Research Article

Socio-economic status and self-rated health: Are they good predictors of income? An analysis of survey panel data from Turkey

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ABSTRACT

Background: The socioeconomic dynamics and economic status of households are changing rapidly all over the world, especially for middle-income and developing countries such as Turkey. It is well known that income is one of the most important determinants of socioeconomic status (SES) and health. There is a need to analyze changing trends and relationships among SES variables over time. Unfortunately, such changes remain undetected in cross-sectional studies. However, panel data cover multiple sequential time periods for the same firms or individuals and allow analysis of these changing patterns. **Objectives:** This study aims to determine predictive factors of income on a decision tree and to observe changes of predictive role of SES and health indicators over time, to predict income using three different panel datasets. **Materials and Methods:** Data from the Income and Living Conditions Survey in Turkey between 2008 and 2011 were used. A random effects and expectation maximization tree algorithm were also used in the analysis. **Results:** This study results show that education is the variable that is the most influential in predicting income between 2008 and 2011 and between 2009 and 2011; on the other hand, current economic status is a determining factor of income between 2010 and 2011. **Conclusion:** Experimental results highlight that education outperforms SES and health indicators in the prediction of personal income.

KEY WORDS: Income and Living Condition Studies; Self-rated Health; Income; Panel Data; Turkey

INTRODUCTION

Income determines and affects the socioeconomic status (SES), health, and living conditions of households and individuals. It is an indicator of consumption and savings of households and individuals; it is also an indicator of poverty and a great social and political issue.[1] Individuals who have more income have higher SES, live healthier, and can afford better health care.[2] Moreover, more income is a determining factor in the level of development. People living in more developed countries, such as Organization for Economic Co-operation and Development countries, have higher incomes in comparison with others, thus obtaining a higher SES. These high-income countries help low- and middle-income countries to improve their SES and health systems. As a result, there is an increasing number of studies focused on the income and living conditions of people in underdeveloped and developing countries.[3]

On the other hand, there is a very significant body of literature examining the relationship between income and health. The main focus of these studies is to analyze the relationship

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between income inequality and poor health status.[4] Most of these studies are focus on the objective measures of health status, however, there is a scarcity of knowledge in the literature about the relationship between subjective assessment of SES and health.[5] The relationship between income and health grabs the attention of researchers. Barsky et al.[2] studied the relationship between health and income and found a dual relationship. Healthier individuals are much more productive and have higher incomes in comparison with others. Healthy eating habits are one of the major factors of health promotion and one of the ways to improve public health. Nakamura et al.[6] are of the opinion that a higher SES and income are associated with healthy eating habits among men and women. On the other hand, some diseases such as diabetes are more common among the socioeconomic elite. Monteiro et al.[7] are of the opinion that diabetes is one of the diseases that can be seen as a predictor of income.

As a continuation of this literature background, there are number of studies in the literature about the relationship between socioeconomic status, self-rated health, and income. Literature suggests that sociodemographic indicators such as education, age, marital status, and health status are the major determinants of income. Groffen et al.'s[8] study on the relationship between age, income, and health and states that old age is associated with a decrease in income. Moreover, older people live with more social anxiety and poorer health. Similarly, Osborne et al.[9] analyzed the relationship between marital status, age, income, and health status. Their results suggest that marital status has a significant impact on mortality for women in the high-income group. Marital status is an important determinant of income, and there is a dual relationship between income and marital status. This relationship states that a wife's strong economic position is associated with an increase in the risk of divorce.[10] Krueger and Lindahl found that economic growth depends positively on human capital.[11] Education and economic status are major determinants of the qualification of human capital. This study results suggest that education has little effect on economic growth. In addition to that people living in rural areas of the country headed by educated people are more likely to participate in non-farming sectors than those headed by illiterate people.[11]

