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What Drives People to Return to Fukushima?:

An Assessment using Decision tree Approach

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What Drives Evacuees to Return to Fukushima?: A Decision Tree Approach*

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Abstract

Machine Learning's Decision Tree approach is used to gain new insights by assessment of effects of various factors which impact the habitants of the areas effected by 2011Tohoku Earthquake to return to their original residences. The learning model has 70% prediction accuracy (based on out of sample prediction). The effect of various variables affecting the return decision, categorized into hazard, finance and time related variables as well as interactions, have been assessed; using marginal effect diagrams. The learning model predicts that radiation decontamination of the affected areas will not have significant impact on changing of the opinion of individuals to return, and 43% return rate of the people will not increase in case of decontamination.

Key words: 2011 Tohoku Earthquake, migration, return decision, machine learning, decision tree analysis.

JEL classifications: H84, Q54, O53, Q01.

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1 Introduction

Disasters impact various aspects of the community, such as economy, health (psychological and physical) and environment. Post-disaster recovery requires understanding existing risks, rethinking land use, finding ways to correct deficiencies in public infrastructure, and providing incentives for economic recovery that will give firms and households an opportunity to survive and thrive (Landry et al., 2007). All of which rest on having profound understanding of the behavior of the population effected by the disaster. For example, the economic, social, and cultural feature of the region would be significantly influenced by who will return (Landry et al., 2007). Moreover, migration could have other effects on the economy. For instance, net migration is one of the forces, which causes removal of earning differentials. Some developments have followed natural disasters (Strobl and Walsh, 2009). They reported that destruction caused by hurricanes in US has caused 25 percent increase in country level employment in construction industry 2011 Tohoku Earthquake has made this disaster a unique case. The disaster caused by Great East Japan Earthquake and Tsunami has been described as "low probability, high impact" in the report prepared by world bank (Bank, 2012; Rose, 2011). They have investigated major types of post disaster resiliencies, and concluded that only those disasters that are related to nuclear contamination (Chernobyl and Fukushima) seem to have threatened the survival of the host region.

The economic, social, and cultural features of the region affected by the disaster depends on who decides to return. Moreover, the recovery would not seem possible without return of the local population, as human capital is one of the major (if not the main) drivers of economic growth. Therefore, this paper focuses on evaluating the effects of various factors, which have impact on the decision of the local population to return. Moreover, having better understanding about the decision criteria of the residents of these regions is essential for making effective policies for recovery and improvement of the conditions of the region.

The analysis of the return decision to the original residence after disaster is categorized under the broader subject of return migration analysis (Landry et al., 2007). This is because all factors that effect the normal return migration are found to be effective in the case of migration due to disaster. Sjaastad (1962) has defined migration as a decision, which involves the problem of a household's attempt to maximize the economic return on human capital. In same way, Landry et al. (2007) have shown that post-disaster return decision is influenced by economic factors, such as real wage difference between home and host region and ownership. The potential effects of various factors have been examined on the return decision.

Elliott and Pais (2006) have considered the effect of social differences, such as race and class on the return decision after occurrence of hurricane Katarina, and showed that these factors have relatively smaller effects comparing to other factors such as finance related factors. Myers et al.(2008) have found correlation between the independent variables such as percent of disadvantaged population, density of built environment and percent of housing with damage. Rofi et al.(2006) have considered the mortality effect of 2004 Asian tsunami on displacement of the local population in Aceh province of Indonesia. In a more broader approach, Fussell et al.(2014) have approached the human migration influenced by disaster more systematically, basing their study on demographic data and methods such as fertility, mortality, and migration. Groen and Polivka (2010) have shown that evacuee's age and the severity of damage in an evacuee's county of origin are important determinants of whether an evacuee returned during the first year after the storm or not. The experience of disaster has psychological effect on disaster victims, as it was shown in studies such as Neuner et al. (2006) investigated about the post-traumatic stress disorder caused by 2004 tsunami on children due to trauma exposure and loss of family members. The psychological effects caused by experiencing disasters could effect the return decision. Looking at various methodological approaches for empirical analysis of social behaviors related to disasters in mentioned papers, it could be seen that regression methods have been widely used for analysis of effect of various parameters. Although regression methods have been widely accepted and practiced due to their effectiveness in identifying the correlations between various control variables and the predicted variable, use of other methodologies for assessment of data such as machine learning techniques have been shown to be effective in gaining new insights and understandings. It could be recognized from previous researches that the trend of the individual's response towards different variables could change in different circumstances. For example variation in the trend of effect of different variables' was observed as the data was categorized and analyzed according to the age and region (Sanaei et. al., 2018). This observation implies nonlinear the existence of nonlinear correlations between some of the decision variables and the dependent variable. Use of a modeling tool, which could best reflect such variation, could be advantageous in comparison to the conventional regression methodologies –such as logit method.

This paper aims to use one of the machine learning methods known as decision tree method to assess the effects of various parameters on the decision to return to the original residences in the area's effect by 2011 Tohoku Earthquake. Machine Learning techniques have been effectively used in various fields including social sciences. Oh and Kim (2010) used decision tree method for making a model to predict the demand for health metrological information. In the mentioned paper, the individual's decision was modeled as a binary variable. Individual customer's credit risk has been evaluated using various machine learning techniques, such as Random Forests, k-Nearest Neighbor methods (Kruppa et al., 2013). The machine learning techniques have proven to be effective for prediction, for example forecasting the next day electricity prices in European energy market using Support Vector Machine technique (Papadimitriou et al., 2014). In cases where understanding each parameter's effect and it's impact are important, methodologies such as decision tree analysis are much of use. Kim et al.(2005) have used the decision tree analysis for investigating the effect of various parameters on the customer behavior change.

The remainder of this article is organized as follows: The description of the machine learning methodology used and the independent variables used for empirical analysis in the Methodology section. The numerical results are presented in the Results and Analysis section. Summery of finding and main conclusions will be discussed in the Conclusion section.

2 Methodology

This paper aims to take advantage of the machine learning tool and its potential abilities to gain additional meaningful insight into how each parameter effects individual's decision to return. In its very core, machine learning is based on improving the performance of a program (a model) by learning from previous experiences (Mitchell, 1997). The trained model is able to obtain a generalized relationship between the independent variables and dependent variable with certain degree of precision. Using this generalized rule, the model is able to predict the outcome of other cases not experienced. The consistency of the logic of the chosen learning model with the problem under study is one of the deciding factors, which impact how well a trained model could be generalized. For instance the Neural Networks uses concepts borrowed from an understanding of human brain in order to model the arbitrary functions (Lantz and Brett, 2013). In terms of ability to interpret the results and complexity of the mathematical system used, the machine learning methods are in general either transparent or black box. The methods such as Neural Networks or Support Vector Machine are known as black box methods (Lantz and Brett, 2013). These methods have displayed good predictive abilities. However, there are cases where model's transparency is important; such as cases when the criteria should be transparent for legal purposes. For example, credit scoring, which is a criterion, which the applicant is accepted or rejected, should be well specified. There are many cases such as present work, which there is need to interpret the effect of various variables and prediction is not the sole purpose. In these cases the black box methods cannot be normally used and more transparent methods such as decision tree method is useful. The decision tree algorithm makes a model in the form of a tree structure. Each branching point resembles a logical decision, which each of its branches (decisions) lead to other branching points (decisions) or leafs nodes where the branching stops. The leaf nodes are the result or outcome of making a series of choices. Since the decision tree is a flow chart, it could clearly display the relation of each variable on the dependent variable.

