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A Fresh Look at Out-of-Pocket Health Expenditures after More than a Decade Health Reform Experience in Turkey: A Data Mining Application

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ABSTRACT

Strategies to combat with poverty are at the top of the agenda of Turkish health reform process. Health reform completed more than a decade and improvements in insurance coverage, incorporating green card scheme into the system are major parts of these reform process. There is a need to fresh look at the long term effects of this reform process on out-of-pocket (OOP) health expenditures and predictors of these expenditures. This study aims to fill this void by examining the trend of OOP health expenditures in Turkey from 2003 to 2015 and predictors of OOP health expenditures. Data came from Turkish Statistical Institute (TURKSTAT). Random forest (RF) and neural network (NN) methods were compared to find predictors of OOP health expenditures for the year 2015 by generating a decision tree. RF outperforms NN and showed classification accuracy, sensitivity and specificity, value of 0.5352, 0.2925, 0.7855 respectively. The area under the ROC curve was 0.5539. Study results revealed that OOP health expenditures increased from 2003 to 2015. Moreover, education, marital status, being 65 years of age or older, income group and household size are important variables to predict OOP health expenditures respectively. This paper provides a current look at the effect of poverty alleviation strategies on OOP health expenses and emphasize that OOP health expenses have an increasing trend despite poverty reduction policies. New policies are needed to control increasing trend of OOP health expenditures in Turkey, it is hoped that this study will inspire health policy makers to fight against continuously increasing trend of non-zero OOP health expenditures in Turkey.

Keywords: Out-of-Pocket Health Expenditures, Poverty Alleviation, Turkey, Random Forest, Neural Network
JEL Classifications: I10, I32, 053, C53, C53

1. INTRODUCTION

Effective health system is essential for developing a strong economy, because economy and health system have a close relationship (Leach-Kemon et al., 2012). Developing countries like Turkey should make a priority to improve their health care services. Current evidences state that in Turkey the impact of government expenditure on health has a positive effect on economic growth (Kurt, 2015). Rapid decline in the poverty is parallel with a growth of middle income class and there has been improved access to basic services such as health and education in Turkey. Turkey experienced significant economic growth after 2001. World Bank (WB) emphasize this growth and state that the growth of Turkey is relatively socially inclusive and a rapid decline in the poverty rate observed after that time (WB, 2014). Improved access to basic services has been made possible by increases in public spending after the 2001 economic crisis that Turkey faced. Acemoğlu and Üçer (2015) called the growth of Turkish economy during 2002-2006 as "high-quality economic growth" because of institutional reforms, improvement in competitive private sector and better participation of education and health services emerged. Pamuk (2007) maintains that after financial crisis the priority of the government is to reduce public dept and this has led to some "economic stability" rather than economic growth. After 2001 the government was able to reduce service burden, because of public sector reform and that create a fiscal space to facilitate the increases in spending in health and to improve socially inclusive growth (WB, 2014).

