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# CHARACTERISTICS OF UNDER EMPLOYMENT IN EL SALVADOR AND ITS POST-PANDEMIC IMPLICATIONS

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**Abstract:** The outbreak of the coronavirus disease or COVID-19, Originated in Wuhan, the capital of Hubei Province, China, at the end of 2019; it spread rapidly internationally generating a global health crisis. El Salvador, on March 21, 2020, began, under Executive Decrees, the limitation of economic activities, even causing business closures. Based on the information contained in the Multiple Purpose Household Survey (EHPM), carried out by the General Directorate of Statistics and Census of El Salvador, a classification model is implemented through the decision tree method, which allows people to be classified as Fully Employed or Under employed, in such a way that the impact of the pandemic on urban under employment in El Salvador can be investigated, analyzing the variables that determine it. Among the main variables found in the analysis are: social security contributions and poverty as determinants of under employment.
**Keywords:** decision tree, pandemic, poverty, employment, covid19.

## INTRODUCTION

With the health crisis generated by the emergence of Covid-19 in the country, a series of executive and legislative decrees were issued in mid-March 2020 with the aim of containing the spread of the virus. These decrees limited economic activities to those considered essential (food, beverages, pharmaceutical products), which led to the closure of companies nation wide, while those that produced essential products remained open.

Global economic growth projections show a drop in economic activities greater than those recorded during the 2008 financial crisis, and El Salvador is no exception. The World Bank estimates a negative global economic growth projection of -5.2%; while for El Salvador a rate of -5.4% is estimated for 2020, higher than the -3.6% expected in the Central American region (WB, 2020).

With the decline in economic activity and the restriction of economic sectors, employment has been affected. According to the IDB (2020), the percentage of decline in formal jobs in El Salvador will be -8.6% if the crisis is short-term, that is, if the recovery begins before the end of the year. Meanwhile, there would be a drop of -15.4% for a crisis in the medium term if it extends for three consecutive quarters and -23.9% for a prolonged recession, that is, not overcome in the medium term. With the decline in economic activity and the restriction of economic sectors, employment has been affected. According to the IDB (2020), the percentage of decline in formal jobs in El Salvador will be -8.6% if the crisis is short-term, that is, if the recovery begins before the end of the year. Meanwhile, there would be a drop of -15.4% for a crisis in the medium term if it extends for three consecutive quarters and -23.9% for a prolonged recession, that is, not overcome in the medium term.

Likewise, contributions to the country's Pension Savings System -as of April 2020- register a loss of 45,569 contributors compared to February (the month in which the quarantine had not yet started); that is, a significant loss of formal jobs.

Considering that, in 2018, according to the Multiple Purpose Household Survey (EHPM), of the total Economically Active Population, 55.9% were fully employed and 34.7% were under employed, (see table 1).

| PEA | Participation percentage |
|---|---|
| Fully occupied | 55.9% |
| Visible under employment | 5.7% |
| Invisible under employment | 29.0% |
| Unemployed | 7.6% |
| Applicant | 1.8% |
| Total | 100.0% |

TABLE 1. COMPOSISITION OF THE ECONOMICALLY ACTIVE POPULATION. YEAR 2018

Source: EHPM 2018

In addition, the situation observed in the economy due to the Covid-19 emergency, which directly affects employment due to restrictions on the operation of companies, raises the need to know the implications of changes in employment. Therefore, through the analysis of decision trees, we seek to know what characterizes urban under employment[1]. In this sense, the years 2008 and 2009 are analyzed to record the change in the face of an economic crisis and, in turn, the analysis of the behavior of the years 2016 to 2018 (most recent years available from the EHPM) to observe how the characteristics of under employment change.

The International Labour Organization (ILO) defines under employment as: *"under utilization or inefficient use of a worker's skills, qualifications or experience or when a worker is unable to work as many hours as he or she would like"* (ILO, 2018). Therefore, two forms of under employment are taken into account: that generated by insufficient income to reach the minimum wage or insufficient hours working less than 40 hours per week, which affects people's standard of living. The loss of formal employment and the need for income in families motivate informal activities, many of which are under employed.

