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Analysis of evacuation behavior in a wildfire event

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ABSTRACT

Disasters and extreme events, both natural and man-made, can have dramatic implications in terms of loss of human lives, well-being and economic costs. Understanding the demand for travel during disaster events, in particular when evacuations take place, is critical for the efficient management of the event. The usual activity and travel patterns may be completely broken and not at all relevant during an event, when completely different considerations take priority.

A large-scale wildfire took place in Haifa on November 24, 2016. On that day, starting at around 10 a.m., a series of wildfires occurred in the city. As a result, about 40,000 inhabitants (15% of Haifa's population) were evacuated. Shortly after the fire events, a web survey was developed and administered in order to collect data on the activities that residents of the affected areas undertook on that day.

This paper presents analysis of this data to evaluate the choices of individuals whether to evacuate or not, the main factors that affect these decisions and related choices. The results are compared with findings from previous studies of evacuation behavior in the literature

1. Introduction

Disasters and extreme events, both natural and man-made, can have dramatic implications in terms of loss of human lives, well-being and economic costs [34]. Natural disasters include volcano eruptions, earthquakes, tsunamis, cyclone and hurricane storms, floods, and wildfires. Man-made disasters are caused by industrial, transportation and nuclear accidents, chemical spills, and military and terrorism activities. Leaning and Guha-Sapir [25] report that natural disasters tripled between the decades of the 1980s and 2000s. They attribute most of this increase to global warming. Within the last year alone, major events included hurricanes Harvey, Irma and Maria in the Caribbean Sea and Gulf of Mexico, Earthquakes in Mexico and Italy, wild fires in Portugal, France and Western USA and Canada. In Israel, large forest fires with severe results occurred in 2010 and 2016. These exemplify an observed rise in the frequency and the size of affected areas of forest fires [43].

Disasters vary widely in their characteristics, such as warning times, duration of the event itself, immediacy, spatial and temporal extent of the impact and so on [11]. These have substantial implications on response planning. However, in all cases, efficient management of the transportation system is vital in order to facilitate evacuation of the affected populations and movement of relief and response personnel and equipment [35].

The inability to predict the exact circumstances of a disaster event means that proposed evacuation and transportation plans need to be adapted and evaluated to a wide range of scenarios in terms of the nature of the event and its impacts on the transportation system [44]. Models of the transportation systems are necessary to support the development of such plans, and potentially also be used at the operations management centers when an event occurs [7]. The supply side of the transportation system may be affected during a disaster event through closure of roads and public transportation services and reductions in capacities [42]. Traffic management decisions that affect the network supply, such as contraflow lane reversal, may also take place. The demand effects may be more complex and difficult to predict. Therefore, understanding the demand for travel during disaster events, in particular when evacuations take place, is critical for the efficient management of the event [45]. The usual activity and travel patterns may be broken and not at all relevant during an event, when entirely different considerations take priority [31]. These depend on the nature and extent of the event, on the information and instructions provided to the population and on the locations and activities that household members undertake when the event begins. Interactions and dependencies among the behaviors of different household members, as well as with others in the extended family and social network are also critically important and may dictate movement patterns [44]. For example, in an evacuation situation, adults may first need to pick-up dependent children or other individuals that need help, before evacuating themselves. These tasks can be assigned to specific household members, based on

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their physical or social proximity to the individuals that need help, availability of vehicles and so on [30].

Despite the importance of modeling travel demand during evacuations, there is limited literature on the subject [20]. The purpose of this paper is twofold: First, it presents a comprehensive review and summary of the findings from the literature regarding the main factors that affect travel choices (e.g. whether or not to evacuate and the evacuation mode and destination) during evacuations. Then, the findings from the literature are used as a benchmark for comparison with the results of analysis of a dataset on the travel behavior of individuals during the evacuation of several neighborhoods in the city of Haifa Israel. The evacuation was ordered following the occurrence of multiple wildfires in the city on a single day in November 2016. This dataset was collected through a web-based survey that was conducted shortly after the event took place.

The rest of this paper is organized as follows: the next section provides a review of studies on individuals' choices whether or not to evacuate, other related choices and the factors that affect them. Section 3 describes the wildfire event that took place in Haifa in November 2016 and the design and implementation of the survey of travelers' actions during the evacuation that was conducted shortly after the events. Section 4 presents statistical analysis and modeling of the collected data set, a discussion of the results and their comparison to those found in the literature. The last section provides conclusions and an outlook for further research and analysis of evacuation behavior data.

2. Evacuation behavior literature

Brachman and Church [7] distinguish between modeling travel behavior in advance-notice and no advance-notice evacuation events. In the former, the focus is on the design and execution of response plans, thus the travel demand is represented at a lower level of detail. It is often assumed that the population will be informed and follow the instructions from the authorities. In the latter, these assumptions are less reasonable.