Historically, Turkey established a public health capacity for health care services since the late 1940s. Significant changes in health system started since the establishment of Health Transformation Program (HTP) in 2003 (WHO-Europe, 2012). Primary aim of this transformation program is to improve effectiveness, efficiency and to constitute equality of access to health care services (Yilmaz, 2013). Addressing shortcomings related with financial protection, improving health outcomes and protecting financially disadvantageous populations are major aims of this reform process (Atun, 2015). However, health expenditures increased during the years between 2003 and 2008 concurs with the time periods of high-quality economic growth (Acemoğlu and Üçer, 2015). In these circumstances, HTP address two major financial shortcomings. The first one related to low health expenditures, the second one is unequitable health insurance system (Atun et al., 2013). One of the substantial parts of poverty alleviation strategies is including consolidation of insurance schemes under one institution, to achieve this objective most comprehensive part of reform policies completed in 2008 by introducing general health insurance (GHI) (Hazama, 2015). GHI Law bring together the five health insurance funds within a unified GHI integrated within the social insurance organization (Sosyal Güvenlik Kurumu-SGK) (Atun et al., 2013). Another major change of Ministry of Health (MoH) is transfer of all public hospitals formerly owned by social security funds to the MoH (Yilmaz, 2013). These considerable changes reduce the gap between different occupational status in terms of health expenditures. There exist 3 million increase in green card users from early 2000s to late 2000s (Atun et al., 2013). As a result of all of these regulations, there is a considerable increase in general satisfaction with health care services. According to the life satisfaction survey study results, general satisfaction from health services up 39.5% in 2003-75.9% in 2013 (TURKSTAT, 2011). In addition to that, literature suggests that high levels of informality because of high level of informal employment makes co-ordination and co-operation of health care services more difficult before 2006 (Yilmaz, 2013). To overcome these difficulties in 2006, as a part of health reform, patients are obliged to pay contributory payments in order to have outpatient health care services and medication. It has been stated that contributory payments is a kind of a regulation to prevent unnecessary outpatient visits and excessive use of medications (Hazama, 2015), this is expected to reduce out-of-pocket (OOP) health expenditures.

Despite, health transformation led to profound changes in health financing and takes great interest of researchers, recent studies reported that the level of OOP health expenditures increased during health reform period. Erus and Aktakke (2012) state that non-zero OOP health expenditures increased from 2003 to 2006. Yardım et al. (2014) show that the volume of OOP health spending increased between 2003 and 2009. Both of these studies are based on a nationally representative health survey data, but they are failed to provide information about whether poverty reduction strategies are effective to fight against increasing trend of OOP health expenditures. Because these studies are not providing information after 2008, which is the time when poverty reduction strategies started to observe. This study was originally conceived to fill this void by providing a fresh look at OOP health expenditures after more than a decade health reform experience in Turkey. After determination of the level of OOP health expenditures for the years between 2003 and 2015; predictors of OOP health expenditure examined by using a data mining approach for the year 2015. The organization of this paper as follows: Section two explains materials and methods of this study, section three presents study results, section four discusses study results, section five is conclusion part of this study.

2. MATERIALS AND METHODS

2.1. Data

Data came from TURKSTAT household budget survey (HBS) for the years between 2003 and 2015. HBS is a national survey mainly focus on consumption expenditure. Income, expenditure and socio-demographic characteristics of households and household heads can be obtained from this dataset. Data collected from a representative stratified clustered sample and gathered from the sampled households. 25.764, 8.544, 8.559, 8.558, 8.548, 8.549, 10.046, 10.082, 9.918, 9.987, 10.060, 10.122 and 11.491 represents total number of households in the survey for the years 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014 and 2015 respectively. The total number of households made non-zero OOP health expenditure were 10.512, 3.898, 4.335, 4.501, 4.375, 4.625, 5.956, 6.423, 6.366. 6.358, 7.112, 6713 and 6801 for the years 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014 and 2015 respectively. Mean annual OOP health expenditure of households used as a dependent study variable. Socio-demographic characteristics of households and household heads was used to predict OOP health expenditures for the year 2015.

2.2. Analysis Procedure

Analysis procedure started with presentation of descriptive statistics, after that Pearson correlation coefficient was used to examine multicollinearity among independent variables. Then, natural logarithm of OOP health expenditure was taken to normalize the distribution of that variable. After that, OOP health expenditure variable binary coded by using mean value as a cut-off point. After that, balanced categories of dependent variable is determined and random forest and neural network (NN) data mining methods performed to examine predictors of OOP health expenditure. Figure 1 summarizes the analysis procedure.

As presented in Figure 1, in this study before the analysis procedure, multicollinearity analysis among independent variables was performed by using Pearson correlation coefficient (r_p) which is one of the parametric correlation measures. After multicollinearity detection, natural logarithm of dependent variable, which is annual mean OOP health expenditure, was taken to normalize highly skewed distribution. Taking natural logarithm is common among health economists to deal with skewed expenditure variables (Manning and Mullahy, 2001). Then, mean value of log-transformed OOP health expenditure was used as a cut-off point and balanced groups are obtained for binary coding of dependent variable. Finally, RF and NN was applied on the data for the year 2015 to determine predictors of OOP health expenditure.

