The Causal Effects of Survivors' Benefits on Health Status and Poverty of Widows in Turkey: Evidence from Bayesian Networks

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Abstract

This study examines the effects of survivor benefits on health status and wealth in households of widowed mothers. The analysis relies on the cross-sectional Income and Living Conditions Survey (ILCS) in Turkey over the period 2006-2012. We apply Ordered Logit and Probit models, and we propose the Bayesian Network (BN) framework to explore the causal effects of survivor benefits using observational data. The results show that the widowed mothers who receive the benefits are more likely to report higher levels of health status by 0.11 units on a scale between 1-5. In addition, their wealth is improved. For the sample of the survivor benefit claimants, the effects of the benefits are positive, and they improve health status by about 6 per cent.

Keywords: Bayesian Networks; Directed Acyclic Graphs; Health Status; Poverty; Survivor Benefits

1. Introduction

When a breadwinner dies, a family experiences a loss in earnings and social benefits. Several studies conclude that single parenthood, after a matrimonial termination, has harmful economic and health consequences. It is well documented that poverty rates among women over the years following marital termination are higher than during marriage (Nestel et al., 1983; Duncan and Hoffman, 1985; Morgan, 1989; Holden and Smock, 1991; Smock et al., 1999). Waldron et al. (1996) found that married women report better health trends than their unmarried counterparts. The authors, using panel data from the National Longitudinal Surveys of Young Women in the US, found that marriage has positive effects on health. This holds especially for the unemployed women in lack of financial resources. Many studies have emphasised both physical and psychological consequences of widowhood, and they found that it is one of the most stressful periods in life. Widowhood is associated with lower perceived health status, increase in hospitalisation admissions and risk development of depression and mental illnesses (Avis et al., 1991). Although changes in physical and mental health behaviour were inconsistent with small effect sizes, Wilcox et al. (2003) showed that married women reported better physical and mental health than widowed women.

The relationship between longevity and socio-economic status may partly account for high poverty rates among the older widows. Holden and Zick (2000) in the early 1990s found that the average income of elderly widows dropped 47 per cent after the death of the husband. The authors conclude that losing the partner decreases the household consumption needs, however, this is insufficient to balance the drop in income. Holden and Zick (2000) found that the income of old women is reduced by 20 per cent, and 17 per cent is fall into poverty following the death of their spouses.

This study examines whether the survivor benefits help the widows to improve their health status. As an added source of income, the survivor benefits may allow the widowed households to improve their financial positions and their health conditions. We explore the widowed households in Turkey, because it matches the characteristics of the so-called *Southern European Model of welfare*, which comprises Spain, Greece, Italy and Portugal (Grütjen, 2006). The Turkish society today faces close socio-economic consequences of urbanisation, unemployment and increasing life expectancy, similar to the countries of the South European Union. However, Turkey is a developing country and shares similar socio-economic and cultural characteristics with other countries in the Middle East and North Africa (MENA) region. These characteristics include religion and traditional gender roles. The husband is the main breadwinner, at least in the old-aged households, and the woman has limited access to the labour market. The association among survivor benefits, wealth and health status in Turkey can offer useful insights for policy implications to the MENA and to South European Union countries. Moreover, in Turkey, the Health Transformation Program (HTP), which took place over the years 2003-2008, has improved health care services and health outcomes, such as life expectancy and morbidity rates (Chakraborty, 2009; Brown et al., 2012; Erus and Aktakke, 2012). This reform was unique, as South European Union and MENA countries have not implemented similar policies.

In Turkey, the first law for the survivor benefits passed in 1957. In May of 2006, the social security systems of the public and private sectors merged the employees and the self-employed into one system, under the new Social Security Institution. The spouse is eligible, regardless of any specific age, but being an eligible dependent differs for female and male children. The spouse's survivor pension ceases on remarriage. Survivors are eligible to receive only one survivor pension. In the case where they earn a wage, they can keep their salaries while taking the pension of their deceased spouse.