During the validity of the decrees, the substitution of formal activity by informal activities has been observed (sales of fruit, sales of chemical products, sales of empanadas, etc.)[2].

Taking into account the definition of under employment given by the ILO, those variables that could characterize the under employed and those that - given the new conditions due to covi-19 - would be occurring are analyzed.

## METHODS

Decision trees are a non-parametric supervised classification method for categorical predictor variables (Díaz, 2005). This is one of the most important characteristics for selecting the classification method, since it is not necessary to meet assumptions as in parametric methods; and it allows to discriminate between categorical variables those that explain the model.

For each year studied, the cross-validation technique was used on the database of each year (5 groups or folds), and the following methods were put into competition: Neural Networks, Support Vector Machines, K Nearest Neighbors, Naive Bayes, Random Forests, Boosting and Decision Trees. For the databases of each year, the Decision Trees method was the second best method to classify the under Employed, very close to the first. This method is selected for this article due to its advantage in analyzing the variables that influence this classification. All of the above is done in free statistical software R, generating an R Markdown document. Using the training and testing philosophy for the final model (Trees of Decision), the database was broken down into a training base and a test base. In the first, the model is trained and in the second, its effectiveness in classifying new individuals is confirmed through analysis of the confusion matrix.

1. Urban under employment because in El Salvador the EHPM records information only at the urban level, since there is no measurement for rural under employment.

2. https://www.elsalvador.com/noticias/nacional/artistas-salvadorenos-cocolito-vende-frutas-verduras-cuarentena/715559/ 2020/

For this study, the response variable is the urban occupational status with two possible responses: 0 if fully employed and 1 if under employed. The classification model seeks to obtain high precision, to discriminate between fully employed and under employed, using the confusion matrix as a metric.

For the analysis, information from the EHPM database for the years 2008 and 2009 was used, taking into account that between those years the financial crisis that impacted the country's economy occurred, with the aim of identifying whether there are changes in the characteristics of the under employed. Likewise, the EHPM databases from 2016 to 2018 are used to observe the trend in the characteristics of under employment in more recent years. From the database, 11 significant categorical variables were selected for the study and that would explain under employment.

Within the set of variables, those that directly characterize people have been incorporated: age, sex, family status, kinship relationship, and number of grades passed. In the **age** variable, Categories divided into five classifications were created: 1- from 16 to 29 years; 2- from 30 to 39 years; 3- from 40 to 55 years; 4- from 56 to 65 years; and 5- 66 years or older. In the case of sex, divisions are made 1- male and 2- female. In the **family status** the following categories are taken: 1- accompanied, 2- married, 3- widowed, 4- divorced, 5- separated and 6- single. In the case of kinship **relationships**, it is divided into: 1- Head, 2- Husband, 3- Son, 4- Father, 5- Brother, 6- Son-in-law, 7- Grandson, 8- Father-in-law, 9- Other relatives, 10- Domestic employee, and 11- Others. While for the **number of degrees passed** The categories 0- does not read; 1- reads; 2- third cycle; 3- high school; 4- university; and 5- post-graduation were created.

Likewise, economic characteristics of the individual were incorporated, such as ISSS coverage, the sector in which he or she works, and the occupational category and occupational group (ISCO 88). In the category **ISSS coverage** The same classification of the EHPM of the years 2008 and 2009 is taken: 1- affiliated; 2- beneficiary and 3- does not have; and for 2016-2018 1- affiliated; 2- contributor and 3- does not have; in this case the affiliated category corresponds to the contributor category registered in the most recent years. In the case of **sector in which you work** It is 1- private and 2- public for the years 2008 and 2009, and 1- Private, 2- Public, 3- International Organization and 4- Other, for the years most recent. The occupational category is **occupational group (ISCO 88)** a 1- Armed forces; 2- Executive and legislative branches, administration directors; 3- Professionals, scientists and intellectuals; 4- Technicians and mid-level professionals; 5- Office workers; 6- Service workers and salespeople; 7- Farmers and skilled agricultural workers; 8- Officials, workers and craftsmen; 9- Plant and machine operators and assemblers; and 10- Unskilled workers.