There is a lack of literature about implementation of data mining on health expenditure. Li et al. (2013) stated that machine learning algorithms and RF are effective methods for risk adjustment of patient expenditures. Walczak and Scharf (2000) examine surgical patient costs using NN, study results show that NN is a useful approach to reduce patient costs in surgical care. RF is one of the data mining methods that generates number of trees in the forest and average over many trees. RF uses classification and regression tree (CART) algorithm and proposed by Brieman (2001). CART algorithm produces regression tree when outcome is continuous and classification tree when the outcome is categorical. Number of trees in RF is a kind of a hyperparameter. However, how many trees are needed to gain optimal prediction results is a controversial topic in the literature. Prevailing evidence seems to suggest that as the numbers of trees grow, it does not always mean the performance of the forest significantly better than previous forests. The best way is to benchmark different applications (Oshiro et al., 2012). NN is a nonlinear parallel computing paradigm for information analysis. NN is based the neural structure of the human brain. It can be used for prediction or classification (Witten and Frank, 2005). NN consider classification as one of the most dynamic research and application areas (Saravanan and Sasithra, 2014). A probabilistic NN was used for NN classification problems which is a four-layer feed forward NN. It was derived from Bayesian network and statistical algorithm called Kernel Fisher discrimination analysis (Zeinali and Story, 2017).

In this study k-fold cross validation was used to improve the performance of the predictive statistical models. This is one of the popular model validation techniques, to estimate how accurately a predictive model will perform in practice. Cross validation includes a partitioning a sample of data into complementary subsets, performing training set and validating the analysis on validation or testing set. Performing multiple rounds of cross validation using different partitioning is one of the most common ways to reduce variability (Kohavi, 1995). Classification accuracy, specificity, sensitivity and area under the ROC curve (AUC) are common performance measures of data mining classification methods (Dreiseitl and Ohno-Machado, 2002). Classification accuracy is the number of correct predictions made divided by the total number of predictions made (multiplied by 100 to convert into percentage) (Wheadon, 2014). Sensitivity and specificity are other binary classification performance measures. Sensitivity is the ability of a test to correctly classify true positives (classify an individual as "diseased"). Specificity is the ability of a test to correctly classify true negatives (classify an individual as "disease - free") (Parikh et al., 2008). Finally, AUC measures classification accuracy. This curve is a plot of q = sensitivity and p = 1-specificity for all possible threshold values. The value of 1 show that this test is 100% accurate (Faraggi and Reiser, 2002).