The most studied evacuation-related behavior is the choice whether to evacuate or not. Table 1 summarizes previous studies of the evacuation choice. For each study the table provides details on the type of event (e.g. hurricane, fire), source of data (revealed preferences (RP) or stated preferences (SP), for observed or hypothetical events, respectively) and the method of analysis (sample statistics, a choice model, review of earlier studies or qualitative analysis). In each case, the main factors that were examined as affecting the evacuation choice are classified in four categories, which were defined based on a synthesis of the studies. The first two categories are basic factors related to the socio-demographic characteristics of the individual making the decision and those related to the household that the individual is part of (in some studies, the respondent is the head of the household, in others not necessarily). The third category includes characteristics of the event and its relation to the respondents (e.g. level of risk, the instructions and information provided by authorities or other sources). These factors are external to the decision-makers and describe the specific circumstances of the event that the individual does not have control over. The last category includes other factors, which are mostly additional characteristics of the individual that may be relevant in this context. For each of these factors, its direction of affect is indicated ("+", if higher values increase the probability of evacuation, "-" if they decrease it, "0" if no clear or insignificant affect was found. With review studies, if conflicting results were found, a"?" is shown). Two signs may be shown together (e.g. "+0") if multiple analyses were conducted showing affects only in some cases.

The scenario most commonly studied is that of advance notice events, in particular hurricanes and other weather-related events. The difficulty to obtain detailed travel data in evacuation scenarios dictates that relevant studies often rely on SP data surveys. Those that are based on post-event self-reports of actual behavior (RP) mostly presented simplified choice dimensions and alternatives. As a result, with the exception of Bateman and Edwards [4], the analysis in studies that are based on RP data is based on sample summary statistics (e.g. rates of evacuation in various population groups) or qualitative analysis, and do not develop multivariate choice models. Kang et al. [23] compared the expected evacuation intentions of respondents with their later actual behavior when an event occurred. They found a moderate agreement between the two on the decision whether to evacuate or not, with 68% taking the action that they stated they would. A lower association existed between more specific details of the evacuations, such as the timing, mode or intermediate stops. Thus, the value of SP data in the context of evacuation is rather limited.

The clearest and most consistent effect on evacuation choice is that of the factors related to the characteristics and circumstances of the event. As can be expected, in all studies that considered the risk level, it was found that individuals that face higher risk are more likely to evacuate. This effect remain stable despite the fact that the risk itself is measured in different ways. In some cases it is based on objective variables (e.g. distance, wind direction, intensity of fire or rain storm), while in others respondents reported perceived risk levels. Risk perceptions are affected by the information provided to the public. The orders, guidance or advice provided by authorities or the media has a consistent effect similar to the risk level. Individuals that were instructed to evacuate were more likely to do so, and especially if the evacuation was mandatory rather than voluntary (e.g. [2,3,47]). Furthermore, Baker [3] and Dow and Cutter [15] found that the wording of instructions and the media it is distributed through also affect the response, which has implications on the relevant policies of the authorities. Several studies show that individuals also tend to evacuate more, if others in their surroundings or social networks do so. This may reflect a mechanism they use to form their own risk perceptions. Carnegie and Deka [8] and Koot et al. [24] considered various types of disaster events. Their results show that evacuation rates would be higher with man-made events compared to natural ones. Koot et al. [24] suggest that this may be related to a perception that man-made events are more severe. Finally, Dow and Cutter [15] find that with a very large evacuation for a hurricane, concerns about traffic conditions decreases the probability of evacuation.

A second group of variables that are shown in Table 1 and may affect evacuation choices relates to the socio-demographic characteristics of the individual. The results regarding their effects are inconclusive. Several studies show that females tend to evacuate more than males. Fothergill [18] studies the gender effect in details. She finds differences in exposure, perceptions and actions between males and females and also interactions with other factors. However, other studies do not find significant gender effects. The evidence on other variables is even weaker. While some studies suggest that income and education levels, car ownership, age and ethnicity are associated with higher rates of evacuation, other do not find this effect, especially when controlling for other variables.

Evacuation decisions among household members are inter-related. Therefore, characteristics of the household, beyond those of the individual being studied are also relevant. In some, but not all, studies the presence of children in the household increases the probability of evacuation. There is no similar evidence for the size of the household or the number of adults. Presence of elderly persons, individuals requiring assistance has also been shown to increase evacuation rates. But, these are based on few studies. Several studies examined the effect of pets or animals in the household. They found that either they do not affect evacuation probabilities or decrease them. One study [33] showed that if household members are physically together at the same location when the event begins, they are more likely to evacuate. This result suggests the need to take into account the joint decision-making and correlations in behavior among household members.