Decision tree method is based on a heuristic called recursive partitioning, which could be classified under divide and conquer algorithm. Beginning at the root node, the algorithm chooses the most predictive feature and divides the values according to it. It continues this process of divide and conquer till it reaches a stopping criteria (Lantz and Brett, 2013). Looking at the process of formation of the tree, in which the process of decision-making is broken down into smaller manageable decisions and formation of flow diagram, its similarity to human's decision-making process can be realized. Understanding this, its not surprising that processes, such as medical diagnostic, equipment malfunction and their cause, and evaluation of loan applicants (which people have been involved in), are also cases which use of Decision Tree methods are known to have success in(Mitchell, 1997).

The general mathematical formulation of the Decision Tree method is as follows (Hastie, et. al, 2009):

$$\hat{f}(x) = \sum_{m=1}^{n} c_m I\{X \in R_m\} \tag{1}$$

In the above equation, $\hat{f}(X)$ is the prediction of the dependent variable. The estimated value assigned to each partition is c_m; the overall predicted value is the summation of the effect of points within each partition, is determined by the points within each partition $I\{X \in R_m\}$. As it was mentioned before, an approach based on greedy algorithm is used for building the decision tree. That is in every step of building the decision tree, the best splitting variable and splitting point is found. This is shown in the equation below:

$$\min_{j,s}\left[\min_{c_1}\sum_{x_i\in R_1(j,s)}(y_i-c_1)+\min_{c_2}\sum_{x_i\in R_2(j,s)}(y_i-c_2)^2\right] \tag{2}$$

As it could be seen in the above equation, the choice of the splitting variable j and splitting point s, which determine the structure of the decision tree, depends on inner minimization from which the constant value for each region is found. In a similar way, this process is repeated for each of the two decided regions. The tree grows as this process is repeated, and later the size of the tree is chosen in a way that over fitting or loss of important information is avoided. More detail could be found in (Hastie et al., 2009; Lantz and Brett, 2013).

There are wide variety of methods for increasing the accuracy of the machine learning models. One of the methodologies that have been proven to be effective is called Boosting. The basic idea of boosting method is to combine the output of many weak classifiers (models with slightly better performance than random model) to produce a powerful committee. The gbm package is used in this paper for implementing the Boosting Tree method in R programming environment. The prediction error is calculated using the following formula:

$$e\bar{r}r=\frac{1}{N}\sum_{i=1}^{N}I\left(y_1\neq G(x_i)\right) \tag{3}$$

where the mean error is equal to the ratio of the points wrongly classified by the boosting model $G(\cdot)$. The general concept in the boosting model's tree is to start by assigning equal weights to each of the points and after finding the classification tree in the first step, higher weights are assigned to the point that have been misclassified, and the weight of the points that have been classified correctly are reduced. This process is repeated for M successive iterations. This way the observations that are difficult to classify receive more attention. Separate classifiers are built, every time the weights of the observations are modified. As described before the overall outcome depends on the decision of the committee of the classifiers. However the final classifier is determined by weighted sum of the M classifiers, as shown in Equation 2.

$$G(x) = \text{sign}\left[\sum_{m=1}^{M} \alpha_m G_m(x)\right] \tag{4}$$

We intend to analyze individuals' decision to return. A dummy variable is used for accounting for the return decision as shown below:

$$y_i = \begin{cases} 1 & \text{returning,} \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

The review of previous literature brings to light various parameters, which impact the individuals' decision to return to their original residence. These parameters are classified into four major groups taken from Sanaei et.al., (2016), which are: time related connections, finance related connections, hazard related variables, and interaction variables. Age, duration of residence, first generation, express the time related connections. These variables intend to reflect individuals' root attachment to the region, which is formed by time. Variables such as individuals' income, ownership of residence, and job related to region, could be categorized under the finance related variables. The ownership of residence is costly and it requires long-term investment by most individuals. Having job related to the local region is another finance related attachment to the local region. In addition the finance related factors are important since they play a decisive role in migrations in general. In general migration is not expected if it's not financially feasible for the individuals. Sanaei, et. al, (2016) have found that having related job to the region and also ownership status have the largest impact on the return decision. Factors reflecting feeling of safety and security are also referred to as hazard related variables and are: experience of disaster, the number of death and lost in the region, and radiation level. Having in mind that feeling of safety in individual's living environment is a basic necessity, some previous researchers have located their main focus on the effect of the hazard related variables on individual's decision to return. For example (Alistar and Managi, 2014) have considered the effect of radiation level on decision of people effected by 2011 Tohoku Earthquake to return to their original residences.

For considering the interaction between variables belonging to each of the mentioned groups, interaction variables have been defined. The interaction between the age and having related jobs to the region is considered in order to investigate the degree of which having job related to the region effects people of various ages. Moreover, the interaction between the number of dependents and number of death losses are considered for enabling us to have a judgment on how the number of death losses in same region would impact individuals who have dependents. Due to the importance of understanding the effect of amount of region's degree of radiation on peoples' opinion and also having in mind that decontamination requires large amount of investment by government.,the effect of potential radiation exposure with some key variables from various groups is considered. By doing this additional insight could be gained on the effect of radiation level on various individuals' opinions. The radiation contamination is a source of concern and various previous researches have shown its effect on migration decision. A practical application of the present research is to approximate the effect of reduction of amount of radiation in the effected areas, on decision to return, if decontamination is carried out.

The data used for the imperial analysis in this paper is gathered by interviewing 1510 individuals in various areas affected by 2011 Tohoku Earthquake. The summary of various described variables is shown in Table 1. As it could be seen, 884 (about 58%) of the individuals provided an answer to the question to whether they going back to their original residence or not. As it could be seen there are some variables with even smaller number than 884. The reason for this is because the decision tree method is able to handle incomplete data for independent variables.

3 Results and Analysis

The described methodology for building decision trees are used for construction of decision trees for modeling the decision to return using variables described in Table 1. To maximize the accuracy of the learning model, many decision trees are constructed, which based on each trees performance (error in prediction) its contribution to the learning model is defined (as described in previous section). Two of the decision trees made by the learning model are shown in Figures 2 and 3. The numbers next to the nodes are, node numbers and the numbers within the parentheses indicate the variable used for splitting. For example in node number 0 in Figure 2, number 8 is the eighth independent variable in Table 1. The splitting value for branching is written on the right side branches; as shown in the Figure 2. The predicted decision at each node is written using a plus or minus sign with in each node. The plus sign is for returning and minus for not returning. The nodes, which are the root for other nodes in the lower levels, are parent nodes. The nodes with out branching are referred to as leaves, and they indicate the final decision. Based on the values of each variable, the decision is directed to one of the leaves. As mentioned before, the decision tree method manages missing data. This could be seen in Figure 2, the nodes connected to the parent nodes using hatched lines, represent missing values. The boosting model in this case uses 531 trees (in general similar to the trees shown). This number of trees is the number of trees at which the accuracy of the boosting model improves to.

Table 2 shows the significance and relative influence of each variable. Similar to regression methods, the low values under the significance column (low p-value) reflect the likelihood that the variable is meaningful in explaining the dependent variable. Moreover, the relative influence of each variable is also shown. The variables with larger relative influence values are found to have more impact on individual's decision to return.