From the other point of view, self-rated health, which is one of the subjective health indicators, is a strong predictor of health status and a reliable measure of overall health in all population groups. Fayer and Hays[12] stated that doubts regarding self-rated health assessment can be expressed by "how come a global subjective rating of health performs well?" In daily life, people differ in their preferences. Some respondents probably compare themselves with others of the same age, whereas others consider how they were before they became ill. Frequently used health status measures ask respondents to rate their overall health as good, fair, or poor. In these studies, some study participants think about specific health problems when asked to rate their health, whereas others think in terms of either general physical functioning or health behaviors.[13] Self-reported health information cannot be as reliable as that based on objective measures of health. However, various subjective measures of health have been proven to have substantial value in predicting objective health outcomes, including mortality and morbidity.[14,15] Mossey and Shapiro[16] examined self-rated health among the elderly. Their results show that the way a person views their health is related to subsequent health outcomes. Idler and Benyamini[15] analyzed the relationship between self-rated health and health outcomes using mortality as an outcome measure. Their results show that global self-rated health is an independent predictor of mortality. Self-rated health can be used to examine the prevalence of high-risk diseases such as diabetes and depression. Khan et al.[17] examine associated factors with diabetes in an urban population. The study results show that prevalence of diabetes is higher among men than women. It was found to be significantly associated with the increasing age, positive family history, and high educational attainment. Safwi et al.[18] examine gender differences in the prevalence of depression and study results show that the prevalence of depression is high among females.

The literature suggests that self-rated health assessment is related to a number of factors, including age, employment, education, and income, which affect health.[19] Krause and Jay[13] support the view that self-rated health status assessments vary by age. Furthermore, Miilunpalo et al.[20] studied the effectiveness of self-rated health assessment as a health measure. The results showed that subjective health assessments are valid health status indicators for the middle-aged population and that they can be used in studies involving population health monitoring. Bobak et al.[21] analyzed the relationship between socioeconomic factors and self-rated health assessment. The results found that education to be strongly related to the accuracy of self-rated health information. Griep et al. (2016)[22] analyzed the relationship between unemployment and perceived job security and compared their association with psychosomatic complaints by examining the relationship between self-rated health assessment and life satisfaction. The results state that insecure employment and long-term unemployment relate to more subjective complaints and poorer health compared with secure employment. In the light of presented literature, it is seen that there is a large literature on the relationship between SES, income, and health. In addition to that SES, income, and health variables are affected by structural changes in the economy, sociodemographic, and economic trends of any country.

Whether predictors of income are changing over time is a controversial issue in the literature. One of the reasons of this scarcity of knowledge is due to the lack of data to examine long time changes. Panel data can be used to fill this void. However, panel data analysis has rarely been used in previous

empirical research. Most of these studies in this field examine the relationships between these variables using cross-sectional analysis. Panel data is appropriate to see changing trends over time. This is also called time-series cross-sectional data and are characterized by repeated observations on fixed units, such as nations or states.[23] Longitudinal (panel) data refer to the situation where repeated observations are available for each sampled object.[24] Panel data refers to datasets for a cohort of agents, which may be individuals or aggregated data for an entire city or region, gathered over a period and indexed by both the time and cohort variables. It is a multidimensional time series coming from the continuous observation of cross-sections. Nie et al.[23] opine that the advantage of panel data analysis is the detection of differences that cannot be identified in the traditional data structure. The synthesis data include information with regard to time, cross-section, and index. There are several models for the analysis of panel data: Pooled regression analysis, fixed effects models, random effects (RE) models, etc.[25] Income and living condition studies are one of the reference panel studies for determining the SES of people with the aim of improving global health. These studies provide detailed information about household income, SES, and health indicators, and socioeconomic trends. Looking at trends using panel data or cross-sectional studies over several years is an important step to analyze these trends. Moreover, it is possible to identify the determinants of income and other socioeconomic factors using data from income and living conditions studies.

One of the most well-known panel datasets comes from the European Union Statistics on Income and Living Conditions (EU-SILC) surveys. This instrument collects timely and comparable cross-sectional and longitudinal multidimensional microdata on income, poverty, social exclusion, and living conditions and belongs to the European Statistical System.[26] Other examples of panel studies are the British Household Panel Study and German Socio-Economic Panel studies. These panels incorporate an increasing number of concepts from the fields of medicine and psychology.[27] Panel datasets have been increasingly used in economics to analyze complex economic theories. One of the attractions of panel datasets is the option to use an extended dataset to obtain information about parameters of interest, which is assumed to have common values across panel units.[28] The advantage of panel data is to detect differences that cannot be identified in traditional data structures. The experimental results support this view. According to Nie et al.,[23] the number of samples detected as noise under the same parameter setting is higher when panel data are used. Cavallo et al.[29] analyzed trends in the self-rated health status in European and North American adolescents from 2002 to 2010 in 32 countries. This study results indicate a trend in Europe that has a higher population of adolescents rating their health as excellent. According to comparisons based on gender status, girls were found to rate their health as poorer in comparison with their male peers in all countries. Age is a very stable trend, and there is a decreasing rating of health with increasing age. The authors speculated that the decrease in health ratings between 2002 and 2006 is a signal of the socioeconomic difficulties in Europe over the last part of this decade.[29]