And finally, a set of characteristics of the environment in which people develop is included, such as the **number of members in the household**, the poverty status of the household and the department where they live. In the case of the number of household members, the following categories were created from the numerical variable: 1- one or two members; 2- three members; 3- four members; 4- five members; and 5- more than six members. On the other hand, the **poverty condition** of the household was taken into account in the predefined categories: 1- extreme poverty; 2- relative poverty; and 3- not poor. Regarding the **department** of origin, the following categories were created: 1- West; 2- Central; 3- Paracentral; and 4- East.

## RESULTS

In the decision tree method obtained for the year 2008, the probability of the model correctly predicting an under employed person (positive precision) is 57.9%. While the probability of predicting that a person is not under employed when, in fact, he is not, is 77.3% with the set of variables selected.

When performing the discrimination, the tree takes as root variable "Social Security" which establishes whether the person is affiliated (1), beneficiary (2) or does not have social security (3). Thus, the first partition performed defines at 0.17 the probability that a person who is affiliated to social security has of being under employed, and where 34% of the population is found.

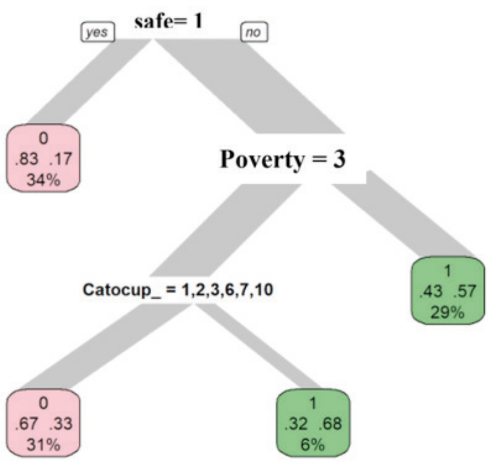


Fig. 1 Decision Tree 2008

If the person is a beneficiary or does not have social security, a new segmentation is made, using the variable "Poverty" as a criterion. This variable contains three categories: extreme poverty (1), relative poverty (2) and not poor (3). In this case, the reference category used is the people classified as "Not poor". If the people are beneficiaries or do not have social security and, in addition, do not belong to the category of "Not poor" but rather, are distributed between extreme and relative poverty; then they have a 0.57 probability of being under employed. 29% of the population is in this situation.

On the other hand, if the person is actually in the "Not poor" category, a new segmentation is made based on the "Occupational Category" variable. This variable has ten categories: employer or boss (1), self-employed with premises (2), self-employed without premises (3), cooperative member (4), unpaid family member (5), permanent employee (6), temporary employee (7), apprentice (8), domestic service (9) and others (10). Categories 1, 2, 3, 6, 7, 10 are used as a reference. If the person is in any of these categories, and, additionally, is considered not poor and is not affiliated with social security (is a beneficiary or does not have social security), then he or she has a probability of being under employed of 0.33, and approximately 31% of the population is in this combination of categories. Whereas, if you are not affiliated with social security, you are classified within the non-poor category but do not belong to categories 1, 2, 3, 6, 7, 10, if not, on the contrary, you are within one of the remaining categories: 4, 5, 8, 9; the person has a 0.68 probability of being under employed, where 6% of the population has these characteristics in 2008. The tree stops with these variables since it does not improve when incorporating the other variables even if they are used to determine the classification accuracy.

When applying the method to the EHPM sample for 2009, the year in which the financial crisis in the country worsened, the positive accuracy or correct detection of under employed people by the selected method is 57.6%, while the negative accuracy or correct detection of non-under employed people is 81.5%.