It is intended to have an assessment of the effect of the significant independent variables on the return decision. All the variables have been centered and scaled. The average value of the variables has been used for entering and standard deviation of each data has been used for scaling. The effect of age has been shown in Figure 3. As it could be seen the model indicates that people of different age groups behave differently. A negative trend could be seen in the effect of age from -2 to -1; which suggests that people from age 20 to about 33 are not likely to return. This is the age range where normally individuals choose their career directions. This result may suggest that: given the choice, people of this age range prefer to choose their carrier in other places. In the age range from about 33 years to about 38, there is a positive tendency to return; establishment of roots in the region such as having jobs related to the region may be a causal effect. However there is another decrease in the tendency to return for the people of age ranges from approximately 38 to 50. Normally the people of this age range are specialized in their jobs, making them a valuable human resource asset. It's needed to be mentioned that effect of job, which we have used for explaining the behavior of different age groups, is differs from *Local Job*, which we have used here (and has small relative influence). The tendency for return shows an increasing trend for people older than 50 years of age. This could be explained by root connections to the region.

The duration of residence of individual in the region is found to have the highest influence on return decision (according to Table 2), but small significance. As it could be seen in Figure 4, the average trend of the effect of duration of residence on the decision to return is increasing. This again explains the decision of the people above 50 years of age, which was previously explained. The other time related variable: First generation, is found to have small relative influence. This suggests that attachments that could be imagined to exist due to living of previous family generations do not have strong influence on the decision to return; in comparison with other factors.

Looking at the effect of death toll (Figure 5), as one of the hazard related variables, we could see that the model has not been able to capture the decision response under influence of this variable, consistently. The sharp fluctuation up to and little over the average death toll figure is the reason for this.

Another important hazard related variable is the amount of radiation level in the region. As it could be seen in Figure 5, the tendency to return, is likely to sharply decrease as the radiation exposure level increases. The decreasing trend is immediately followed by constant trend which reduces stepwise at about 1.75 (equivalent to 4.5μSv). The sharp decrease observed followed by a constant trend could suggest that the sole knowledge that the amount of radiation level has increased in a region (even by and small amount) is sufficient for having a negative impact on the decision to return. The increase in the amount of radiation level is likely to not effect the return decision; until the radiation exposure levels reach high values (such as 4.5μSv and more). This kind of reaction also suggests that there is not much understanding about the values of the radiation levels, and the mere knowledge on increase of radiation is enough for impacting the decisions for return.

The effect of having experienced previous disasters could be seen in Figure 6. It could be seen that people, who have experienced previous disasters, are less likely to return. Having experienced previous disasters and/or experienced the harm from may have caused these individuals to take the possible continuing risks from this disaster and other possible disasters more seriously;

and therefore reducing their incentive to return to their original residence.

Analysis of the effect of the income value on the return decision (Figure 7) suggests that in general (with the exception of small income range) there is more tendency to return, for individuals with higher income. The cause for this behavior maybe the tendency to return to their previous conditions that they were relatively successful at. Moreover, the ability to rebuild and restart life in devastated areas is financially demanding and this task becomes easier for people with higher income values.

Individuals, who own residential units, are more likely to return according to Figure 8. Ownership of one's own residence is normally considered a large financial step, which is not possible for everyone. It would be expected that the value of residential property would drop following the occurrence of disaster in the region. Therefore, the owner would be forced to sell the residential unit under its normal market value. This loss of asset resulting from undervalue selling of the house, would make it difficult for the owner to purchase a house in other places (Sanaei et al, 2018).

By looking at relative significance of each variable in Table 2, it is noteworthy that the learning model has found that the effect of the finance related variables: *Income*, *Home Ownership*, *Local Job*, in terms on their estimated influence on individuals' decision to return is relatively small. However, the effect of financial factors is shown to enable one to compare the results obtained in this research with other researches, which have considered the effect of finance related variables.

As it is shown in Figure 9, having local jobs, such as farming, fishery, teaching, provides positive incentive for people to return to their original residences. In addition to social attachments, some jobs such as farming and fishery require local investments.

The interaction variables have been considered for gaining a more in-depth insight into partial effect of various variables on the return decision. Looking at the interaction of radiation exposure level and number of dependents in Figure 11, we can see agreement with the overall trend of the effect of the radiation on the decision to return. This similarity suggests that both people with and without dependents respond in the same way to increase of the level of radiation.

The death toll in the region has been classified as a hazard related variable. Similar to the effect of the number of death losses (Figure 12) previously discussed, similar conclusion could be drawn by looking at Figure 12. The interaction of the number of dependents and death losses, suggests that people who have dependents act differently towards the number of death losses in their region; however in the areas where there has been a large number of death losses, the number of death losses does not have impact on individual's decision to return.

It could be understood from Figure 13, that the tendency for returning increases as the amount of income increase -even in presence of radiation. However, for the people with higher income, the increase of radiation does not effect their decision.

One important factor that has impact on population's decision to return is their feeling of safety from potential effects of radiation exposure in the area where they lived. Understanding this there has been a considerable debate on whether reduction of the level of radiation by decontamination is effective or not. Due to high economic cost of decontamination, it is important to have estimation about the extent at which decontamination would effect the return decision. The developed learning model is used for predicting (with certain accuracy) the effect of decontamination on increase (or decrease) of percentage of the people whom would decide to return. As it could be seen in figure 15, the developed learning model predicts that about 43% would return; and decontamination does not have any significant effect on population's decision to return.

4 Conclusion

In this paper assessment of the effect of various factors on the decision -of individuals that have been affected by 2011 Tohoku Earthquake to return to their original residences is performed.

In contrast to regression methods, taking advantage of the machine learning's Decision Tree method has enabled us to gain additional insight in to dynamic effect of each of the variables on the return decision. Marginal effect diagram for each variable has been used for displaying the changing trend in the return decision, as each variable changes. By using this tool, various thresholds for each variable have been recognized. For example, the marginal effect diagram for age (Figure 3), implicitly categorizes the people affected by the disaster in to four age groups: 20 to 33, 33 to 38, 38 to 50, and above 50 years old. The classification for age and other variables such as income becomes evident by observing the variations in the trend of each variable ' s effect on the return decision. This result is robust in a sense that classification is directly derived from outcome of the model analysis. Moreover, the transparency of the decision tree method (as shown in Figures 1 and 2) in being able to see the role of each variable in the modeling the decision process makes explanation of the outcome of the model easier and more acceptable.

The ability of the model to be generalized has been tested using 25% of the original data as test data. The generalization accuracy of the model is found to be 70%.

In terms of relative influence of variables on the return decision, the hazard related variables (which reflect the feeling of safety), such as number of death and losses in the region and the level of radiation are shown to have relatively high influence on the return decision. As for the finance related variables, the results show that the individual's income has higher relative influence than having related job to the region. Moreover the influence of age on the return decision is notably high.

The predictive ability of the Decision Tree method has been used for predicting the effect of decontamination on the return decision. The learning model ' s prediction is that decontamination of region will not significantly result in an increase in the percentage of the people returning to their original residences, and about 43% of the people are likely to return.