Preliminary study results about the relationships between SES, self-rated health, and income indicators show that further studies are needed to examine long-term changes in economic and health trends of any country. Monitoring changes over time may provide useful information to inspect changes in SES and health. Furthermore, it has been stated that SES and health indicators have rapidly changing trends and generates problems for the planning and implementation of health interventions.[30] What's more examining SES and health trend of countries where health system is under transformation, especially important to make inferences about changing trends of health and economic indicators, which are major development indicators of a country. Turkey is one of the developing countries and experienced significant reforms in general economy and health in recent years. However, to the best of our knowledge, there is a scarcity of knowledge about changing trends of SES, health, and income variables over time. This study aims to identify predictive factors of income while using SES and health variables as covariates in Turkey. Another aim of this study is also to explore changing trend of predictors of income in a decision tree over time. To achieve these aims, income was used as the predictor variable, while SES indicators and health status were used as predicting variables in this study. This paper is structured as follows. The following section provides information in brief regarding the dataset and data analysis procedure. The third section presents descriptive and inferential statistics. The fourth section is a discussion of the study results of the RE and expectation maximization (RE-EM) model and pros and cons of the study. The final section concludes study results.

MATERIALS AND METHODS

Aim

The relationship among the sociodemographic variables, self-rated health status, and income is a controversial issue, and panel data allow the analysis of changes over time. This study aims at investigating the predictors of income using socioeconomic and health status measures as predictor variables.

Data

Data came from the Turkish Statistical Institute (TURKSTAT) "Income and living conditions survey (ILCS)"[31] for the 4 years including 2008, 2009, 2010, and 2011. The ILCS is conducted annually and uses a panel survey technique to display income distribution between individuals and households. Survey respondents are monitored during the 4 years of the survey and cover indicators on income

distribution, poverty, social exclusion, living conditions, housing facilities, problems with the environment, housing costs, and the financial situation of households in Turkey. This study comprised four subsamples on an annual basis; in addition, a rotational design is used in the survey. Households in the 4-10 subsample were interviewed between 2008 and 2011. According to the survey methodology, one part of the household stays in the sample frame from 1 year to the next, and instead of other households in the sample frame, new households enter the sampling frame. Up to 75% of the sample has been seen to leave a panel from 1 year to the next. Items within the dataset include the marital status, education, self-rated health status, and current economic status of the household members aged 15 and above between 2008 and 2011. All study variables are in categoric form, except for an indicator that represents personal income, which is the total value of the incomes received in the income reference period.

Analysis

The analysis is performed at the individual level. There are six categoric variables and one, annual personal income, in continuous form. Income variables belong to 4, 3, and 2 years' panel data and are deflated according to the TURKSTAT consumer price index using the 1st year as the base year (2008 is taken as base year for the 2008-2011 period, 2009 is taken as base year for the 2009-2011 period, and 2010 is taken as base year for the 2010-2011 period).

In this study, the RE-EM tree model is applied to different datasets covering the periods 2008-2011, 2009-2011, and 2010-2011. The outcome variable of this study is personal income. This represents the total value of income received in the income reference period. The RE-EM model is a regression tree-based model with RE for panel data.[24] This model merges the flexibility of tree-based predictive models with the structure of mixed effects models for panel data.[32] RE-EM trees are low sensitive to parametric assumptions and have good predictive power when compared with linear models with RE and regression trees without RE.[21] Sela and Simonoff[24] recommended an estimation method that uses a tree structure to estimate and also integrates object-specific RE. Neither RE nor fixed effects are known, and we alternate between estimating the regression tree, assuming that our estimates of the RE are correct and estimating the RE, assuming that the regression tree is correct. The interchange between estimating different parameters is similar with the EM algorithm used by Laird and Ware.[33] For this reason, Sela and Simonoff[24] named the estimator an RE/EM tree or RE-EM tree.