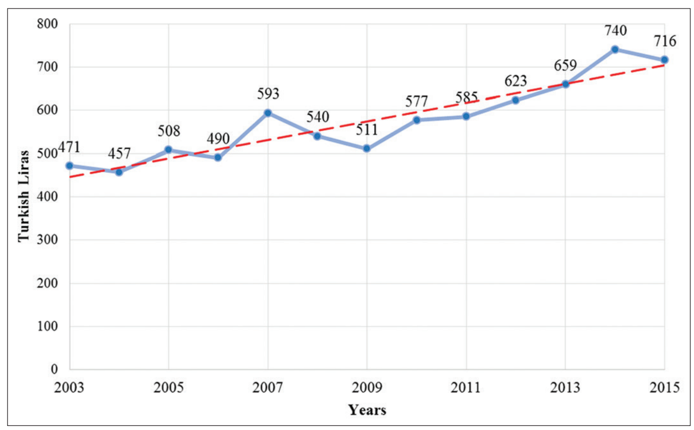
3. RESULTS

3.1. Descriptive Statistics

3.1.1. Mean annual OOP health expenditures from 2003 to 2015

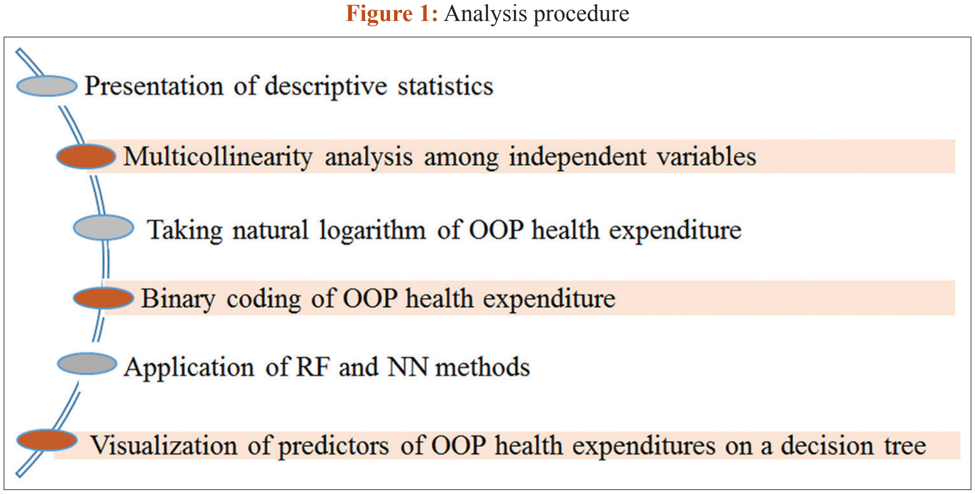
Graph 1 shows mean annual values of non-zero OOP health expenditures from 2003 to 2015. OOP health expenditures are deflated by using 2003 as a base year and consumer price index values. It is seen that OOP health expenditures rises from 471 ₺ in 2003 to 716 ₺ in 2015. It is clear to say that non-zero OOP health expenditures increased nearly two times for Turkey after more than a decade experience of poverty alleviation strategies in

Graph 1: Mean annual non-zero out-of-pocket health expenditures from 2003 to 2015



[a]Mean annual out-of-pocket (OOP) health expenditure per households. [b]OOP health expenditures representing those with non-zero OOP health expenditure. [c] OOP health expenditures are deflated by using 2003 as a base year (100) and consumer price index values. [d] In 2003 1.49 Turkish liras = 1 US $ (average), (Central Bank of the Republic of Turkey-CBRT: http://www.tcmb.gov.tr)

Figure 1: Analysis procedure



health. It is necessary to notice that, continuously increasing trend of OOP health expenditures is obvious for the years 2009-2014.

The following sections present descriptive statistics about socio-demographic characteristics of households and household heads and normalization process of OOP health expenditure for the year 2015 respectively.

3.1.2. Descriptive statistics about socio-demographic characteristics of households and household heads

Table 1 shows descriptive statistics about socio-demographic characteristics of households and household heads for the year 2015. It is seen that proportion of those with non-zero OOP health expenditure is higher for male (86.4%), <65 years of age (80.4%), formally educated (85.9%), married (84.4%), insured (95.9%), currently employed (66.4%) headed households. Additionally, the proportion of non-zero OOP health expenditure is high for households representing high income quantiles (82.9%) who are faced with more OOP health expenditures than households belonging low income quantiles. Finally, average annual non-zero OOP health expenditure of households is 1134 (standard error [SE] = 0.73) and mean household size (HHS) is 3.64 (SE = 0.02) for the year 2015. In this classification, high risk groups to face with high OOP health expenditure are coded as 1 and low risk groups are coded as 0.

3.1.3. Multicollinearity analysis of independent variables

Figure 2 presents correlogram graph for independent variables generated by using Pearson correlation coefficients (r_p). It this figure yellow and red colors are representing negative correlation coefficients, whereas light and dark blue colors are presenting positive correlation coefficients. It is seen that correlations among independent variables are low ($r_p < 0.70$) apart from the relationship between gender and marital status ($r_p = -0.74$, $P < 0.01$). To avoid collinearity, we excluded one of these variables from the analysis (Gen: Gender).