Finally, additional variables that have been found to contribute to evacuation rates include past experience with evacuations (even ones

Table 1
Studies of evacuation choice.

Source	Event type	Data source [sample size]	Analysis method	Factors affecting evacuation propensity			
				Socio-demographic	Household	Event	Other individual characteristics
Alsnih et al. [1]	Wildfires	SP [257]	Binary choice model	Female (+) Age (-) Cars (-)	Children (-) Adults (+) Elderly (+)	Risk level (+)	Time in area (-)
Auld et al. [2]	No notice evacuation	SP [205]	Sample statistics	Income (+) Education (+) Cars (+)	Children (+) Adults (0)	Risk level (+) Instructions (+) Others evacuate (+)	-
Baker [3]	Hurricane	Previous RP studies	Review of sample statistics	Elderly (+) Several other are insignificant	Children (0) Pets (0)	Risk level (+) Instructions (+) Others evacuate (+)	Experience (+) Mobile home (+) Time in area (?)
Bateman and Edwards [4]	Hurricane	RP [1029]	Binary choice model	Female (+) Retired (+) Cars (0) Several other are insignificant	Children (0) Adults (-) Help needy (+)	Risk level (+) Others evacuate (+)	Mobile home (+) Evacuation plan (+)
Carnegie and Deka [8]	Various	SP [2218]	Binary choice models	Female (0) Elderly (−0) Education (0) Cars (0) Ethnicity (0+)	Children (+0) Help needy (−0) Pets (−0)	Risk level (+) Event type	Experience (0)
Dixit et al. [13]	Hurricane	RP [429]	Binary choice model	Child (+)	-	Risk level (+) Instructions (+) Time of day	Time in area (-)
Dow and Cutter [15]	Hurricane	RP [536]	Sample statistics	-	-	Risk level (+) Instructions (+) Traffic problems (-)	Experience (+) Work obligation (-)
Fischer et al. [17]	Chemicals fire	RP [83]	Sample statistics and interviews	-	-	Instructions (+)	Experience (+)
Fu and Wilmot [19]	Hurricane	RP [428]	Binary choice model	-	-	Risk level (+) Instructions (+) Time of day	Mobile home (+)
Koot et al. [24]	Various	SP [1008]	Choice model: evacuate, wait, stay	-	-	Risk level (+) Event type	-
McLennan et al. [31]	Wildfire	RP [49]	Interviews, sample statistics, MANOVA	Female (+)	Pets (0) Size (0)	Risk level (+)	Stay plan (-)
Mozumder et al. [32]	Wildfire	SP [1018]	Binary choice models	Female (+) Age (0) Education (0) Retired (0)	Pets (0) Size (0)	Risk level (+)	Experience (+) Destination Political affiliation
Murray-Tuite and Wolshon [33]	Various	-	Review paper	Female (+) Age (?) Income (?) Ethnicity (?)	Children (+?) Pets (?) All together (+)	Risk level (+) Instructions (+) Others evacuate (+)	Experience (0) Social network (+) Time in area (-) Work obligation (-)
Pfister [36]	Flood	RP [205]	Qualitative interviews	-	Pets (0)	Risk level (+) Instructions (+)	Experience (0)
Yang et al. [46]	Hurricane	SP [1221]	Ordered choice model	Female (+0) Age (-) Income (0) Education (-) Ethnicity	Children (+) Pets (-) Help needy (+)	Risk level (+)	Mobile home (+) Work obligation (-)
Yin et al. [47]	Hurricane	SP [2679]	Binary choice model	Income (+) Education (+)	Children (+) Pets (-) Help needy (+)	Risk level (+) Instructions (+)	Mobile home (+) Work obligation (-)

that proved to be unnecessary), having a prior plan or living in houses that offer weaker protection (e.g. mobile homes or no fire protection). In contrast, having work obligations or owning a business in the area negatively affects evacuation rates.

Some researchers combined the study of evacuation choices with other decisions, such as the timing of evacuation, type and location of destination, intermediate stops and mode choice. The timing of evacuation is most relevant in event with pre-notice, such as hurricanes. Sadri et al. [38] modeled the evacuation timing as an ordered probit choice using RP data on hurricane evacuations. Fu and Wilmot [19], Alsnih et al. [1], Koot et al. [24] and Dixit et al. [13] modeled evacuation choices as a dynamic process. Thus, evacuation times emerge as outcomes of decisions made repeatedly until an evacuation takes place. But, data limitations negatively affect the reliability of results of these studies. Alsnih et al. [1] and Koot et al. [24] use SP data with repeated experiments for wildfire and hurricane scenarios, respectively. Fu and Wilmot [19] and Dixit et al. [13] use RP data of hurricane evacuations with 6-h aggregations. In addition to the factors mentioned above, the evacuation timing choices (if at all) are also affected by the time of day, familiarity with the area and the condition of evacuation routes.