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Variable	Observation	Mean	St.Dev.	Min	Max
Returning	884	.33	.47	0	1
Age	884	47.84	14.216	20	84
Duration of Residence	881	25.47	20.78	0	81
First Generation	883	.54	.50	0	1
Death Toll	825	879.47	1252.11	0	3961
Rad Exposure	838	1.18	2.19	0	12
Dependents	871	1.71	1.15	0	6
Disaster Experience	884	.85	.36	0	1
Income	859	4.21	3.17	1	15
Home Ownership	884	.60	.49	0	1
Local Job	884	.39	3.17	0.49	1

Table 1: Basic statistics of evacuees' characteristics

Variable	Significance	Relative Influence
Age	.03	6.54
Duration of Residence	.11	16.45 **
First Generation	.01	1.67*
Death Toll	.07	11.28*
Rad Exposure	.03	6.02**
Number of Dependents	.04	6.97**
Disaster Experience	.00	1.02**
Income	.03	7.53**
Home Ownership	.02	3.88 **
Local Job	.00	.04 **
Age×Local Job	0.02	2.69**
Rad Exposure×Number of Dependents	.00	8.63**
Rad Exposure×Income	.03	6.45**
Rad Exposure×Home Ownership	.01	3.18**
Rad Exposure×Local Job	.01	0.87**
Rad Exposure×Duration of Residence	.06	13.14*

Note: * and ** denote that the corresponding variable is statistically significant at 10% and 5% level respectively.