This is the first attempt to examine the effects of survivor benefits on poverty and health status of widowed mothers in Turkey using a Bayesian Network framework. Earlier literature has not explored these relationships in Europe, the MENA region and in other regions around the world, except for the US. Thus, examining those effects, other countries may follow Turkey as an example to improve the health status and to decrease the poverty of the widowed households. The analysis relies on a detailed micro-level data from the cross-sectional Income and Living Conditions Survey (ILCS) of Turkey during 2006-2012. In addition, following the ordered Logit and Probit regression analysis, we estimate a Bayesian Network model to examine the impact of the survivor benefits on health status and wealth. The causes and effects between these variables and other factors are incorporated into a graphical representation through Directed Acyclic Graphs (DAGs). We propose the BN framework, because it allows us to test for causal effects without using instrumental variables and when the ordering of the events and variables is unknown.

The results derived from the ordered Probit and Logit models show a significant relationship between survivor benefits and health status, equal to 0.053 and 0.109, respectively. In addition, the findings confirm that the survivor benefits reduce the incidence of poverty and help the households to avoid poverty traps. BN estimates show a significant effect of the survivor benefits to health and wealth. Overall, the results suggest that the survivor benefits reduce the poverty rate by 17 per cent. The poverty gap between the households receiving the survivor benefits and those that do not is 23 per cent. Those who receive the survivor benefits report a higher health status level by 0.11 units, on a scale measured from 1 to 5.

This paper is organised as follows: In the next section, we present a brief literature review of the previous empirical researches about the effects of income on poverty and health. In Section 3, we present the data, and in Section 4, we describe the methodology followed. We report the empirical results in Section 5, and in the last section, we provide concluding remarks.

2. Literature review

The literature has analysed the association between survivor benefits and poverty outcomes in the US. The work by Myers et al. (1987) is one of the novel studies on the survivor benefits and poverty outcomes. The authors used data from Ten-Year Longitudinal Retirement History Study and analysed the effect of joint-and-survivor benefits on poverty outcomes of women. They found that, on average, women have higher levels of poverty as widows than when they were married (e.g., Sandell and Iams, 1996; Iams and Sandell, 1998). A study that analyses the German Social Security system shows that this system is not so successful in maintaining the living standards of widowed women compared to married counterparts (Hungerford, 2001). Siegenthaler (1996) also emphasised that Germany has a serious poverty problem among elder widows, even though it has often been singled out as one of the richest European Welfare States. Scholars show that more than a third of Egypt's women-headed households are living below the poverty line (Assaad and Rouchdy, 1999). Despite the fact that divorce is uncommon in the developing countries, death and desertion produce single parent families, usually headed by women (Kinnear, 1999). Across the Western world, about 15.9 per cent of children live in single-parent households. The United States is listed as the highest in the single-parent ranking; 25.8 per cent of the children in the US live with one parent, which is usually the mother. Turkey, following Finland, Greece, Italy and Luxembourg, is the fifth to last country, where 7.2 per cent of the children live with the mother and 0.6 with the father.

Lee et al. (2001) found that it is more likely women to become widowed than men for two main reasons. First, women in the majority live longer than men, and, second, they marry older men, although this age gap has been narrowing in recent years. Because of these facts, the odds for women to become widowed are much higher. Relevant literature suggests that the widows and their children present poorer health status levels and spend more on health care compared with the general population (Springer, 1984). Losing a spouse is one of the most intensive and dramatic events that a person can experience, next to the loss of a child (Bennett et al., 2005). One of the main causes of mental and physical problems is the economic hardship and burden, especially for the women whose husband is considered as the principal breadwinner. The death of a husband leads to the deprivation and the collapse of the family nucleus (Fasoranti and Aruna, 2007). This economic deprivation can have additional effects on the health status of women and children. We expect the survivor benefits, as a financial contribution and part of personal income, to have positive effects on health outcomes. Earlier research studies found a strong relationship between income and health status. On average, individuals belonging to the most advantaged social groups are healthier. Furthermore, household income is associated with children and youth development (Haveman et al., 1991; Huston et al., 1994; Brooks-Gunn and Duncan, 1997). Many of these studies show the adverse physical and psychological effects following the death of the spouse but not the effects of the survivor benefits.