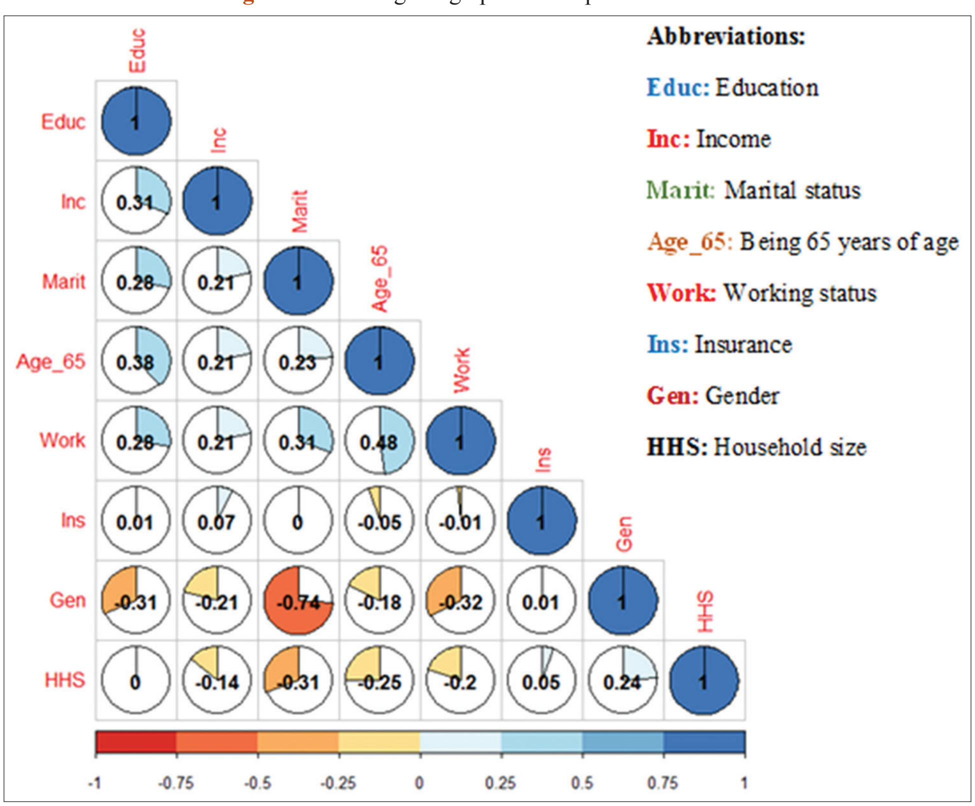
3.1.4. Normalization of the distribution of OOP health expenditure

As a part of the preliminary analysis procedure, the distribution of OOP health expenditure examined and it is seen that the distribution is highly skewed (Graph 2a). Health economists state that, taking natural logarithm of positively skewed health expenditure variable leads to solve analytical problems (Manning and Mullahy, 2001). In accordance with the literature, in this study before performing data mining methods and to determine predictors of OOP health expenditure, natural logarithm of OOP health expenditure was taken. Graph 2b shows that the distribution of OOP health expenditure become normal after transformation.

3.1.5. Binary coding of OOP health expenditure

Literature suggest that balancing the groups of dependent variable is essential to improve prediction accuracy of prediction models (Witten and Frank, 2005). As a part of the preliminary analysis procedure, natural logarithm form of OOP health expenditure was used to generate balanced groups to improve prediction accuracy of the model for predicting OOP health expenditure. Log-transformed version of OOP health expenditure divided into two balanced groups. Mean value of log-transformed version of OOP health expenditure of households was determined as a cut-off point to categorize dependent variable. Table 2 shows

Figure 2: Correlogram graph for independent variables



Graph 2: Histogram graph of out-of-pocket health expenditure before (a) and after (b) taking natural logarithm