Table 2: Relative influences to the returning decision

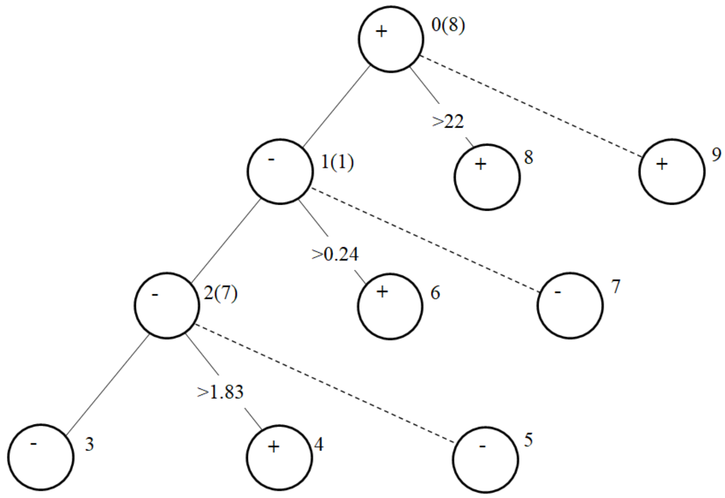

Figure 1: Sample decision tree 1

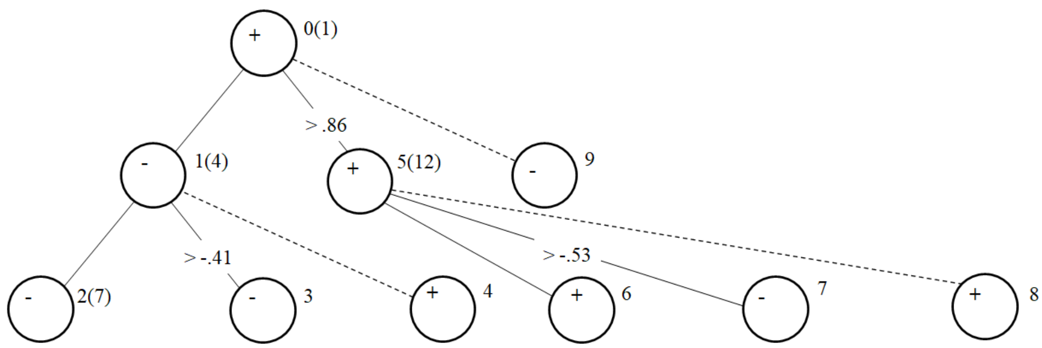

Figure 2: Sample decision tree 2

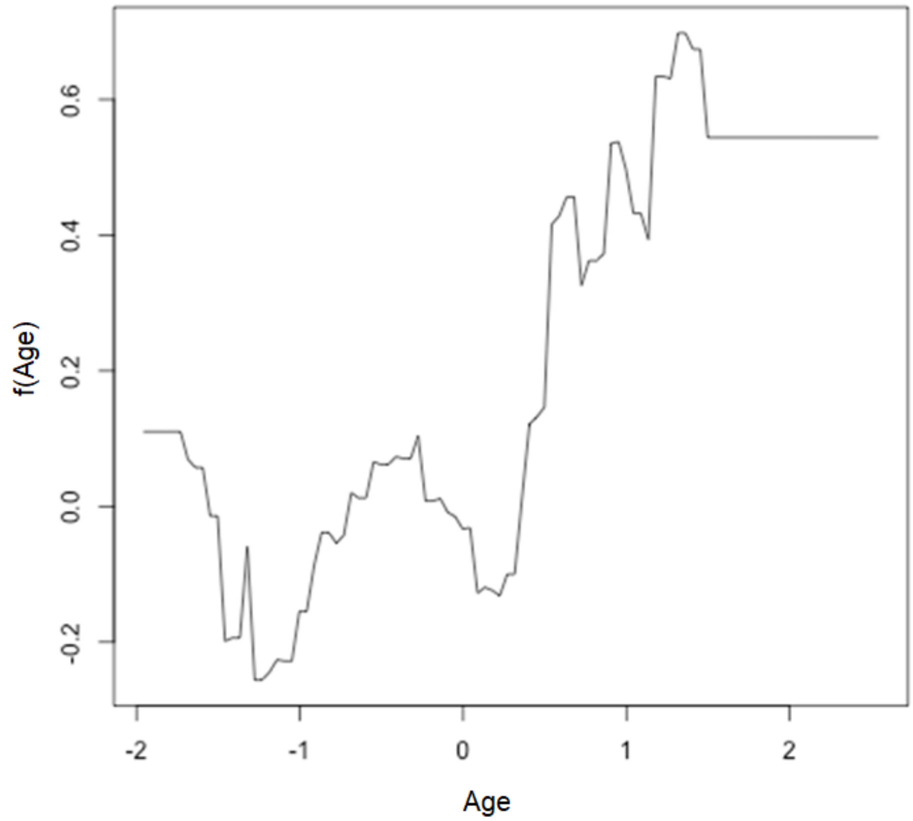

Figure 3: Effect of the age on the decision to return

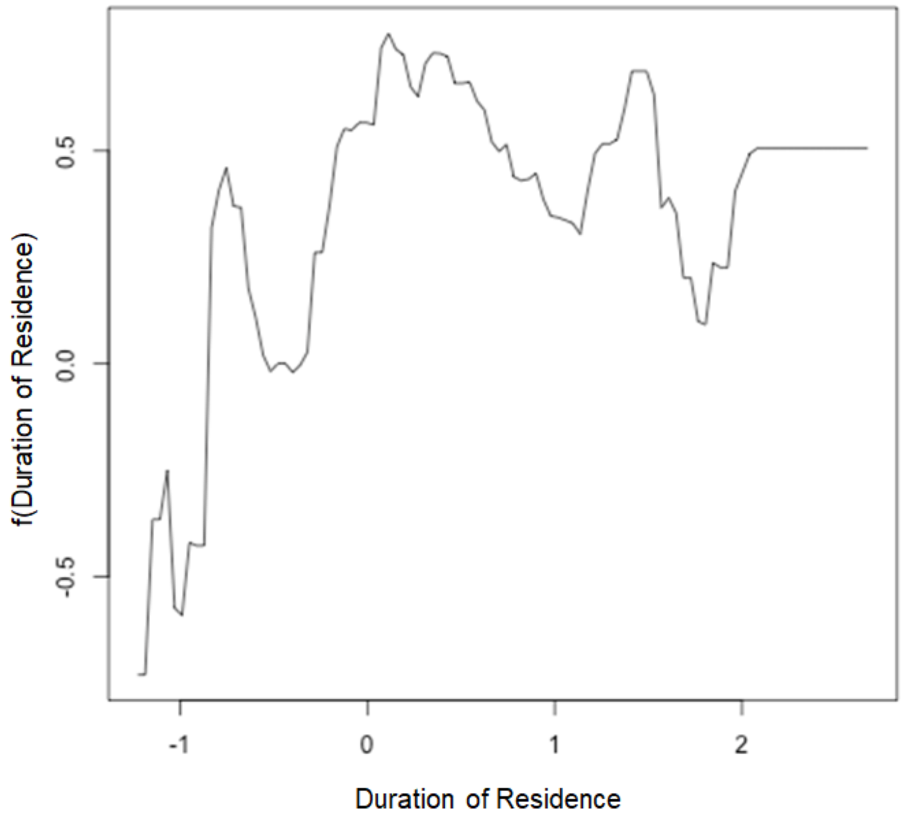

Figure 4: Effect of the duration of residence on the decision to return.

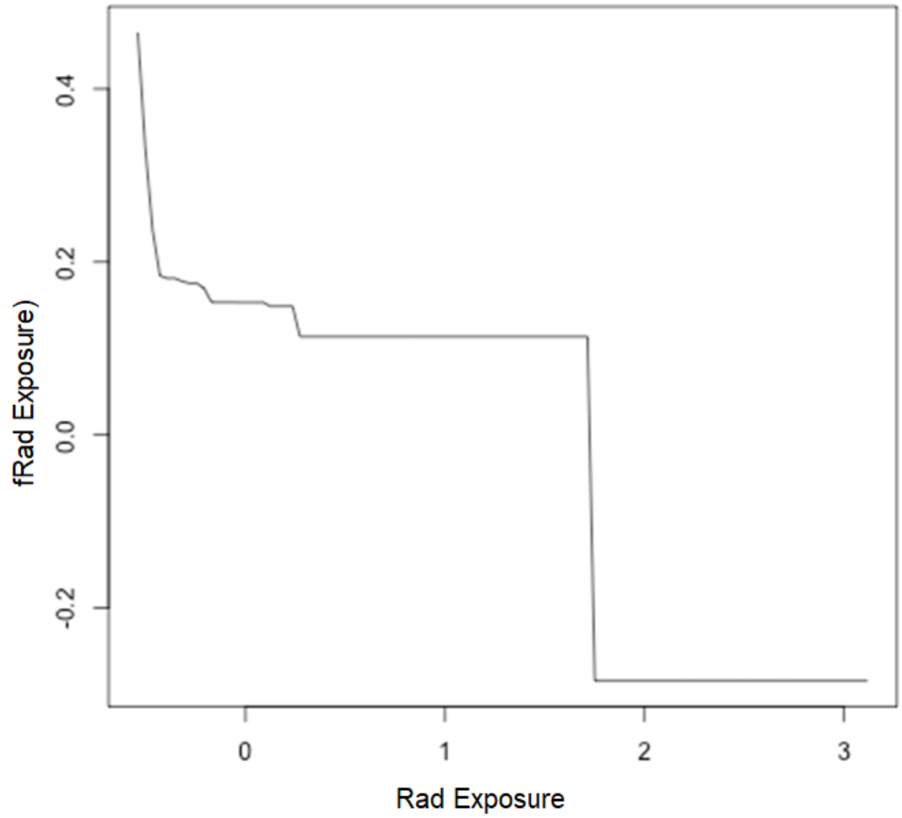

Figure 5: Effect of the death toll in the region due to disaster on the decision to return.

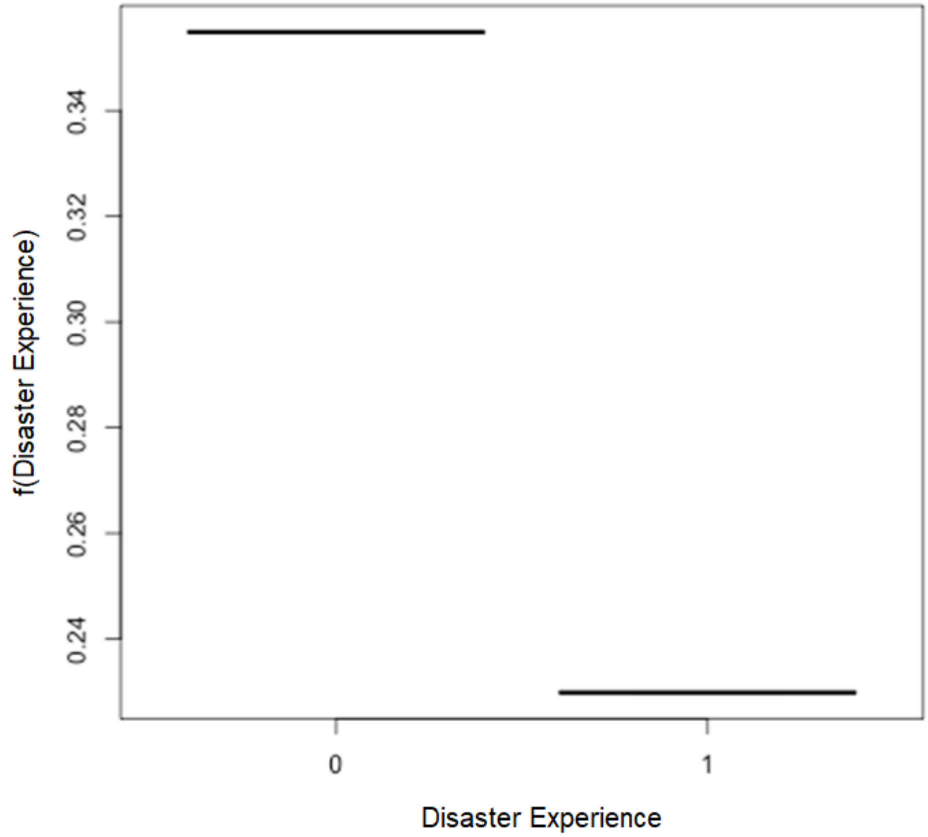

Figure 6: Effect of the radiation exposure level on the decision to return.