When analyzing the decision tree, it is observed that the root variable remains "Social Security" as in 2008, with the reference category “affiliated”, which has a probability of 0.17 of being under employed, and where 56% of the population is classified in this category.

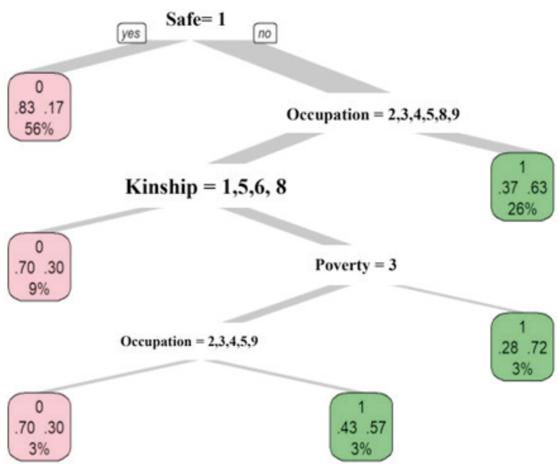


Fig. 2 Decision Tree Year 2009

If the person belongs to the beneficiary or non-affiliated categories of social security, a new classification variable is opened: “Occupation”. This variable is composed of ten categories: Armed Forces (1), Executive Branch, Legislative Branch, Directors of public administration (2), Professionals, scientists and intellectuals (3), Technicians and mid-level professionals (4), Office Employees (5), Service workers and sellers in shops and markets (6), Farmers and skilled agricultural and fishing workers (7), Officials, Operators and craftsmen of mechanical arts and others (8), Operators of facilities, machines and assemblers (9) and Unskilled workers (10). Categories 2, 3, 4, 5, 8, 9 are used as a reference to perform the segmentation. This way, if people do not belong to any of these mentioned categories (but rather to categories 1, 6, 10), their probability of being under employed is 0.63. Approximately 26% of the population has this condition.

On the contrary, if the persons are within the reference categories of the variable “Occupation”, the decision tree uses the variable “Kinship” to establish a new decision rule. This variable refers to the relationship that the person has with the Head of Household. It contains 11 categories: Head of Household (1), Wife, Partner (2), Son (3), Father/Mother (4), Brother (5), Son-in-law/Daughter-in-law (6), Grandson (7), Father-in-law (8), Other Relatives (9), Domestic Employee (10) and Others (11). The reference categories used are 1, 5, 6, 8. If the person belongs to any of these categories, in addition to belonging to categories 2, 3, 4, 5, 8, 9 of the variable “Occupation” and being a beneficiary or not having social security, then the probability of the person being under employed is 0.30. Within this probability is 9% of the population.

If within the variable “Kinship” people belong to categories 2, 3, 4, 7, 9, 10, 11, the variable “Poverty” is used to establish a new classification. Category 3 (Not poor). In this sense, if people do not belong to this category, but instead belong to the categories of extreme and relative poverty, they have a 0.72 probability of being under employed. 3% of the population is in this situation.

Now, if the person is in the “Not poor” category, the “Occupation” variable is used -once again- to perform the segmentation. In this case, 2, 3, 4, 5, 9 are used as reference categories. If the person is in these categories, he or she has a probability of 0.30 of being under employed (3% of the population). Whereas, if he or she is not in these categories, his or her probability of being under employed is 0.57 (3% of the population).

Based on the results for the decision trees for the years 2008 and 2009, we proceed to analyze the EHPM information for recent years.

In 2016, the positive accuracy of the decision tree model is 76%, while the negative accuracy is 84%. Once again, the root variable of the decision tree is “Social Security”. This variable contains a new categorization as of this year. Thus, category 1 refers to “Affiliates”, category 2 contains "Contributors" and category 3 refers to people who "Do not have social security". At this point, it is essential to establish the difference between affiliates and contributors. According to ECLAC (2018), the term affiliate refers to the person who is registered with social security without necessarily making regular contributions to their individual fund. While the contributor is the person who transfers the mandatory percentage of the gross salary to their individual account.

