4
storm surge	820	309	135	62	254
Being able to return to					
your home right away	820	309	135	62	254
after the hurricane					
Being able to protect your					
home from crime and	821	310	135	62	254
looting					
Being able to keep family					
members together after	819	308	135	62	254
the hurricane					
Medical or other needs of					
you or other household	820	309	135	62	254
members					
The needs of pets or	910	308	135	62	257
animals	019	508	133	02	234
	Extremely important				
	Somewha	t important	Not at a	l important	
	No answe	r		·	

Figure 8: Legend for the importance charts.

Table 3: Survey issue variable descriptions. Respondents were asked to give the importance of each issue in deciding what to do. Choices (and values) are: (1) extremely important, (2) very important, (3) somewhat important, (4) not important.

Variable	Description
TRAFFIC	The possibility of traffic delays
TIMELEFT	The amount of time left before the hurricane arrives
EVORDERD	Evacuation orders given by government
READY	How ready your home is to withstand hurricane winds
FLOODING	Possibility of flooding or storm surge
RETURN	Being able to return to your home right away after the hurricane
LOOTING	Being able to protect your home from crime and looting
TOGETHER	Being able to keep family members together after the hurricane
MEDICAL	Medical or other needs of you or other household members
PETS	The needs of pets or animals

If we consider the survey responses as information about the respondents rather than a statement of their preference, responses in which all the issues were ranked as extremely important provide as little information as no response at all. In information theory, a metric of relative information is information entropy (Shannon and Weaver, 1948),

$$H_k = -\sum_{j=1}^N p_{jk} \ln p_{jk}$$

where

 H_k = information entropy for respondent k N = the number of issue score values p_{jk} = probability mass function for issue score value j and respondent k

	entropy clusterNo	variables: tegories of:	Summary for by cat
ſ	sd	mean	clusterNo
195	.1997639	.2665148	1
206	.0822766	.705656	2
213	.049981	.9673461	3
207	.0931159	1.214324	4
821	.3667116	.7974974	Total

Figure 9: Information entropy of responses to the ten issue-related survey questions. Statistics of information entropy showing the mean, standard deviation, and number of respondents in quartiles.

Assuming that all issues have equal weight, and that the specific values (from *extremely important* to *not important*) have equal weights, the probability mass function can be expressed

$$p_{jk} = \frac{\sum_{i=1}^{N_k} \delta(x_{ik}, X_j)}{N_k}$$

where

 N_k = the number of issues for which respondent k gave scores x_{ik} = score on issue igiven by respondent k X_j = issue score value j $\delta(x_{ik}, X_j)$ = 1 if $x_{ik} = X_j$, 0 otherwise

The higher the information entropy, the more information about the respondent contained in the responses. If we compute the information entropy for the responses to the issuesrelated questions, the respondents fall into the quartiles show in Figure (9).

4 Regression results

The exploratory probit model incorporates all variables for which there is a high level of response in the survey data. A stepwise probit regression reduces the model to predictors with significance 0.10 or better, then those variables are regressed against all available

Probit regression Log likelihood = -291.27654					er of obs ii2(12) > chi2 o R2	=	578 217.56 0.0000 0.2719
EVACUATD	Coef.	Std. Err.	Z	$\mathbf{P} \! > \! \mid \! \mathbf{z} \mid$	[95% 0	Conf.	Interval]
LOOTING	.1355793	.0672797	2.02	0.044	.00371	35	.267445
HIGHSCHL	3572989	.1593221	-2.24	0.025	66956	545	0450332
FLOODING	1325794	.0626329	-2.12	0.034	25533	75	0098213
COLLDEGR	2216676	.1406164	-1.58	0.115	49727	07	.0539355
EVACORDR	1.25652	.1254024	10.02	0.000	1.0107	36	1.502305
PETS	.1309697	.0556069	2.36	0.019	.02198	22	.2399571
HIDMGLK	.0097966	.0020276	4.83	0.000	.00582	27	.0137706
TOGETHER	0632685	.0748671	-0.85	0.398	21000	54	.0834684
TIMELEFT	1654393	.0786212	-2.10	0.035	31953	39	0113446
CONDO	.5271074	.4101979	1.29	0.199	27686	57	1.33108
HISPANIC	.5199718	.1680714	3.09	0.002	.1905	58	.8493856
OWNER	.4207763	.1853361	2.27	0.023	.05752	42	.7840283
_cons	-1.290518	.2934471	-4.40	0.000	-1.8656	64	7153723

Figure 10: Stata results of probit regression of the decision to evacuate. All respondents, with variables identified by stepwise probit with threshold significance of 0.1.

data, with the result shown in Figure 10. The results show that an evacuation order, EVACORDR, influences in favor of evacuation, as do being a condo dweller, CONDO, being Hispanic (HISPANIC), and being a property owner (OWNER). Having a high school (HIGHSCHL) or college education (COLLDEGR) are influences against evacuation.