In addition to the evacuation choice, Deka and Carnegie [12], Auld et al. [2], Yin et al. [47] and Yang et al. [46] studied evacuation destinations (e.g. shelter, family/friends, hotel/motel or other) and distances. They find that these choices depend on income and education levels, ethnicity and the presence of children or pets in the household.

For the purpose of predicting traffic demands, several authors examine the number of vehicles used. Both Dow and Cutter [15] and Kang et al. [23] argue that an overwhelming majority of evacuees use private cars. Dow and Cutter find that 25% of households use two or more cars to evacuate. Kang et al. [23] find that an average of 1.62 cars is used by each household for the evacuation. The results of Yin et al. [47] show that car use for evacuation increases with the household size, experience with prior evacuations and presence of pets in the household.

Auld at al. (2012) examined also statistics of the intermediate stops made. Over 50% of stops made were for purposes of picking up or meeting household members, especially children. Lin et al. [27] and Liu et al. [29,30] also found a stronger tendency to pick up children in an evacuation situation compared to normal conditions. Liu et al. [29] and van der Gun et al. [45] model the choices of household members to wait for other members and car sharing choices for the evacuation trips. Urata and Hato [44] extend the interactions in evacuation decisions beyond household members also to other in their social network. These results are also in line with the findings of Sorensen [40], Dow and Cutter [16] and Dobler et al. [14] that suggest that household members tend to gather together and evacuate together.

In summary, the literature review reveals that there is significant research on various aspects of evacuation behavior, in particular the choice whether to evacuate or not. However, these studies are not without limitations. The majority of studies are related to advance-notice events, mostly hurricanes. Many studies are based on SP data, to a large extent due to the difficulty to obtain ample RP data in evacuation scenarios.

3. Haifa wildfire data

A wildfire took place in Haifa Israel on November 24, 2016. On that day, starting at 10 a.m., a series of wildfires occurred at various locations at the southern part of the city. This is a primarily residential area. The residents of several neighborhoods in this area were asked to evacuate. In total, orders to evacuate were in place for about 40,000 inhabitants (about 15% of Haifa's population) for at least one night. The evacuation was not actively enforced and so the choice whether or not to evacuate remained up to the residents themselves. The fires were extinguished on the following day and residents were able to return to their homes. The map in Fig. 1 shows the locations of the wild fires within the city.

Shortly after the fire events, a web survey was developed and administered in order to collect data on the activities that residents of the affected areas undertook on that day. The information collected includes all the locations that they stopped at, the activities they undertook at these locations and the durations of stay. Travel modes, travel times and the identity of other individuals that traveled with them were reported for each trip between stops. Data was collected for all members of the respondents' household and for all their trips until they evacuated from the area affected by the wildfires or until the last stop they made on that day, if they did not evacuate. A set of socio-demographic variables were also collected. The survey was administered using Qualtrics [37], an online survey software. It was advertised through various mailing lists and social media groups of residents in the relevant area. Participation was voluntary, with no compensation of any form to the respondents. The questionnaire was available to any individual that declared that they are over 18 years old and that had at least one stop within the affected area on that day.

The resulting data set includes complete data on 640 individuals within 327 households. Of these, a subset of 537 observations are relevant for the evacuation choice, i.e., in which the individuals' home is within the evacuated area. The results presented below refer to these observations. Table 2 presents summary statistics of key socio-demographic characteristics of the respondents, their household and their activities on that day. The sample is almost gender balanced. The car ownership, income and education distributions may be due to differences in the willingness to participate in the survey or artifacts of its administration using the internet. They may also in part reflect the above average affluent economic status of the population in the area affected by the wildfire.

4. Evacuation analysis results

4.1. Evacuation rates and propensity

The differences in the evacuation rates between various groups that are defined based on characteristics of the individual, the household it is part of and the fire event are evaluated. Table 3 presented the evacuation rates. In each case, a statistical test for the equality of rates is conducted (two tail *t*-tests for binary variables and chi-square tests for multinomial ones). The table reports the p-value of these tests.

Overall, 83% of the respondents evacuated from the area of the fires. The Factors of age and presence of children and elderly persons in the household are associated with the evacuation rates. 91% of the children under 18 years old in the sample evacuated. Among adults, 86% of those in households with children evacuated, but, only 72% of adults in households without children. Individuals in the older age groups, and those in households with elderly persons (defined here as 65 years or older) are significantly less likely to evacuate. Individuals in household with pets are also less likely to evacuate. There are no differences in evacuation rates based on gender or education levels. Evacuation rates are higher for individuals with high income compared to both those in lower and very high income levels. For those in the highest level a possible explanation may be that the wealthiest neighborhood in the area was only marginally affected by the wildfires.