Overall, the previous literature explored the effects of other social benefits, including parental or maternity leave (Huang and Yang, 2014; Khanam et al., 2016). However, prior studies have not explored the relationship of the effects of the survivor benefits on health and wealth, especially in Turkey. The main theme of those studies was the income and wealth differences exploration between married and unmarried women, including widowed and divorced.

The most relevant study is by Holden and Zick (2000), who found that younger women report 15 per cent lower income than older women when they become widows. In addition, Holden and Zick (2000) found that in the early 1990s, the pension income fell by 58 per cent on average. This accounts for 21 per cent of the decline in income associated with widowhood. The findings of this study show that the poverty gap between households receiving survivor benefits and those that do not is 23 per cent, while the poverty is reduced by 17 per cent. We extend the previous literature, exploring the effects of survivor benefits on wealth and health status of widowed households. Moreover, we propose a Bayesian Network framework to explore the effects of the survivor benefits on wealth and health status using observational data.

3. Data description and variables

We use the cross-sectional Income and Living Conditions Survey (ILCS) in the period 2006-2012, covering respondents over 14 years old (Turkish Statistical Institute, 2013). The main health outcome is the self-assessed health (SAH), defined by a response to the question "What is your general health status: very good/good/fair/bad/very bad?" To give meaningful interpretations in the coefficients, the health status variable is recoded between 1 (very bad health status) and 5 (very good health status). In Table 1, we present the summary statistics of the variables used in the analysis. We apply a factor analysis to construct the wealth index, based on the household belongings. More specifically, the household belongings refer to: whether there is a bath, an indoor toilet, a piped and hot water system in the dwelling, a telephone, a washing machine, a refrigerator, a car, leaking and roof problems in the dwelling, if the household can afford to go on holiday and whether the household can afford to have a meal with meat or fish two days in a row. Other items included in the index are: whether the household can keep the house warm, whether the household has the capacity to face unexpected financial expense arrears on mortgage, utility bills and hiring purchase instalments, if there is darkness in the rooms and shortage in the space of the dwelling. The fuel type for the main heating source of the dwelling and whether the household spends more than the 40 per cent of the net income on housing are included too. Higher values correspond to greater levels of wealth.

The index is constructed based on whether the households can afford a set of assets and items, such as durable goods and financial expenses, including the utility bills and arrears on mortgage we described earlier. In this case, the set of variables takes value 1 if the household can afford them and 0 otherwise. Following Filmer and Pritchett (2001), we apply the procedure of principal components to determine the weights for an index of the asset and the financial capacity variables described so far. Principal components is a technique allowing the extraction of orthogonal linear combinations of a set of variables that provide and capture the common information most successful. In this procedure, the first principal component of a set of variables is the linear index of the variables capturing the largest amount of information common to all the variables. Next, using the estimated PCA coefficients, we take the predicted or constructed wealth index (for more technical details, see Filmer and Pritchett, 2001).

The remaining variables used in the regression analysis are the controls. Based on the earlier literature, the main socio-economic variables include age, education level, employment status, house tenure, dwelling size and household size. It is well known from the literature that age is an important determinant for both health status and wealth. Old-aged people are more likely to present negative effects of health. On the other hand, older people can be wealthier, because of the wealth accumulation over years, higher wages due to increased productivity and working experience. Similarly, education and income are important factors, since more educated people have better knowledge about healthy life style and various effects of other factors, including smoking, food diet and sports. Higher income results from high educational qualifications, since these people have more opportunities in the labour market, implying higher wages. Income allows people to have access and to buy better-quality health services. Employment status can be considered as an effect of education, while income can result from employment status, as we discussed earlier. Since the employed are more likely to earn more, they can be wealthier than the unemployed, retired and those who are disabled and unable to work. The house tenure and the house size can be effects of income and education (Avis et al., 1991; Assaad and Rouchdy, 1999; Huang and Yang, 2014; Khanam et al., 2016)

In addition, we include in the analysis extra covariates, such as whether the people are exposed to air pollution problems in the neighbourhood and whether they have heating problems, since these factors can affect the health status. For instance, it is well known that air pollution has negative effects on health and the overall well-being of people. Fuel type is important, as the coal, dried cow dung and wood have a negative effect on health outcomes. We should note that fuel type refers to the source used for heating, including coal, wood, electricity, natural gas, fuel-oil and dried cow dung. The main reason we consider this variable, is that coal and dried cow dung have a negative effect on an individual's health, including asthma and other respiratory diseases (Ozdamar and Giovanis, 2014).