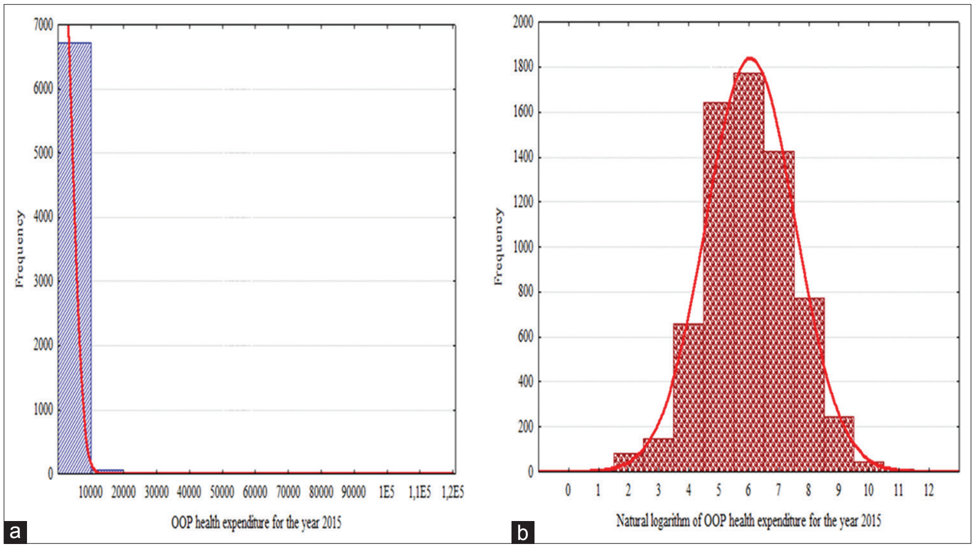


Table 1: Socio-demographic characteristics of non-zero OOP health expenditure households and household heads for the year 2015

Categoric variables	Code	n (%)*
Gender		
Male	1	5903 (86.4)
Female	0	898 (13.6)
65 years of age or older		
<65	0	5537 (80.4)
≥65	1	1264 (19.6)
Education		
No formal education	1	842 (14.1)
Formal education (primary, secondary, high school, university, master and doctorate)	0	5959 (85.9)
Marital status		
Married	0	5804 (84.4)
Not married (never married, divorced and widowed)	1	997 (15.6)
Health insurance		
Insured (compulsory insurance, optional insurance and green card)	0	6529 (95.9)
Uninsured	1	272 (4.1)
Employment status		
Currently employed	0	4519 (66.4)
Currently not-employed	1	2282 (33.6)
Income quantiles		
Low income quantile (20%)	1	1016 (17.1)
High income quantiles (40%-60%-80%-100%)	0	5785 (82.9)
Total**		6801 (100)
Continuous variables	**Mean**	**SE**
Annual OOP health expenditure of households***	1134	0.73
HHS	3.64	0.02

*Descriptive statistics presented by using unweighted numbers (n) and weighted percentages (%). **Total number represents households made non-zero OOP health expenditures for the year 2015. ***Annual non-zero OOP health expenditure of households represents for only the year 2015 (not-deflated). SE: Standard error, OOP: Out-of-pocket, HHS: Household size

balanced groups when log-transformed mean value was used as a cut-off point.

3.1.6. Application of data mining classification methods to predict OOP health expenditure

Table 3 presents RF and NN performance results to predict OOP health expenditures for the year 2015 from model 1 to 10. It is seen that prediction accuracy values for RF are higher than NN. Higher prediction accuracy results (AUC) were obtained for both of two methods, when "k" parameter determined as 9, for model 9, for RF (100 trees) (AUC = 0.5539) and NN (AUC = 0.5528) respectively. Classification accuracy, sensitivity and specificity results are; 0.5352, 0.2925, 0.7855 for RF (100 trees) and 0.5345, 0.4199, 0.6526 for NN for model 9 respectively. Moreover, RF is faster in the computing speed in terms of running time values.