In this sense, the contributors represent a subset of the affiliates.

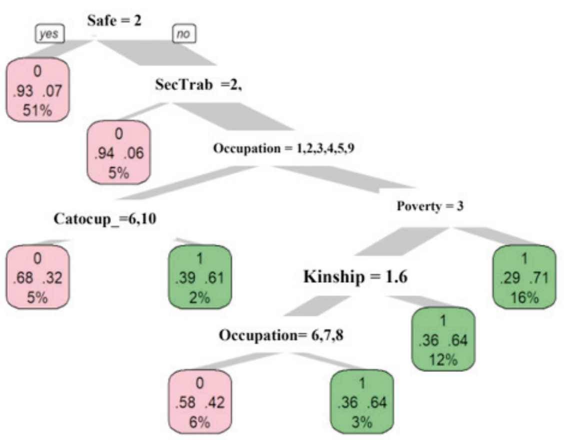


Fig. 3 Decision Tree 2016

In this case, the reference category is "contributor". Thus, if a person is a contributor to social security, he or she has a 0.07 chance of being under employed. Approximately 51% of the total population is in this category.

If, on the other hand, the person is in the affiliated category or does not have social security, a new segmentation is made based on the variable "Work Sector". The variable is divided into three categories: Private (1), Public (2), International Organization (3) and Other (4). For the decision rule, the categories Public and International Organization are taken. In this sense, if the person belongs to one of these two work sectors, he or she has a 0.06 probability of being under employed. 5% of the population is not a contributor to social security (that is, they are affiliated or do not have it) and work in the public sector or in an international organization.

Now, if the person works in the private sector or another, a new partition of the decision tree is opened using the variable "Occupation". The methodology uses categories 1, 2, 3, 4, 5, 9 to establish the decision rule. If the people belong to these categories, a new branch is opened within the decision tree with the variable "Occupational category" from which it uses the categories permanent employee (6) and others (10). This way, if the person belongs to any of these occupational categories and, in addition, belongs to categories 1, 2, 3, 4, 5, 9 of the variable "Occupation", belongs to the private sector or another and is not a social security contributor (affiliated or does not have social security), then the person has a probability of 0.32 of being under employed. 5% of the population meets these characteristics. On the contrary, if the person belongs to categories 6 and 10 of the variable

"Occupation" people have a 0.61 probability of being under employed. 2% of the population belongs to this group.

On the other hand, if people do not belong to categories 1, 2, 3, 4, 5, 9 but rather are within categories 6, 7, 8, 10, a new division is opened based on the variable "Poverty" with the reference category Not poor (3). If the person belongs to one of the categories of the variable "Occupation" 6, 7, 8, 10 and, in addition, belongs to the categories of extreme and relative poverty, then he or she has a 0.71 probability of being under employed. 16% of the population met these conditions in 2016.

On the other hand, if the person belongs to the Non-Poor category, then a new decision rule is established with the variable "Kinship". Categories 1 and 6 are used as reference. Thus, if the person does not belong to these categories, he or she has a 0.64 probability of being under employed. Approximately 12% of the population is in this situation.

When the person does belong to categories 1 and 6, a segmentation is carried out again with the variable "Occupation" taking categories 6, 7, 8 as a reference. If the person does not belong to these categories, they have a probability of 0.68 of being under employed (3% of the population), while if they are located within one of these categories, the probability of being under employed is 0.42 (6% of the population).

In 2017, when applying the decision tree method to the database, the positive accuracy of the model is 73%, while the negative accuracy is 79%. For this year, the result is that the root variable is still "Social Security" with reference category 2; that is, that the person is "Contributor". It is observed that, if the person is in this condition, he or she has a probability of 0.15 of being under employed. Approximately 52% of the population is in this situation.