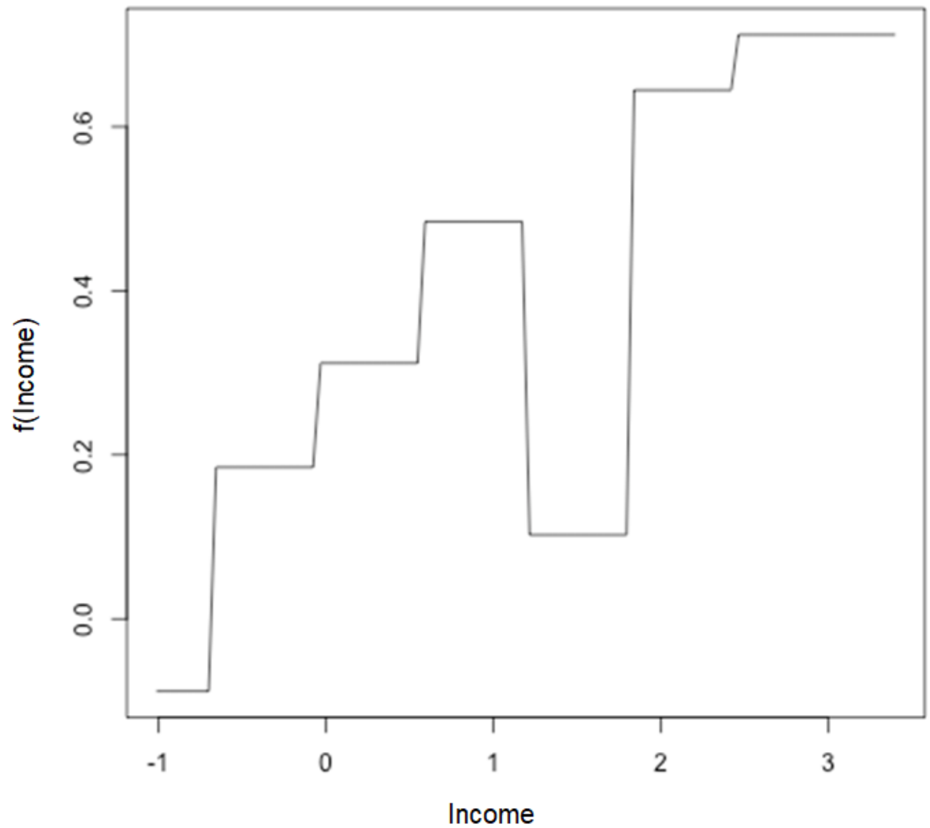

Figure 7: Effect of the level of income on the decision to return.

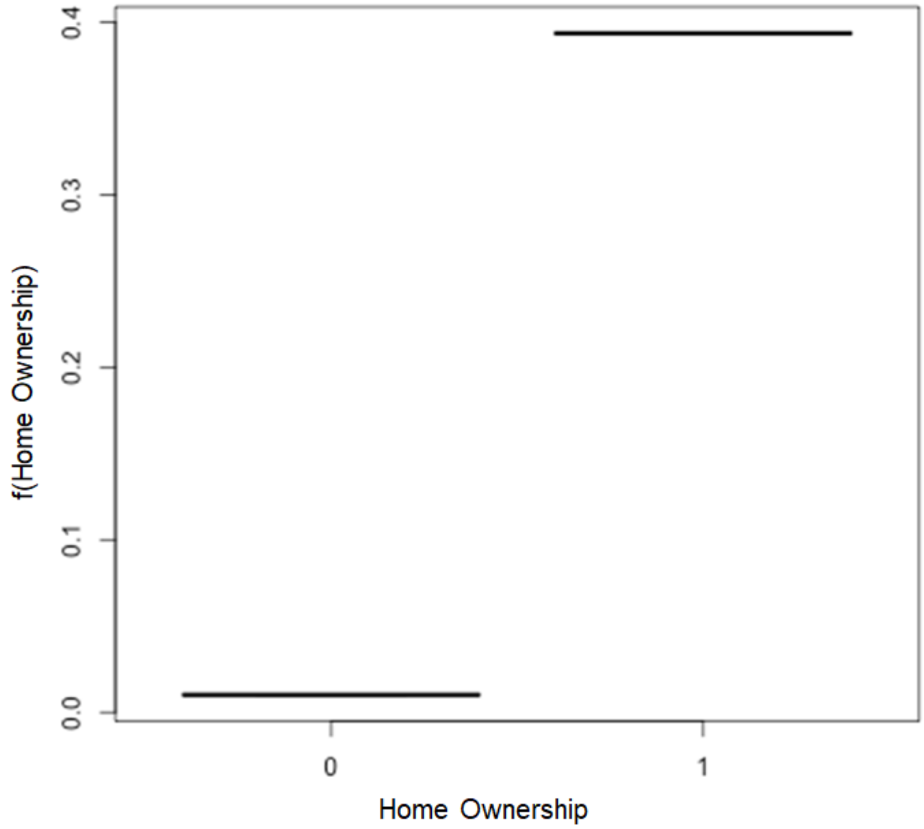

Figure 8: Effect of the home ownership in the effected area on the decision to return.

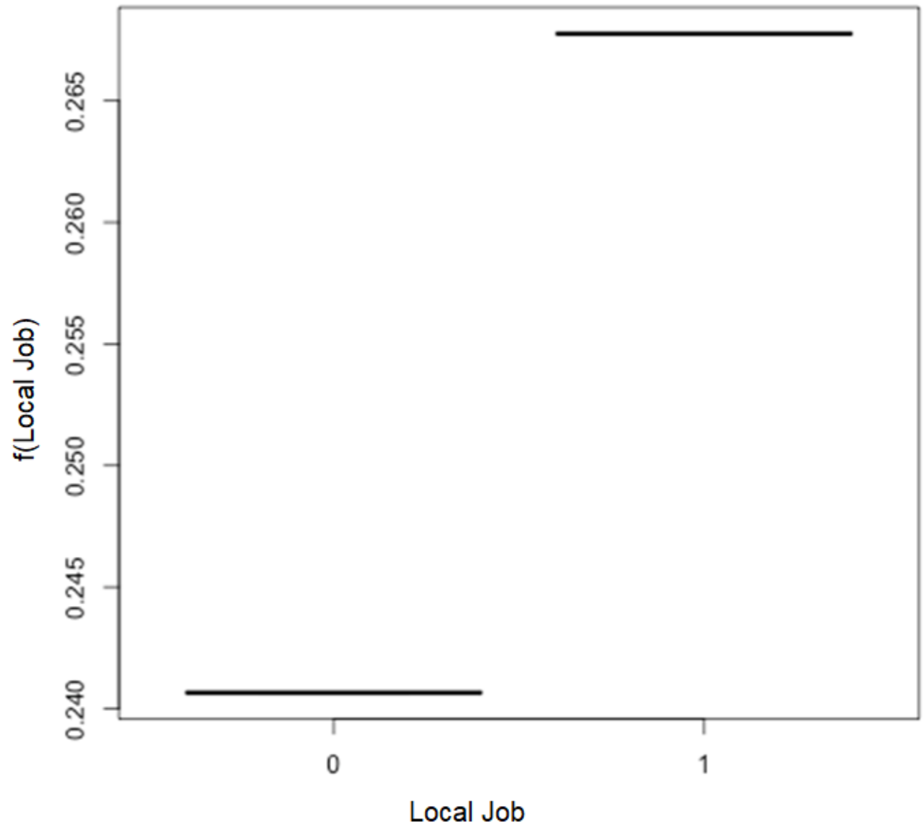

Figure 9: Effect of having local job to the region on the decision to return.