As expected, individual's whose home was at high risk (defined by a self-report by the respondents whether or not houses on the same street as their home or in close proximity to it were damaged) were more likely to evacuate. This is consistent with findings of previous studies. The circumstances of the event, in terms of the location of the individuals when they first learned about the wildfire made no significant difference in evacuation rates. Although not statistically significant, the results show that the further away individuals were when the event occurred, the lower their evacuation rates were. Similarly those that were at work evacuated less compared to those that were at home or other locations.

The statistical tests shown in Table 3 treat each variable independently. However, the variables are correlated (e.g. age, presence of children and household size). Therefore, a binary choice model that incorporate multivariate explanatory variables was developed for the decision whether or not to evacuate. The model is based on 516 observations, excluding some in which the evacuation was necessary because the individuals' home was burnt and observations with missing values for the explanatory variables. With the Logit model form that was used, the probability that an individual n evacuates is given by:

$$P_n(evacuate) = \frac{1}{1 + \exp(-V_{evacuate,n})} \tag{1}$$

Where, $V_{evacuate,n} = \beta' X_n$ is the systematic utility of evacuating. It is specified as a linear function of the vector of explanatory variables X_n, and the corresponding parameters β.

The model was estimated using the mlogit package in R [10]. Estimation results of this model are presented in Table 4. The results show an effect for factors related to all of the characteristics of the individual the household and the event itself. The age of the individual affects evacuation probabilities. The base group in the estimation are adults 35–54 years old. Compared to them, Children, and especially younger ones, are more likely to evacuate. The group most likely to evacuate are

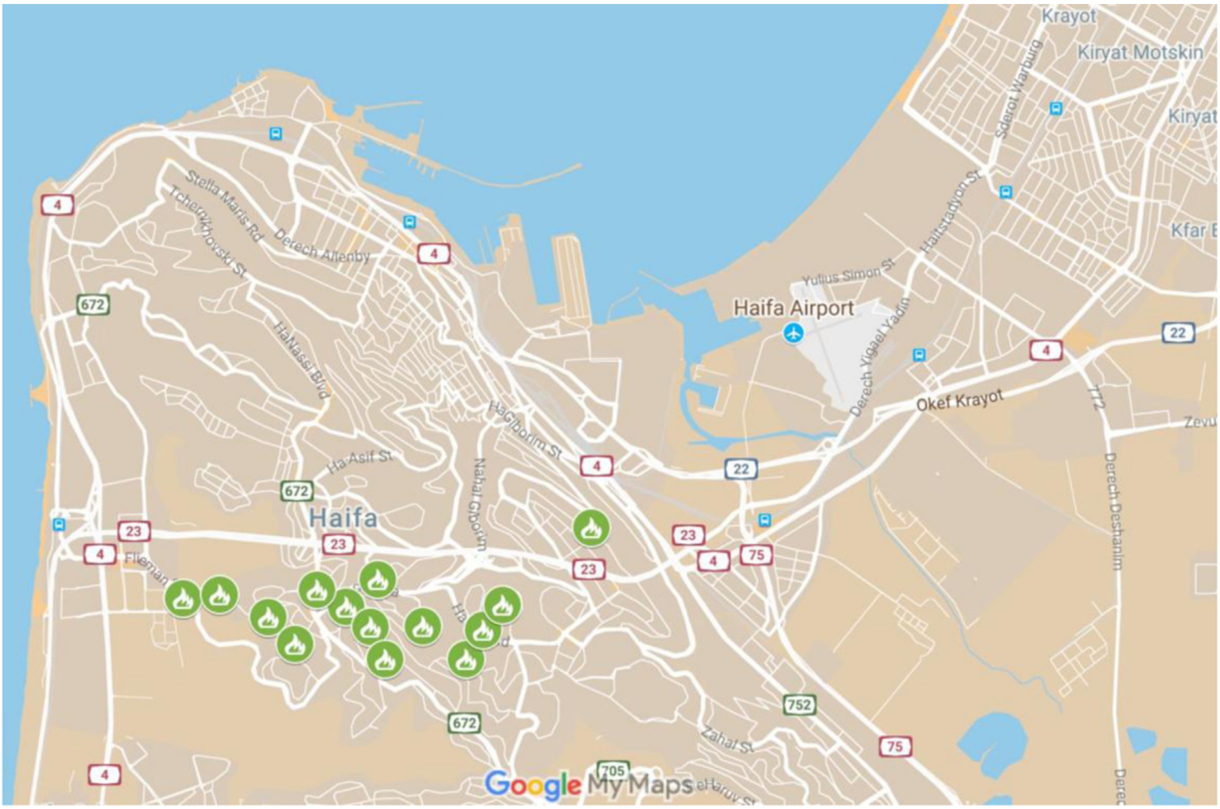

Fig. 1. Map of Haifa wild fires.
(Source: [22]).