The responses for the issue variables are coded such that a higher number means less interest. That is, a positive coefficient means that the issue is an influence against evacuation, while a negative coefficient is an influence in favor of evacuation. Thus, increasing fear of looting (LOOTING) and concern for pets (PETS) are influences against evacuation, while increasing fear of flooding (FLOODING), increasing concern with keeping the family together (TOGETHER), and increasing concern about the time left before the hurricane (TIMELEFT) are influences in favor of evacuation.

The preceding probit model is a predictor for respondents who evacuate when ordered to do so, so it remains to identify two other groups: those who don't evacuate despite orders, and those who evacuate even without evacuation orders. Nothing in the survey data produces a significant predictor of the former group, but the latter group can be modeled with a stepwise probit with threshold significance 0.10. The variables identified by the stepwise regression are subject to probit regression selecting all respondents not subject to an evacuation order, with the results shown in Figure 11. This model is similar to the full-data results as far as HIDMGLK and TIMELEFT are concerned, but Hispanics are somewhat more likely to evacuate in this model, while larger family sizes decrease the

Probit regression					Number of obs $=$		
Log likelihood		Prob Pseud	> chi2 o R2	=	$\begin{array}{c} 1 \ 0 \ . \ 2 \ 2 \\ 0 \ . \ 0 \ 0 \ 1 \ 0 \\ 0 \ . \ 0 \ 4 \ 5 \ 1 \end{array}$		
EVACUATD	Coef.	Std. Err.	Z	P > z	[95%	Conf.	Interval]
NUMBINHH HISPANIC HIDMGLK cons	$\begin{array}{c}1202122\\ .6851226\\ .0078455\\8573833\end{array}$	$\begin{array}{c} .0550357\\ .2241196\\ .0030625\\ .1548495\end{array}$	$ \begin{array}{r} -2.18 \\ 3.06 \\ 2.56 \\ -5.54 \end{array} $	$\begin{array}{c} 0 . 0 2 9 \\ 0 . 0 0 2 \\ 0 . 0 1 0 \\ 0 . 0 0 0 \end{array}$	$2280\\.2458\\.0018\\-1.160$	801 562 431 883	$\begin{array}{r}0123442 \\ 1.124389 \\ .0138479 \\5538839 \end{array}$

Figure 11: Stata results of probit regression of the decision to evacuate. Only respondents not under order to evacuate, with variables identified by stepwise probit with threshold significance of 0.1.

probability of evacuation.

This new probit model will be used to inform the next iteration of the ABM. In addition to reinforcing the growing consensus that experience and concern for pets are predictors of evacuation choice, this result also provides new insights for policy-makers. For example, these results suggest that evacuation planners may increase compliance by providing means for families to keep together through evacuations and storms. Further research is needed to understand the causality behind the reluctance to evacuate in areas with high incomedisparity, and that research may provide further insights into reassuring the residents of those areas that evacuation is safe and preferable.

The results of a stepwise probit regression of the highest entropy (highest information) quartile is shown in Figure (12). For this group of respondents, 51 percent of whom evacuated, the most significant predictor is still the evacuation order. The other significant predictors include if the respondent is Hispanic, the likelihood of damage less than one-third home value (LOWDMGLK), the influence of neighbors (NEIGINFL), and the issues of time left before the hurricane (TIMELEFT), keeping the family together (TOGETHER), and crime and looting after the hurricane (LOOTING). Hispanics are more likely to evacuate than non-Hispanics, neighbors tend to be an influence against evacuation, and increasing likelihood of damage is an influence in favor of evacuating, as is increasing concern with keeping the family together. Increasing concern with crime and looting is an influence against evacuation.