3.1.7. Predictors of OOP health expenditures

Graph 3 figures out results of a decision tree by using RF algorithm which was generated by 100 trees. The decision tree graph shows that education is the most important in the prediction of OOP health expenditure. Marital status, being 65 years of age or older, income group and HHS are other important variables to predict OOP health expenditures respectively.

4. DISCUSSION

Study results show that after more than a decade health reform experience to combat with poverty in Turkey, the level of non-zero OOP health expenditures has an increasing trend from 2003 to 2015. It is clear to say that this increasing trend became obvious from 2009 to 2014 refers to the time period of integrated insurance system come into force and implemented more than 5 years started from 2008. Poverty reduction strategies become obvious during that time and patients have an incentive to use more health care services than before. This is consistent with the literature that insurance reduces financial risk and encourages people to seek care (Wagstaff and Lindelow, 2008).

Additionally, results of this study shows that education is the most important predictor of OOP health expenditures. Other important predictors are being married and being 65 years of age or older.

Table 2: Balanced categories of OOP health expenditure

Group code	Group code represents for	Log-transformed OOP health expenditure value	Number of households in groups	Percent
0	Low OOP health expenditure households	<6.01	3453	50.8
1	High OOP health expenditure households	≥6.01	3348	49.2

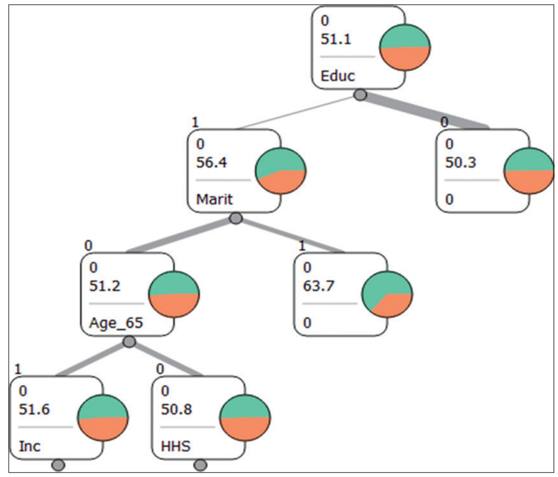
OOP: Out-of-pocket

Table 3: RF and NN performance results to predict OOP health expenditure

Model	RF (100 trees generated)					
	k-fold CV	CA	Sens.	Spec.	AUC	Running time (s)
1	k=10	0.5337	0.2968	0.7781	0.5505	0.09
2	k=20	0.5359	0.2931	0.7864	0.5508	0.19
3	k=30	0.5379	0.2980	0.7852	0.5538	0.32
4	k=40	0.5364	0.2960	0.7843	0.5527	0.49
5	k=50	0.5345	0.2931	0.7835	0.5532	0.49
6	k=60	0.5365	0.2960	0.7846	0.5519	1.39
7	k=70	0.5361	0.2879	0.7921	0.5527	1.39
8	k=80	0.5332	0.2916	0.7823	0.5499	1.39
9	k=90	0.5352	0.2925	0.7855	0.5539	1.39
10	k=100	0.5318	0.2919	0.7793	0.5529	1.39
Model						
	k-fold CV	CA	Sens.	Spec.	AUC	Running time (s)
1	k=10	0.5299	0.4211	0.6422	0.5464	0.33
2	k=20	0.5359	0.4243	0.6511	0.5495	1.12
3	k=30	0.5355	0.4188	0.6559	0.5514	1.57
4	k=40	0.5354	0.4220	0.6523	0.5522	2.21
5	k=50	0.5340	0.4286	0.6428	0.5509	2.59
6	k=60	0.5375	0.4173	0.6616	0.5518	6.10
7	k=70	0.5374	0.4185	0.6601	0.5512	5.52
8	k=80	0.5356	0.4182	0.6568	0.5524	5.53
9	k=90	0.5345	0.4199	0.6526	0.5528	5.57
10	k=100	0.5370	0.4222	0.6553	0.5521	5.54

CV: Cross validation, Sens.: Sensitivity, Spec.: Specificity, AUC: Area under the ROC curve, RF: Random forest, NN: Neural network, OOP: Out-of-pocket