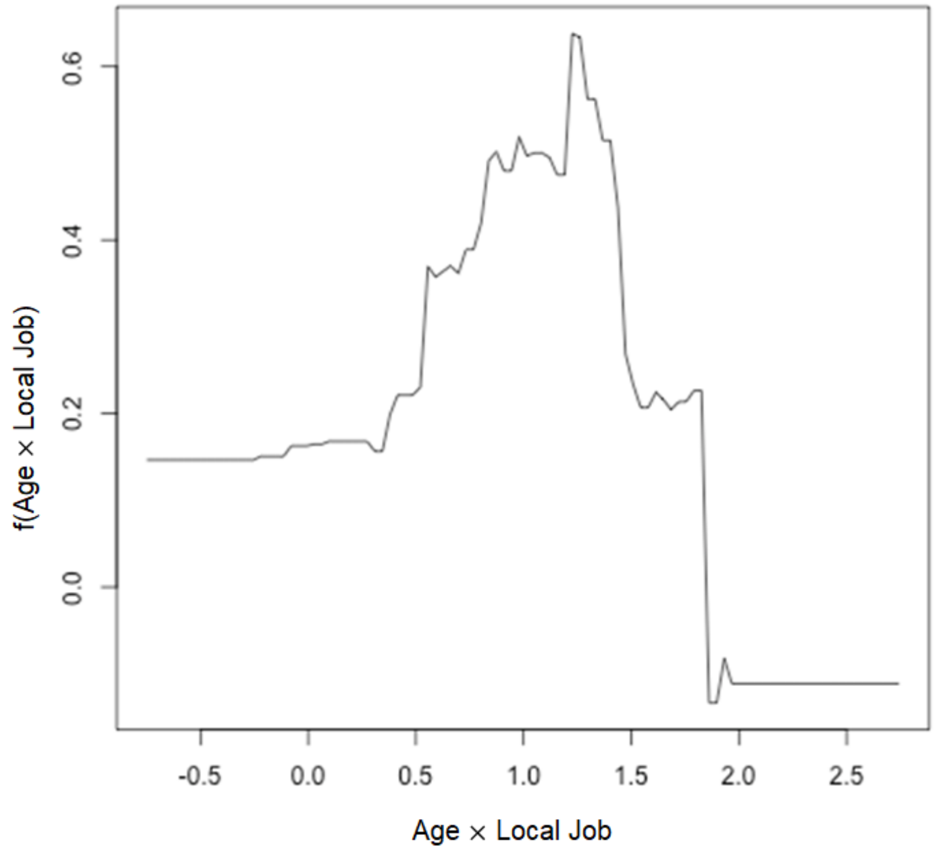

Figure 10: Effect of interaction of age and having local jobs on the decision to return.

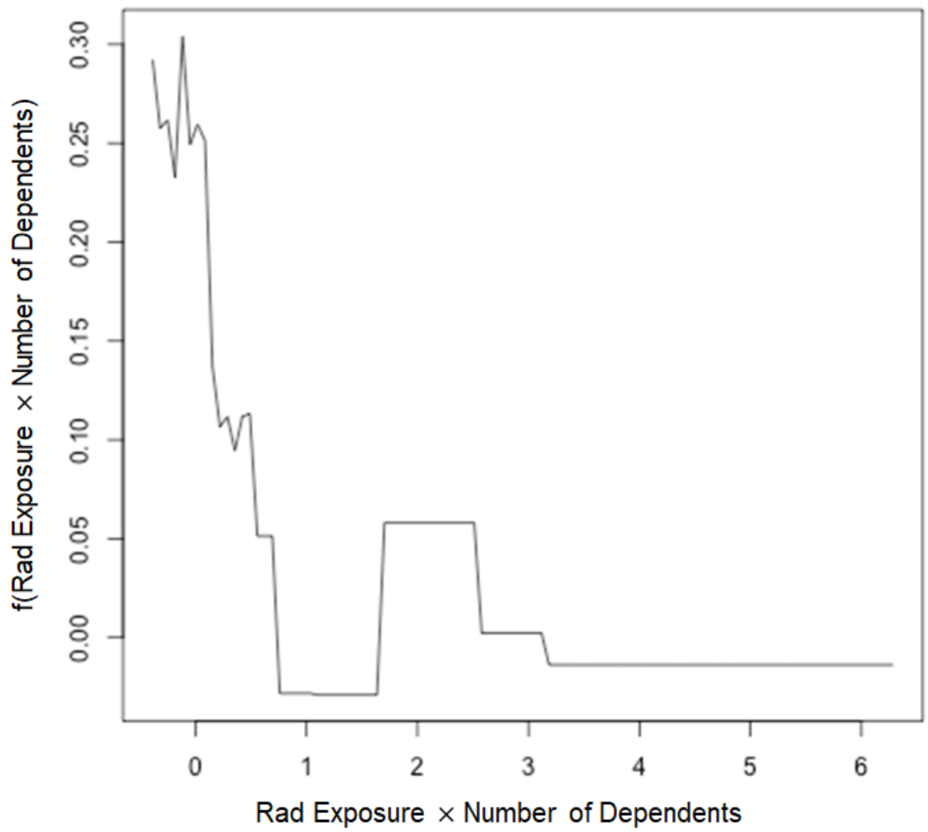

Figure 11: Effect of interaction of the radiation exposure and the number of dependents on the decision to return.

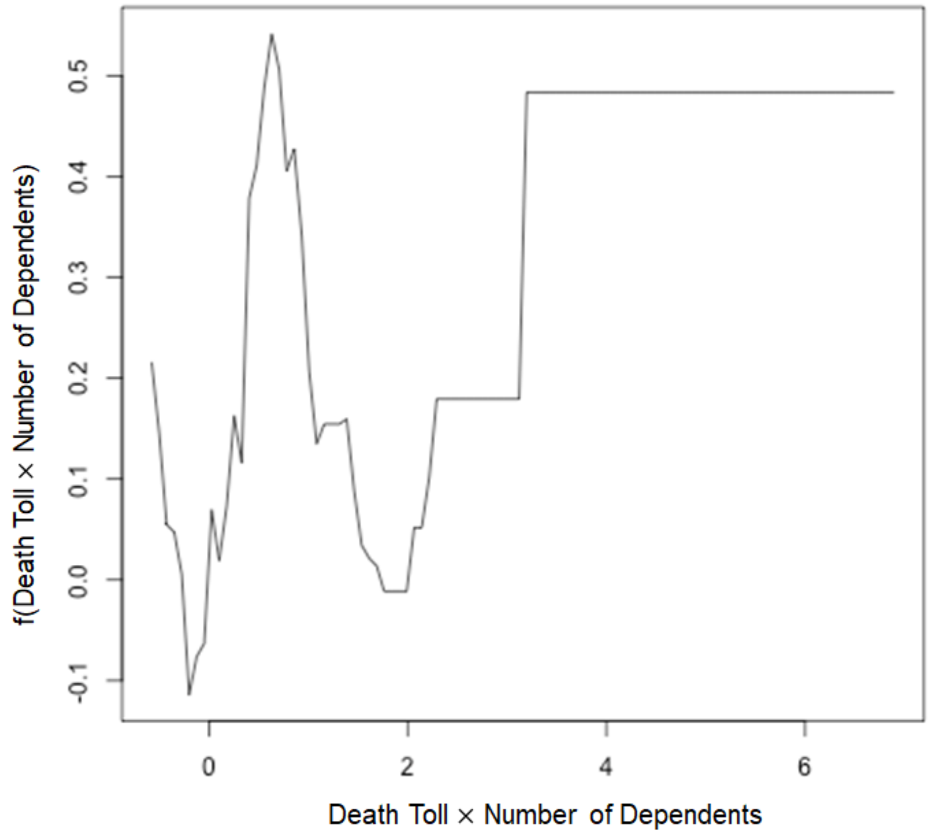

Figure 12: Effect of interaction of the death toll and the number of dependents on the decision to return