RESULTS

Descriptive Statistics

Table 1 below presents the descriptive statistics of the study variables for the period 2008-2011. Descriptive statistics belong to a total of 27482 individuals with whom we followed up between 2008 and 2011. The numbers of individuals aged 15 years and above and observed for 4 years are 6514 in 2008, 6792 in 2009, 6993 in 2010, and 7183 in 2011. Table 1 shows that study variables are related to sociodemographic variables, health, and labor status. It can be seen that 73.4% of individuals were married and 38.6% of them had graduated from the primary school. For the perceived health status, 53.6% self-reported "good" and 68.9% stated they did not suffer from any chronic illness or condition. However, 20.8% of them declared they suffered from limitations in their daily activities due to a health problem (physical or psychological problem going on for at least 6 months). Finally, 40.6% described their current economic status as working full-time. Mean values are marital status 1.89 ± 0.54; education 2.51 ± 1.64; general health status 2.40 ± 0.89; suffer from any chronic illness 1.69 ± 0.46; limitation in daily activities 2.64 ± 0.62; and self-described economic status 3.75 ± 2.64. Annual personal income, which represents the total income received in the reference period, has a mean value of 6.358 (minimum. 0, maximum. 112.649). During the normality analysis of the predictor study variable, it is seen that the distribution of personal income is high positively skewed. To overcome this non-normal distribution problem of the total income variable and to improve predictive performance, the natural logarithm was taken for annual income.

The next section is about estimation results of RE-EM tree model on three different data sets covering the periods 2008-2009-2010-2011, 2009-2010-2011, and 2010-2011.

RE-EM Tree Model on Three Different Data Sets

RE-EM tree models of the datasets from 2008 to 2011, 2009-2011, and 2010-2011 are displayed in Figures 1-3, respectively. The outcome variable is annual personal income (log-transformed). Sociodemographic indicators and self-rated health status measures were used as predictors. The logarithmic form of individual annual income was used as a predictor variable for all four-panel datasets. Predicting variables, sociodemographic variables, and self-assessment of health are used in the form of marital status, self-rated general health status, suffering from any illness, limitation in daily activities, and self-described current economic status. Figure 1 shows the RE-EM tree combining all categoric predictor variables for 2008-2011. It is observed that in this period, the most influential predictor variable of income is education. In other words, the root node is split according to education. Individuals on the lower nodes are divided according to their current economic status and marital status on the right-hand side and education and current economic status on the left-hand side. In other words, current economic status and marital status are determining factors of annual income apart from education.

Figure 2 presents the RE-EM tree estimated on the data from 2009 to 2011. We can state that the splitting variables were

Table 1: Descriptive statistics for the year 2008-2011

Categoric variables	Variable categories	*n* (%)	Mean±SD
Marital status	1 - Never married	5439 (19.8)	1.89±0.54
	2 - Married	20163 (73.4)	
	3 - Widowed	1465 (5.3)	
	4 - Divorced	415 (1.5)	
Education	0 - Illiterate	3603 (13.1)	2.51±1.64
	1 - Literate but not a graduate	2317 (8.4)	
	2 - Primary school	10615 (38.6)	
	3 - Secondary, vocational secondary, or primary education school	4382 (15.9)	
	4 - High school	2653 (9.7)	
	5 - Vocational or technical high school	1772 (6.4)	
	6 - Faculty/university, college, or higher education level	2140 (7.8)	
Health			
General health status	1 - Very good	2977 (10.8)	2.40±0.89
	2 - Good	14731 (53.6)	
	3 - Fair	5986 (21.8)	
	4 - Bad	3308 (12.0)	
	5 – Very bad	480 (1.7)	
Suffer from any of a chronic (long-standing) illness or condition	1 - Yes	8549 (31.1)	1.69±0.46
	2 - No	18933 (68.9)	
Limitation in daily activities because of any physical or psychological health problems ongoing for at least 6 months	1 - Yes: Strongly limited	2117 (7.7)	2.64±0.62
	2 - Yes: Limited	5713 (20.8)	
	3 - No: Not limited	19652 (71.5)	
Labor			
Self-defined current economic status	1 - Working full-time	11148 (40.6)	3.75±2.64
	2 - Working part-time	1484 (5.4)	
	3 - Looking for a job	1112 (4.0)	
	4 - Pupil, student, or unpaid work experience	1658 (6.0)	
	5 - In retirement or in early retirement or has given up business	2178 (7.9)	
	6 - Old. permanently disabled and or unfit to work	1450 (5.3)	
	7 - Fulfilling domestic tasks and care responsibilities	8189 (29.8)	
	8 - Other inactive person	263 (1.0)	
Total		27482 (100)	

Continuous variable	Explanation of the variable	Minimum	Maximum	Median
Personal income	Personal income [total value of the incomes received in income reference period (TL - Turkish Liras)]	0	112649	6358

SD: Standard deviation

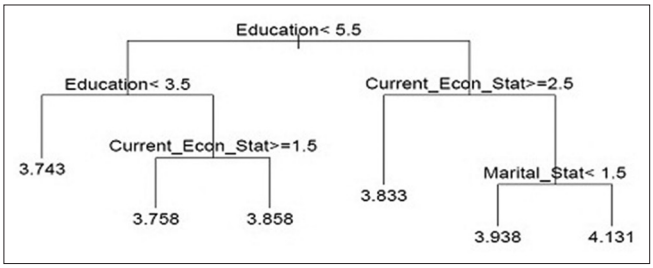

Figure 1: Random effects and expectation maximization tree estimated for 4-year panel data (the period 2008-2011)

similar to the first tree and that the most influential variable for predicting individual annual income is education. The other predicting variables are current economic and marital status on both the right and left sides of the tree.