Table 2
Survey sample summary statistics.

Variable	Distribution in sample
Evacuated	Yes: 83.2%, No: 16.8%
Gender	Female: 53.3%, Male: 46.7%
Age	12 or younger: 31.8%, 13–18: 5.0%, 19–34: 25.0%, 35–54: 22.7%, 55 or older: 15.5%
Household size	1: 4.8%, 2: 18.2%, 3: 14.0%, 4: 33.7%, 5: 19.6%, 6 or more: 9.7%
Car ownership	0: 5.2%, 1: 33.7%, 2 or more: 61.1%
Pets	Yes: 42.1%, No: 57.9%
Income	Very low: 16.8%, Low: 13.2%, Average: 15.6%, High: 29.3%, Very high: 25.1%
Education	High school or lower: 4.9%, Post high school: 5.5%, Academic: 89.7%

young adults 19–34 years old. In Haifa, these are likely to be students. Older adults, ages 55 or over are also more likely to evacuate. Within this group, no further differences were found for elderly persons (adult age groups were defined in intervals of 10 years). Note that this result seems to contradict the one in Table 3 that show that older adults evacuate less than younger ones. The reason for this is that the multivariate model also captures other effects that are correlated with the individual's age. In this case, there is a strong positive effect of children in the household on evacuation rates. Older adults are less likely to have small children in the household and so, accounting for the presence of children, the older adults are more likely to evacuate than younger adults. Differences were also not found between males and females and based on education or car ownership levels. For the last two variables, this may be due to low variability in the sample (especially in education level), and their correlation with income. The results regarding children and the elderly are consistent with earlier studies, and so are the lack of effect of education and car ownership. But, the results regarding gender contradict the majority of studies that found that females are more likely to evacuate.

Several variables related to the household were found to be significant in the model. As noted above, presence of children (not the individual making the decision him/herself) in the household increases the probability of evacuation. These results are more conclusive than the ones found in the literature. Individuals in households with 6 or more members were also more likely to evacuate. There were no significant differences among individuals in smaller households. Individuals in households with pets were less likely to evacuate, but the magnitude and significance of this result is lower. This is in line with earlier results that mostly shows a small negative or no effect on evacuation rates. Individuals in households with low or very low income were less likely to evacuate relative to those with average incomes. Those with very high income levels were the least likely to evacuate. It is possible that these results reflect, at least in part, the spatial distribution of household incomes. In this specific fire event, areas with very high incomes within the fire area were generally less affected.

Finally, as with all previous studies, higher levels of risk for the home was related to a higher probability of evacuation. The relevant variable is the individual's perception of risk when the event took place. However, this is a latent variable that can only be indicated on indirectly. As a results of difficulties with further increasing the length of the survey and the fact that the data was collected in retrospect, it was decided to use more objective risk indicators. Risk was measured in several different ways, based on information from the fire department on neighborhoods and streets in which houses were burnt, and based on responses to a question on whether or not there were houses in ‘close proximity’ to the respondents’ home that were damaged or burnt. The latter may implicitly incorporates subjective perceptions or risk through the perception of proximity. This variable showed the strongest association to the evacuation choice, and is used in the model as a dummy variable.

Table 3
Evacuation rates for various groups in the sample.

Variable	Values	Evacuation rates [sample size]	p-value
Individual characteristics			
Gender	Female	0.835 [285]	0.825
	Male	0.828 [250]	
Age	12 or younger	0.930 [171]	< 0.001
	13–18	0.778 [27]	Only youngest and oldest
	19–34	0.836 [134]	groups differ from other ones.
	35–54	0.811 [122]	
	55 or older	0.663 [83]	
Household characteristics			
Household size	1	0.692 [26]	< 0.001
	2	0.724 [98]	Households of three or less
	3	0.787 [75]	Significantly differ from
	4	0.878 [181]	those with four or more.
	5	0.838 [105]	Differences within these two
	6 or larger	0.981 [52]	clusters are insignificant.
Presence of children	12 or younger	0.919 [321]	< 0.001
	13–18	0.659 [41]	Households with younger
	No	0.706 [175]	children differ from other ones.
Presence of elderly	Yes	0.667 [21]	0.041
	No	0.837 [516]	
Car ownership	No	0.815 [27]	0.942
	1	0.840 [175]	
	2 +	0.832 [317]	
Pets	Yes	0.788 [226]	0.024
	No	0.862 [311]	
Income	Very low	0.857 [84]	0.005
	Low	0.773 [66]	High income differs from all
	Average	0.808 [78]	other groups. Differences
	High	0.918 [146]	among other groups are not
	Very high	0.760 [125]	significant.
Education	High school or lower	0.923 [26]	0.413
	Post high school	0.828 [29]	
	Academic	0.821 [477]	
Event characteristics			
Risk level	High	0.861 [295]	0.002
	Low	0.747 [186]	
Initial location	Work	0.788 [170]	0.074
	Home	0.817 [153]	
	Other	0.874 [214]	
Initial area	Fire area	0.857 [371]	0.338
	Haifa	0.802 [116]	
	Near Haifa	0.789 [19]	
	Further away	0.769 [26]	

Table 4
Estimation results for the model whether or not to evacuate.