Graph 3: Decision tree graph



Educ: Education, Marit: Marital status, Age_65: Being 65 years of age or older, Inc: Income group, HHS: Household size

According to this decision tree graph the first groups conssists of individuals who are formally educated (primary, secondary, high school, university, master and doctorate), whereas the second group conssists of individuals don't have any formal education and not married (never married, divorced and widowed). Being 65 years of age is an another important variable that determines third group and others. In Turkey, parallel with economic, cultural changes and under the effect of policies put into effect with HTP, patients become more interested to read, understand and integrated with their health procedures than before. As a result of that, health literacy become one of the most popular topics in health care. Literature suggest that educational attainment is the most important demographic characteristic related to the health literacy in Turkey (Özdemir et al., 2010). Moreover, it has been known that marriage itself seems to improve health (Koball et al., 2010) and being older age is a risk factors for OOP health expenditures (Erus and Aktakke, 2012). The results of this study, consistent with previous research and indicate that education, marriage and older age are primary indicators of OOP health expenditures. These results form a basis for a recommendation for future studies to further identify interrelationships between socio-demographic indicators of OOP health expenditures by using multivariate analysis techniques.

This study broadly draws attention to the increasing level of OOP health expenditures in Turkey after strategies to combat with poverty and incentive policies to invite more people into the system come into effect. Study results confirm that despite poverty reduction policies, non-zero OOP health expenditures continue to increase. This brings into mind the question that graps attention of researchers looking from equalitarian perspective - does OOP health expenditure risk equally distributed among rich and poor population groups? One of the recent studies by Erus et al. (2015) answers this question and revealed that lack of health insurance coverage appears to be translated into not using healthcare and making relatively high OOP health expenditures in compulsory cases, so non-zero OOP health expenditures increases. There are two reasons for this. First, there were co-payments for households including those under green card scheme. Second, the prevalence of informal payments to public providers is high in Turkey (Tatar et al. (2007) found 25% of all OOP health expenditures are informal in Turkey). As a support for this statement, Yılmaz (2013) is of the opinion that income becoming a new source of differentiation among citizens in health care services in Turkey. What's more, Hazama (2015) maintains that the UHI by the HTP give rise to a new inequality based on income in Turkey. We hope that further studies about equality in health financing will help to shed light on this issue. Moreover, this study specifically concentrates on Turkey as a single country case. Further comparative studies with other developing countries on health financing systems will allow to better understand international differences in terms of the distribution of OOP health expenditures.

To the best of our knowledge, this study is the first application of data mining techniques on OOP health expenditures. Data mining techniques are useful to detect household characteristics by using nationally representative household datasets (Annoni et al., 2006). In this study RF outperforms NN in terms of AUC and running time. Decision tree graph for RF which was generated by 100 trees visualize predictors of OOP health expenditures. Despite, modeling health expenditure is difficult because of right skewed and not-normal distribution, it is advisable to use data mining methods for prediction, because these methods are helpful to discover patterns in large datasets and improve estimation accuracy of the models (Khalifelu and Gharehchopogh, 2012). Future studies will incorporate other data mining techniques into the system to optimize study results and to achieve better prediction performances.

5. CONCLUSION

To conclude, this study refreshes our previous knowledge about the trend of OOP health expenditure after more than ten years' experience of health reform in Turkey. It is seen that non-zero OOP health expenditures has an increasing trend and this is consistent with the time period that policies to establish UHI system and incentivize more people into the system was emerged. Moreover, education, marital status and being older age are important predictors of non-zero OOP health expenditures for the year 2015. It is hoped that this study will inspire further research to examine the reasons of sustaining increase in the level of OOP health expenditures. Analyzing distributive pattern of OOP health expenditures in terms of income levels is advisable research topic for future studies. Consequently, it seems that there is still a room to improve health policies to control increasing trend of OOP health expenditures and concentrating on the reasons of this increase while protecting poor population groups.

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