Figure 3 displays the RE-EM tree for 2010-2011. In this figure, the predictor variable was changed. For this 2-year period, the root node is split according to the current economic situation. In addition, individuals on the lower nodes are divided according to their education and marital status.

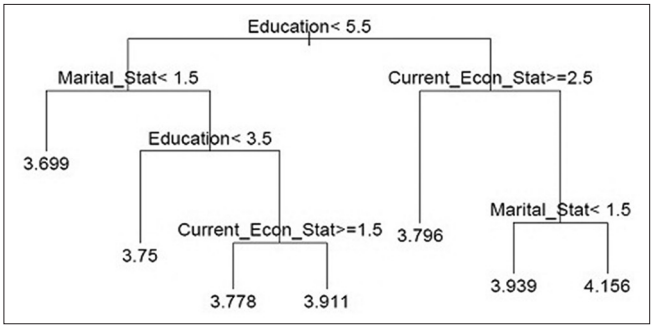

Figure 2: Random effects and expectation maximization tree estimated for 3-year panel data (the period 2009-2011)

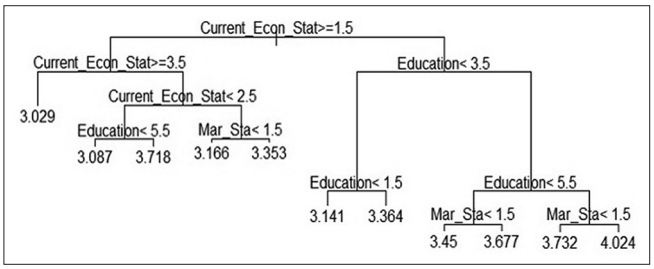

Figure 3: Random effects and expectation maximization tree estimated for 2-year panel data (the period 2010-2011)

Comparison of the RE-EM Model's Performance on the Three Datasets

To compare the RE-EM model's performance on three datasets, autocorrelation test results and error rates are examined. This autocorrelation test keeps the tree structure of the RE-EM tree object and uses a standard likelihood test on the linear RE model.[24] RE-EM tree can be estimated with or without autocorrelation. Furthermore, the estimated tree may differ depending on whether autocorrelation is allowed in the RE-EM tree estimation process. Sela and Simonoff[24] recommended tree estimation with and without autocorrelation. Autocorrelation results examined based on the log-likelihood of the RE models. It is seen that no autocorrelation was detected using three different datasets ($p > 0.05$). According to the estimated variance of error, longer periods of data (2008-2011) have lower error rates (0.0290) than shorter periods (0.0385 from 2009 to 2011 and 0.0389 from 2010 to 2011, respectively). Possibly, we can say that longer data periods lead to lower error rates.

DISCUSSION

In this study, income is used as a predictor variable, and the predicting variables are education, marital status, current economic status, and self-rated health status. This study results show the variables that are the most influential in predicting personal annual income according to the RE-EM tree results. The results cover the periods 2008-2011, 2009-2011, and 2010-2011 and demonstrate that the most important predictor variable is education for the periods 2008-2011 and 2009-2011. Another important predictor variable is current economic status in the period 2010-2011. Marital status is another predictor variable of this study, which is not located in the root nodes in any of the three-panel datasets. On the other hand, due to the comparison of performance on different datasets, no autocorrelation was detected. Moreover, the estimated variance of errors for the longer data periods (2008-2011) was lower compared with the other two-time periods. This result indicates that longer data periods have lower error rates compared with short time periods and improve the predictability of annual personal income. One of the main questions of this study is whether self-rated health is a good predictor of income or not. The results support the view that self-rated health status variables are not influential in predicting annual personal income. This study sought out to move another step forward by testing this relationship using one of the most flexible tree-based methods which is RE-EM tree. The application of tree-based prediction methods to panel data which is one of the common data structures in social sciences strongly advised by Muchlinski et al.[34] in the recent literature. This study provides important and original contribution to the literature using RE-EM tree for the prediction. Moreover, the study results allow us to see changes of predictor variables of income in a dynamic structure over time. This study fills this deficit by predicting income while using subjective SES and health variables and making a comparison between different time periods. In the light of this study, social policymakers in Turkey should need to develop strategies to strengthen education system, which is the most important predictor of income. From the other perspective, the study results call attention to the need to understand the link between education and employment, which is an indicator of the level of income. It is anticipated that further studies will contribute to a better understanding of predictors of self-assessed health using SES variables.