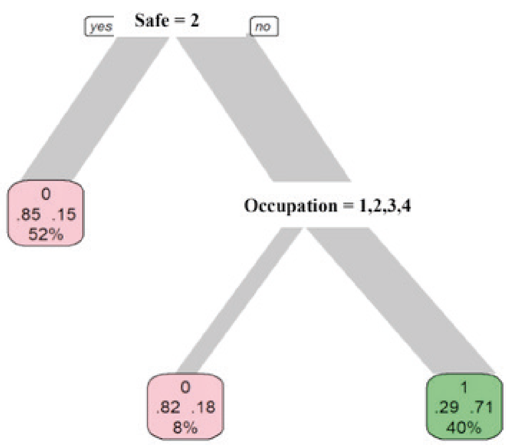


Fig. 4 Decision Tree year 2017

On the other hand, if the person belongs to the categories "Affiliated" (1) and "Does not have social security" a new decision criterion is used with the variable "Occupation" taking as reference categories 1, 2, 3, 4. If the person, apart from not being a social security contributor, is within these categories, he or she has a 0.18 probability of being under employed (8% of the population). Otherwise, that is, if the person belongs to categories 5, 6, 7, 8, 9, 10 - always fulfilling the condition of being affiliated or not having social security - then the probability of being under employed is 0.71. 40% of the population is in this classification.

For the year 2018, the decision tree analysis for 2018 shows that the positive accuracy of the model is 70%, while the negative accuracy of the same is 85%. For this year the root variable continues to be "Social Security" taking as reference category "Contributor".

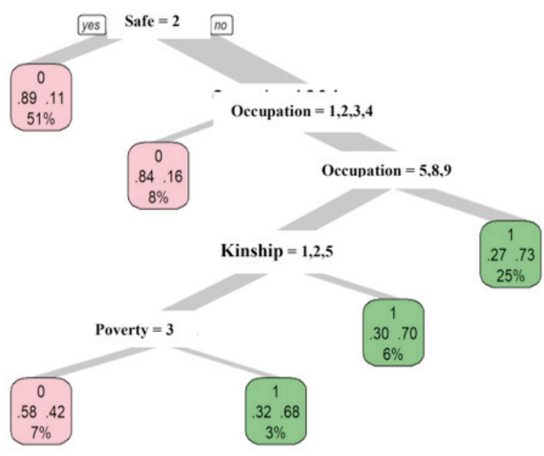


Fig. 5 Decision Tree year 2018

If the person belongs to this category, he or she has a 0.11 probability of being under employed. 51% of the population is in this condition. If, on the other hand, the person belongs to the group of "Affiliated" or "Does not have social security", a new decision rule is established with the variable "Occupation" taking as reference categories 1, 2, 3, 4. If the person belongs to these categories, the probability of being under employed is 0.16. 8% of the population is grouped in this situation.

If not, another segmentation rule is established, always with the variable "Occupation", but this time taking categories 5, 8, and 9 as a reference. Thus, if the person does not belong to these categories (but rather to categories 6 and 10), a probability of 0.73 of being under employed is estimated. Approximately 25% of the population is part of this set. However, if the person actually belongs to categories 5, 8, and 9, a new segmentation is established, taking the variable "Kinship" with reference categories 1, 2, and 5 for the decision rule. If the person does not belong to these three categories, their probability of being under employed is 0.70. 6% of the population is in this condition. If not, another segmentation rule is established, always with the variable "Occupation", but this time taking categories 5, 8, and 9 as a reference. Thus, if the person does not belong to these categories (but rather to categories 6 and 10), a probability of 0.73 of being under employed is estimated. Approximately 25% of the population is part of this set. However, if the person actually belongs to categories 5, 8, and 9, a new segmentation is established, taking the variable "Kinship" with reference categories 1, 2, and 5 for the decision rule. If the person does not belong to these three categories, their probability of being under employed is 0.70. 6% of the population is in this condition. If not, another segmentation rule is established, always with the variable "Occupation", but this time taking categories 5, 8, and 9 as a reference. Thus, if the person does not belong to these categories (but rather to categories 6 and 10), a probability of 0.73 of being under employed is estimated. Approximately 25% of the population is part of this set. However, if the person actually belongs to categories 5, 8, and 9, a new segmentation is established, taking the variable "Kinship" with reference categories 1, 2, and 5 for the decision rule. If the person does not belong to these three categories, their probability of being under employed is 0.70. 6% of the population is in this condition.