Parameter		Value	t-statistic	p-value
	Constant	0.940	1.331	0.183
Individual	Age 12 or under	2.275	3.782	< 0.001
	Age 13–18	1.395	1.718	0.086
	Age 19–34	2.645	3.702	< 0.001
	Age 55 and over	1.679	2.389	0.016
Household	Youngest 12 or under	2.934	4.299	< 0.001
	Youngest 13–18	1.462	1.924	0.054
	Size 6 or more	2.735	2.580	0.010
	Pets	− 0.407	− 1.456	0.145
	Income low/very low	− 0.787	− 2.130	0.033
	Income very high	− 1.487	− 4.264	< 0.001
Event	Fire risk	0.876	3.144	0.002
No. parameters: 12		No. observations: 516		
Null log-likelihood: − 357.66		Final log-likelihood: − 128.37		
Adjusted rho-square: 0.608				

4.2. Evacuation characteristics

In addition to the choice whether or not to evacuate, there are other decisions that individuals make during an evacuation event. These are related to the evacuation mode, destination and intermediate stops made.

Lindell and Prater [28] distinguish between the proximate and ultimate evacuation destinations. The former is defined as the first stop that evacuees make outside the affected area, while the latter is their final destination. In the current survey, in order to simplify and shorten the questionnaire, only information on the proximate destination was collected. Among the individuals that evacuated (N = 446), for 57% the proximate destination was someone else's house (or in a few cases their own, if they have a second one outside the fire area). In 3% and 5% it was a workplace or school respectively. 17% travel to public places (e.g. train stations, bus stops or terminals, shopping malls, public shelters), and 18% to other destinations. Among those who did not evacuate the fire area (N = 91), 99% stayed at their home. In terms of the locations of destinations, 52% of evacuees stopped within the boundary of the city of Haifa, 20% outside the city, but within the metropolitan area and 28% traveled further away. As the majority of stops are at houses, it seems that these results reflect the availability of opportunities to stay with family and friends.

The vast majority of individuals (N = 440) evacuated using private vehicles. 38% drove themselves and 54% were passengers. 4% evacuated on foot or using other non-motorized modes. Only 2% used public transportation and another 2% used other modes. These numbers refer to the last leg of travel before the proximate destination. It should be noted that most of the public transportation services in the area of the fires were cut off due to road closures. Thus, the results highlight the dependence on the private vehicle in such unplanned events. These results are consistent with those reported by Dow and Cutter [15] and Kang et al. [23].

Several authors emphasized the importance of the number of vehicles used for evacuation, as these are the source of traffic demand and the resulting congestion. Among the households in the current sample (N = 188), 22% did not use a vehicle for the evacuation, 66% used one vehicle and 12% used two vehicles. In this context, the use of a vehicle is defined by the household member being a driver. Vehicle use for evacuation is associated with the household size. Table 5 shows the distribution of number of vehicles used by household of various sizes. In general, as can be expected, larger households use more vehicles. The expected number of vehicles used per household for the evacuation is 0.89, which is substantially lower than values reported in the literature for hurricane events (e.g. 1.62 in [23]). This may be explained by the nature of the evacuation which was expected to be short-termed and by lower car ownership rates in Israel compared to the US.

The high fraction of individuals that evacuate with private vehicles, and the relatively low number of vehicles used, means that many individuals evacuate together with others. Table 6 presented the distributions of the number of individuals that evacuate together for

Table 5
Distribution of the number of vehicles used for the evacuation depending on the household size.

Household size [Sample size]	Number of cars used by households (fraction)			Average number of vehicles used
	0	1	2	
1 [18]	0.33	0.67	–	0.67
2 [47]	0.30	0.66	0.04	0.74
3 [32]	0.25	0.69	0.06	0.81
4 [57]	0.12	0.77	0.11	0.99
5 or more [34]	0.21	0.44	0.35	1.14
All [188]	0.22	0.66	0.12	0.89

Table 6
Distribution of the number of individuals that evacuate together depending on the household size.