The results of this study point the importance of education as a predictive factor of income in Turkey. This result based on an observation from a national household survey over time, which is national ILCS. Income and living condition studies collect data on income, poverty, social exclusion, and living conditions as a basis for the statistical comparison of living conditions and income in Europe and present a deeper understanding of poverty among countries, households, and individuals.[35] In Turkey, data on income distribution, relative poverty, living conditions, and social exclusion are collected as panel data through the annual ILCS conducted by TURKSTAT compliance with EU.[31] Supportive studies from the literature set light to the relationships between economic and health indicators. To support our study results, Ostrove et al.[5] state that subjective SES was significantly related to education, income, and education. Another study done by Robert and House[36] state that education and income are both associated

with health throughout adulthood and age. Cundiff et al.[37] also analyzed the relationship between income and education. Their results demonstrated that men appear to benefit more from income than women and that income and education have independent and interactive effects on health. Winkleby et al.[38] analyzed the relationship between SES and health indicators. In that study, education, income, and occupation were determined to be socioeconomic indicators; moreover, it was demonstrated that education is the best predictor of good health when compared with other socioeconomic indicators. According to comparisons between Caucasian and Chinese-American women, income is the most influential variable of SES and health.[5] Arendt[39] analyzed the relationship between education and health using Danish panel data. The results showed that for both men and women, longer education is associated with a better health status.

To improve the compatibility performance among income and living conditions studies, European countries conducted a survey on income and living conditions (EUC-SILC project). This project was launch in 2003 with an agreement among seven European countries (Belgium, Denmark, Greece, Ireland, Luxembourg, Austria, and Norway).[40] Using EUC-SILC data, Angel and Bitsschi analyzed a causal relationship between housing and health using four waves of the EUC-SILC panel data from 2005 to 2008.[41] This data provide a large set of socioeconomic variables that might confound the effect of housing deprivation on health, thus simplifying the identification strategy. The results indicate that living in poor housing is the chief socioeconomic determinant of poor health over the 4-year observation period and concluded that SES affects health.[41] In Turkey, the scope of the ILCS, conducted by TURKSTAT since 2003, has complied with the EU project since 2006. The main aim of this study is to understand the relationship between socioeconomic indicators and health in Turkey. ILCS has both cross-sectional and panel data types in Turkey. The lack of information derived from this data examines the relationship among SES, health, and income in Turkey state that men are more often unemployed than women. In other words, being married decreases unemployment at the household level.[42] Another study that investigated the labor market conditions in Turkey analyzed the wage curve relationship. This study results show that for male workers, the wage curve relationship seems to exist only when the male unemployment rate is used and for female workers [43] According to the best of our knowledge, this is the first study in Turkey detailed examine predictors of income and changing trends of SES and health indicators as predictors of income over time.

Overall, this study makes an important contribution to understand the elusive relationship between self-reported SES and health. This study results form a basis for recommendations for the future studies highlighting the importance of education. We believe that further studies will add more variables into the model and determine the optimal period to predict income and other variables related to income and living conditions at the individual and household levels. We hope that further efforts to detailed understanding of predictors of income will contribute to the socioeconomic planning studies, decrease income inequality, and improve the accessibility of health-care services.

CONCLUSION

This study presents the first attempt by predicting income with using SES and health variables and detailed analysis of predictors of income over time. The study results highlighted that education outperforms SES and health indicators in the prediction of income over time. This study adds literature about that longer data periods improve the predictability of annual personal income which is an important indicator for community health managers to follow socioeconomic and health trends over time. This study results form a basis for the future studies emphasizing the mediating role of education in SES and health variables over time. It is anticipated that preliminary results of this study will encourage health policymakers in fostering a supportive environment for reducing education inequalities to improve health status of the population in the long run. Further studies are needed to better identify long-term relationships between economic and health indicators in Turkey. Reducing education inequalities will be a long-term strategy for community health managers for enabling good health throughout the country in the long run.

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