Contrary to this, if the person belongs to one of the categories 1, 2, 5 of the variable "Kinship", a new division is made with the variable "Poverty" with the reference category "Not poor". If the person does not belong to this category, but rather to the categories "Extreme poverty" and "Relative poverty", the probability of being under employed is 0.68. 3% of the population is in this group. Whereas, if the person belongs to the category "Not poor", their probability of being under employed is 0.42. Around 7% of the population is in this condition.

## DISCUSSION

The results obtained show that the root variable in all the years analyzed is "Social Security" with the same reference category "Contributor". The decision rule always establishes that, by not being a contributor, the probability of the person being under employed increases compared to people who do contribute to social security.

Between the years 2008 and 2009, when the crisis in the country developed, a difference is observed in the improvement of the model in 2009 by incorporating more variables, so a tree with more branches representing the selected variables is presented.

In the most recent years, it is observed that, within the variables included in the model, in all the years included 2008 and 2009, and except in 2017, the variable "Poverty" appears with the reference category "Not poor" as a decision rule. It is observed that, by belonging to the "Not poor" group, the probability of being under employed decreases considerably in each year of study.

Likewise, the variable occupation is crucial in each of the years – except for 2008 – to define the probability of being under employed. The categories: (1) public administration directors (2), Professionals, scientists and intellectuals (3), Technicians and mid-level


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professionals (4) are the reference categories that are repeated in each year in which this variable appears. Belonging to these categories considerably reduces the risk of being under employed.

Considering the variable "Occupation", the categories that are taken as a reference in a smaller proportion than the rest are the categories: Service workers and sellers in shops and markets (6) and Unskilled workers (10). Category 6 is used as a reference only in the year 2016, while category 10 is not used as a reference in any year of the study. This indicates that belonging to any of these categories increases the probability of being under employed.

For its part, the variable "Kinship" is shown in the decision trees of 2009, 2016 and 2018 as a key variable to carry out the segmentation. In each year mentioned, the common reference category is (1) Head of household, establishing in each case that being the head of the household significantly reduces the risk of being under employed.

## CONCLUSIONS

The restrictions on economic activity generated by the Covid-19 pandemic have had an impact on formal employment. In this regard, it is estimated that, as of April 2020, the number of contributors has decreased to the level that existed 4 years ago with a decrease of 6.15% (Superintendencia del Sistema Financiero, 2020). According to the decision tree analysis, contributing to social security is essential to reduce the risk of being under employed. Thus, as the number of contributors decreases, the probability of them becoming under employed increases.

Another finding is that belonging to the extreme and relative poverty categories increases the probability of being under Employed. Along these lines, the Inter-American Development Bank (2020) establishes that, "*The combined impact of the measures and the recession will have significant repercussions at the household level. Micro estimates simulating the shock suggest that the effects at the household level are considerable, and the number of poor people could increase by 600 thousand people*". Given the importance of belonging to the "Not poor" category to reduce the probability of being under employed, the increase in the number of poor people due to the pandemic will influence the increase in under employed people in El Salvador.

Therefore, policy proposals must be aimed at reducing the post-pandemic impact on poverty as one of the characteristics that increase the probability of under employment. Likewise, the period in which restrictions are maintained increases the impact of the decline in formal employment according to the IDB (2020), so short-term measures reduce these effects.

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