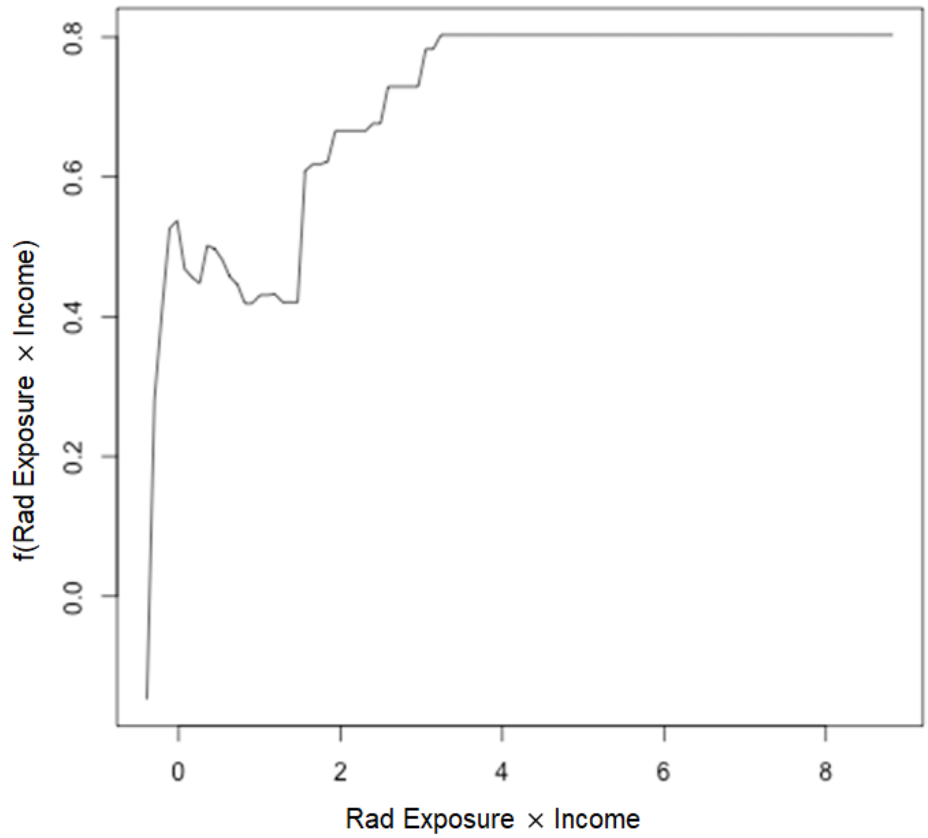

Figure 13: Effect of interaction of the level of radiation exposure and the level of income on the decision of to return.

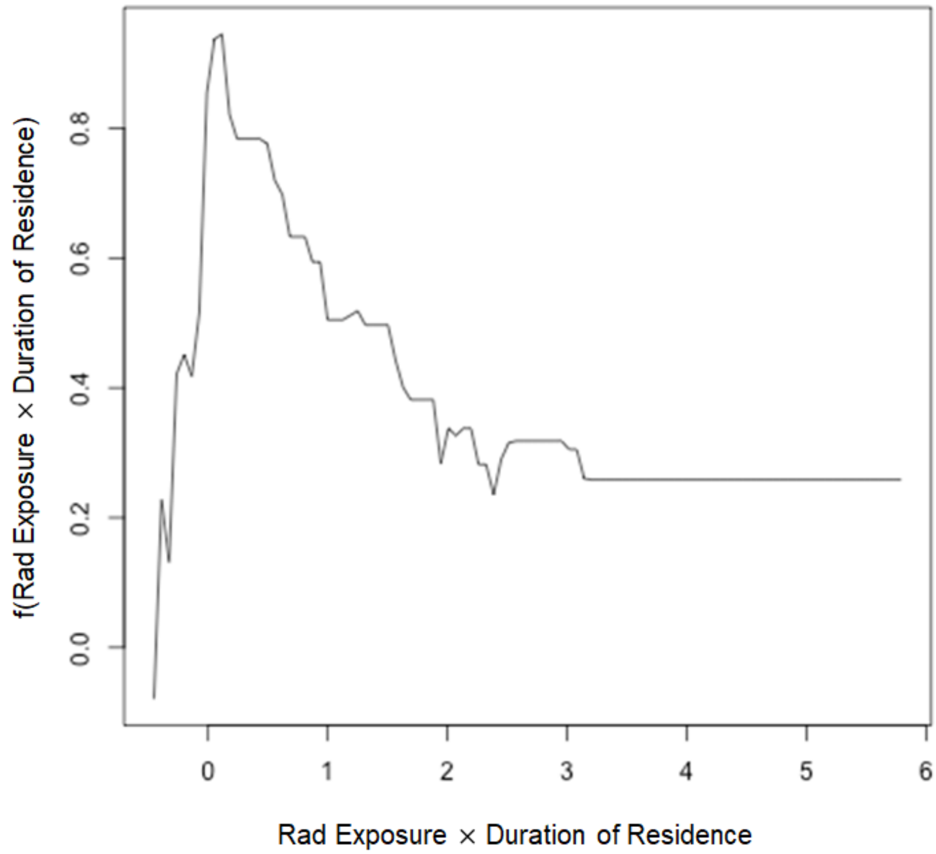

Figure 14: Effect of interaction of the level of radiation exposure and the duration of residence on the decision of to return.

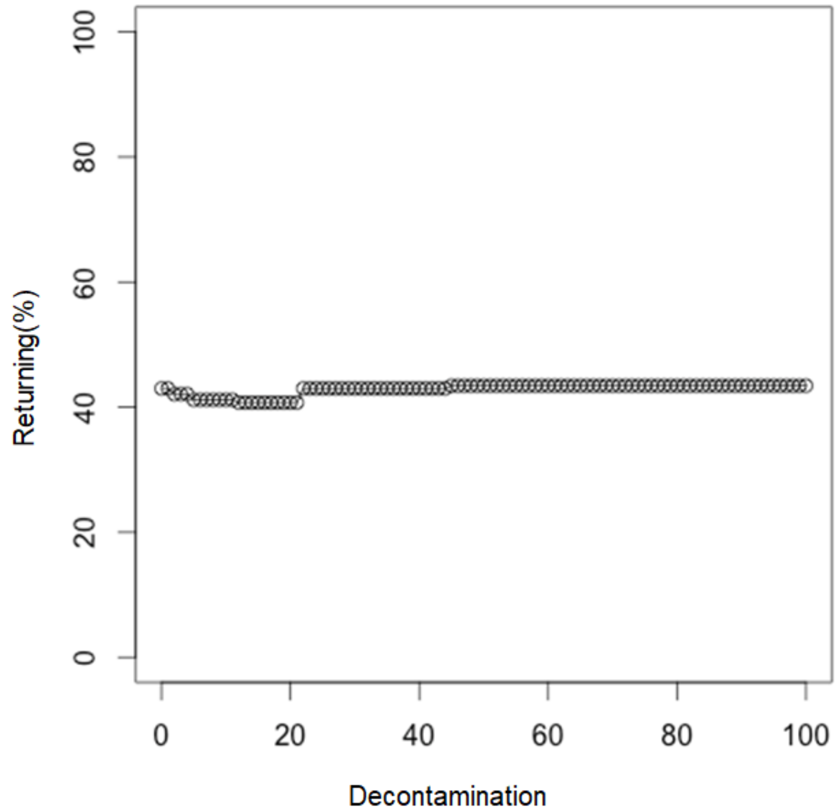

Figure 15: Prediction of the effect of decontamination on the decision to return.