Household size [Sample size]	Size of groups of evacuees traveling together (fraction)					Average group size
	1	2	3	4	5 or more	
1 [18]	0.44	0.56	–	–	–	1.56
2 [71]	0.11	0.75	0.14	–	–	2.03
3 [57]	0.25	0.30	0.42	0.04	–	2.27
4 [157]	0.06	0.24	0.32	0.34	0.03	3.01
5 [86]	0.06	0.33	0.23	0.22	0.16	3.16
6 or more [51]	0.02	0.14	0.16	0.16	0.53	4.43
All [440]	0.10	0.35	0.26	0.19	0.10	2.89

Table 7
Distribution of the number of intermediate stops for individuals that evacuate and those that did not.

Group [sample size]	Number of intermediate stops					Average number of stops
	0	1	2	3	4 or more	
Evacuated [446]	0.37	0.35	0.16	0.07	0.05	1.10
Children [179]	0.46	0.37	0.10	0.05	0.02	0.80
Adults – no children [127]	0.46	0.35	0.11	0.06	0.02	0.83
Adults – w/ children [140]	0.19	0.34	0.28	0.15	0.04	1.51
Did not evacuate [91]	0.41	0.33	0.16	0.03	0.07	1.04
All [537]	0.38	0.34	0.16	0.06	0.06	1.09

households of various sizes. The values in the table refer to the size of a group traveling together in the last travel leg to the proximate evacuation location. Note that individuals may evacuate not only with members of the same household but also with non-members. Only 10% of individuals evacuate on their own. The average size of groups that evacuate together is almost three persons. Furthermore, it increases with the household size. This results further demonstrates the tendency of households to evacuate together, which was also pointed out in the literature.

In order to evacuate together household members need to first gather together. This results in intermediate stops that they need to make before evacuating. Table 7 shows the distribution of number of intermediate stops (excluding the initial location and the proximate location for individuals that evacuated, or the final home location for those that did not evacuate). About 60% of individuals make at least one intermediate stop. Individuals that evacuate make an average of 1.10 intermediate stops. Children under 18 make 0.80 stops. Adults in households with and without children make 1.51 and 0.83 intermediate stops, respectively. These results suggest not only that the travel patterns of children differs from that of adults, but also that their presence in the household affects the behavior of the adults. Counter to expectations, there is little difference in the number of stops between individuals that evacuated and those that did not. This may also be due to intermediate stops to pick up children that were needed even for those that did not evacuate.

5. Conclusion

This paper presented analysis of the choice whether or not to evacuate and related decisions during a no-notice wildfire evacuation event that occurred in Haifa, Israel. The results show that, in addition to variables that capture the level of risk that the wildfire event poses to individuals, variables related to the household they are part of (e.g. its size and presence of children or elderly individuals), as well as circumstances when it occurs (e.g. initial locations of household members) strongly affect the evacuation decisions and associated travel patterns.

Even after accounting for socio-demographic and household characteristics, there is wide variability in behaviors, for example in terms of number of intermediate stops and numbers of vehicles used in the evacuation. The decisions on whether or not to evacuate and on the choice of mode, destination and intermediate stops are inter-related. These inter-relations are not captured in the statistical analysis presented here, but would need to be accounted for in modeling these decisions. Thus, the travel patterns during an evacuation are diverse, complex and may be difficult to predict. A joint model of these decisions would need to take also into account the order and hierarchy of the various decisions and as a consequence they way that one choice dimension affects other ones. Therefore, an integrated model system that captures the various decision dimensions jointly, as opposed to modeling each decision separately, may be useful.

A majority of the individuals that evacuate do not simply travel away from the area affected by the fire. Instead, they make intermediate stops within this area for tasks related to the evacuation, such as to pick-up or meet other household members. Modeling these stops and the tasks that they serve is useful to understanding and prediction of travel patterns within the evacuation event. In travel behavior modeling and prediction, the state-of-the-art approach is the use of activity-based models. In these models, the focus shifts from trip-making toward the activities the passenger participates in, under the assumption that these activities are the underlying motivation from which the demand for travel is derived (e.g., [5,9,39]). Henson et al. [20] and Pel et al. [34] argue that this approach has not been fully applied for evacuation situations, but may be well suited for it and recommend its use. The results of analysis of the current evacuation data supports this conclusion.

Beyond trip-chaining and activity-based modeling, an important aspect in evacuation behavior is the joint decision-making and sharing of travel and tasks among household members, and in some cases also with non-members of the household. The general travel behavior literature acknowledges the existence of intra-household interactions (e.g. [41,26,6,21]). The results reported here support this idea. Specifically it show that the evacuation decisions and travel patterns are affected by the presence of children in the household and that household members tend to meet and group together before evacuating. These findings are consistent with previous studies on decision-making regarding children during evacuation [1,29,31], which strongly supports the need for household-level evacuation models and to capture the dependence of children's behavior on that of their parents.

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