Probit regress	Numbe	er of obs	=	138			
-				LR ch	i2(7)	=	69.75
				Prob	> chi2	=	0.0000
Log likelihood	= -60.415549	9		Pseud	o R2	=	0.3660
EVACUATD	Coef.	Std. Err.	Z	$\mathbf{P}\!>\!\mid\!\mathbf{z}\mid$	[95%	Conf.	Interval]
TIMELEFT	4091618	.1529187	-2.68	0.007	7088	769	1094467
TOGETHER	44337	.1442629	-3.07	0.002	72	612	16062
HISPANIC	1.105881	.5172118	2.14	0.033	.09216	544	2.119598
NEIGINFL	-1.032538	.5289817	-1.95	0.051	-2.069	323	.0042474
EVACORDR	1.462186	.2752259	5.31	0.000	.92275	536	2.001619
LOWDMGLK	.0115517	.0043189	2.67	0.007	.00308	867	.0200166
LOOTING	.3685883	.1272096	2.90	0.004	.11926	521	.6179145
_cons	5292898	.4908631	-1.08	0.281	-1.491	364	.4327841

Figure 12: Stepwise probit regression of the decision to evacuate using only the highest information respondents. The significance threshold is 0.10.

5 ABM model and results

In our model the agents have state variables based on regressions of the survey data shown in Figures 10 and 11, plus a state called *contrarian*. The contrarian state represents an agent's neighbor-based strategy, discussed in the next paragraph. The agents are on a network made up three network types: a network of all immediate neighbors, a random network of other agents in the neighborhood, and a random network of associations with agents drawn from the total set of agents. The radius of immediate neighbors, all of whom are included in an agent's network, is configurable. The other two networks, neighborhood and association, are random networks, so that the degree of each agent's network is stochastic, and the mean degree (average number of connections over all agents) is configurable. Also, the topology of the random networks is configurable, choosing between i) a Bernoulli random network (Erdős and Rényi, 1959), ii) a preferential attachment network (Wilensky, 2005) (a power-law distribution with exponent two and mean degree two), or iii) a truncated preferential attachment network (the power-law exponent is still two, but the mean degree can be greater than two).

In this initial model, the agents have a single behavior rule that incorporates the propensity to evacuate, which is based on the survey and demographic state variables, and the neighbor-based strategy. In a game-theoretical network, neighbor-based decisions can reflect either strategic substitutes or strategic complements (Galeotti et al., 2010). Outcomes in these games are shown to be sensitive to network structure (Dixon, 2011). The decision threshold in the Widener et al. model is equivalent to a strategic complement (do the same as the neighbors), whereas the survey data suggests that, for some respondents, the decision to evacuate reflects a strategic substitute (do the opposite of the neighbors). Differentiating between these two classes of behavior may be helpful in deciding an effective approach to increasing evacuation participation.

The ABM is implemented in NetLogo (Wilensky, 1999), and the model interface is shown in Figure 13. Each agent - called a *turtle* in NetLogo - occupies a *patch*, which is a unit of space, equivalent in this model to the turtle's home. All turtles exist on three simultaneous networks: a network of all immediate neighbors, a neighborhood network made up of a fraction of neighbors in the broader neighborhood, and an association network made up of turtles elsewhere in the model. The model has global attributes that include the number of turtles, the range (in patches) at which a neighbor is considered immediate, the range (in patches) of the broader neighborhood, the topology of the neighborhood network, and the probability of a neighbor being on a turtle's network. Other model attributes are the percent of patches subject to evacuation order, the time (tick) when the evacuation order starts, and the tick at which the hurricane makes landfall, neighbor influence, associate influence, percent contrarian, and threshold multiplier. The influence controls the degree to which payoffs are affected by the behaviors of neighbors and associates, respectively. Percent contrarian determines the approximate number of turtles given the contrarian state, and the threshold multiplier determines the payoff at which turtles switch between strategies to evacuate or not. Attributes for the association network include topology and the mean number of associates for each turtle. Because the networks are constructed stochastically, turtles have a varying number of connections on their networks, resulting in a distribution of degree (the number of network connections) across all turtles. This distribution is shown in the model interface in Figure 13.

Initialization begins by creating turtles in random locations and initializing their states. For continuous state variables, each turtle is given a value taken from a normal distribution with mean and standard deviation from Table 4. For binary state variables, each turtle is assigned that state with uniform probability taken from the state variable mean in Table 4. Each turtle is assigned the contrarian state with uniform probability taken from the percent contrarian control in the model interface (Figure 13). Each turtle is also assigned an influence variable for each state variable. Each influence variable is given a value taken from a random normal draw of the regression coefficients and standard errors in Figures 10 and 11. When the model is initialized, those patches subject to the evacuation order are colored red, while the rest of the map is green. All turtles are represented as white dots, or yellow dots if they are contrarians. When a turtle decides to evacuate, the dot is colored black.

When the model is run, each turtle computes a propensity to evacuate by multiplying the state variables by their corresponding influence variables and summing. Additionally, each turtle sums the number of neighbors and associates who have evacuated already. Each turtle uses one of two possible payoff functions: if the turtle is a contrarian, the *strategic substitute* payoff is used, otherwise the *strategic complement* payoff is used. With the strategic complement payoff, the turtle decides to evacuate if a) the propensity is 0.5 or greater, or b) if a threshold of neighbors and associates have already evacuated. The threshold is computed by multiplying the threshold multiplier, from the interface, times



Figure 13: Screen shot of the ABM.



Figure 14: Evacuation time series.

the mean degree of the turtles (computed in the program and shown in the interface). This strategy reflects the majority of hurricane evacuees who evacuate either because of their own concerns or because a majority of their friends and neighbors have evacuated. With the strategic complement payoff, the turtle decides to stay if the propensity is less than 0.5, or if more than the threshold number of neighbors has already evacuated. This reflects the evacuees who stay behind despite evacuation orders and, perhaps, out of concern for their neighborhood being unguarded during and immediately after the storm. Under either strategy, if a turtle has a propensity to evacuate, the timing of the decision to evacuate is distributed uniformly over the time to landfall,

Figure 14 shows the rate of evacuation for those turtles subject to the evacuation order (red plot) and those not subject to the order (green plot). Compare the sum of these (black plot) with the survey data in Figure 1. Note that a few of each group evacuate prior to announcement of the evacuation order at tick 2000. At this time, the effect of the evacuation order on the propensity (see Figure 10) pushes the majority of affected turtles into the evacuation decision, with their evacuations timed uniformly until landfall at tick 5000. The slow increase in the slope of the green plot is the result of influence from neighbors and associates on both the green and the red sides who have evacuated (strategic complement payoff).

To explore the stochasticity of this simulation, the NetLogo BehaviorSpace tool was used to run one hundred Monte Carlo samples of the same model. The results for those evacuating under order (Red) and those evacuating without order (Green), in terms of mean and standard deviation, are Red (% evacuating) = 42.1 ± 3.06 Green (% evacuating) = 7.58 ± 2.88

Note that, for Red, the standard deviation is only 7% of mean, while for Green, standard deviation is 38% of mean.

One problem, from the point of view of modeling behavior, is that the model in Figure 10 is ex-post of the evacuation order. That is, the survey respondents were not asked, ex-ante, what influence an evacuation order in the future would have on their decision to evacuate. For the first 2000 ticks, then, the ex-post model in Figure 10 may not be appropriate. Perhaps the ex-post model in Figure 11 (weak explanatory power aside) is more appropriate up until the time that the evacuation order is announced. While the number of agents evacuating before tick 2000 is small, as a complex system, the outcome may be sensitive to initial conditions. With this rule used for all agents up to tick 2000, another one hundred Monte Carlo samples were taken. These results show

Red (% evacuating) = 41.8 ± 2.18 Green (% evacuating) = 6.22 ± 2.11

Note that the two sets of outcomes are within one standard deviation of each other.

6 Summary

The goal of this first exercise is to produce a simple ABM of hurricane evacuation that uses survey data as an input and reproduces the known results qualitatively. The model here does reproduce the known evacuation rates qualitatively. The results are plausible quantitatively, though this is due primarily to the regression-based data. The behavior rules could be tuned to more closely reproduce the known evacuation trend shown in Figure 1, but this would provide no new insights, since the tuning parameters are ad hoc. Alternate ex-ante rules are compared but no real difference is discerned, probably because so little occurs in the model prior to the announcement of the evacuation order.

Further studies using NetLogo BehaviorSpace will examine outcome sensitivity to percent of contrarians and to payoff thresholds. Similarly, to explore sensitivity of outcomes to the neighbor and associate network components in terms of network size and topology, while simultaneously exploring the importance of neighbor and associate influence.

Because very little from the survey data illuminates the decision to evacuate, very little can be inferred for behavior rules. The next step, in this regard, will be to identify clusters of respondents based on their state and behavior data, and to infer behavior rules based on the attributes of those clusters. This has already begun using information entropy as discussed above.

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