(Insert Table 1)

4. Methodology

4.1 Ordered Logit and Probit models

The first part of this study examines the relationship between the health status and the treatment group of survivor benefits. The treatment variable is a dummy indicating whether the household receives survivor benefits. Then, we include in the analysis the levels of survivor benefits. In that case, we examine the association between survivor benefits and health status, limiting our interest to the sample of the survivor benefit claimants. The regression model of health status is:

$$HS_{i,h,j,t} = \beta_0 + \beta_1 dben_{i,h,t} + \beta_2 \log(y_{h,t}) + \gamma' z_{i,h,j,t} + l_j + \theta_t + l_j T + \varepsilon_{i,h,j,t} \qquad (1)$$

$HS_{i,h,j,t}$ is the health status for individual i in household h, in the region-area j and in time t; $dben_{i.h,t}$ is the dummy showing whether the individual i in household h receives the survivor benefits or not; $log(y_{i,t})$ denotes the logarithm of household income, and z is a vector of household and demographic factors, discussed in the next section. Set l_j controls for region-12 regions, particularly in Turkey, and θ_t is a time-specific vector of year indicators, while l_jT is a set of area-specific time trends. In addition, we estimate equation (1), replacing $dben_{h,t}$ with the variable $log(ben)_{i,h,t}$, which denotes the logarithm of survivor benefits. Here we control for the household income reduced by survivor benefits. As the dependent variable is an ordered variable, the ordered Probit and Logit models for cross-sectional data are the most common and appropriate techniques[1].

The next outcome of interest is the wealth. Regression (1) remains the same, with the difference that the dependent variable is the wealth index. Since this variable is continuous, we use ordinary least squares (OLS). Various methods have been used to measure deprivation and wealth. However, according to the data availability, we use a wealth index based on deprivation indicators. Townsend (1979) defined a household as deprived if it does not possess three or more items. His work has been subject to criticism, because his method does not distinguish between the respondents that either cannot afford to have these items or

[1] It should be noticed that, using also the Panel Income and Living Conditions Survey during the period of 2009-2012, the same conclusions are derived. We preferred the cross-sectional, since the main conclusions of the study are not different. Also, in the ILCS cross-sectional dataset, there are more years and additional controls, including information at the regional level instead of classifying only at rural and urban areas.

because they do not want them. Another important aspect of criticism is that Townsend (1979) considered no relevant weight assigned to each item. For example, we assume two households possess the following items: computer and TV. The first household, however, also possesses a car, while the second has a phone. We conclude that the second household is deprived, since the value of a phone is usually lower than the value of a car. Moreover, large differences between households having the same items can be present. It makes a difference, whether the phone is a smart phone or whether the car is diesel or electric. We construct the wealth index using the indicators proposed by Guio (2009), and we apply the principal component analysis suggested by Filmer and Pritchett (2001). Next, we follow a propensity score matching to test if there is selection bias between the households that receive benefits and those who do not (for more details, see Rosenbaum and Rubin, 1983). We used various algorithms, including the closest neighbour, Mahalanobis and kernel, leading to the same results.

4.2 Bayesian Networks and Directed Acyclic Graphs

This section describes the Bayesian Networks (BNs) and the directed acyclic graphs (DAGs) used in this study for causal inference. The BNs framework involves two mathematical pieces, the DAG and the probability theory focused on conditional independence. We consider BNs in our analysis for three main reasons. First, are graphical models, so they contain a part that can be depicted as a graph where a class of models is evaluated based on algorithms. Second, as the most applications in the sciences and in economics involve uncertainty, BN framework is used based on the probability theory. Third, the main purpose of this study is to derive cause-effect relationships from observational data.

To understand BNs and the associated learning techniques, is important to mention the Bayesian approach to probability and statistics. The Bayesian probability of an event X is a person's degree of belief about that event. The classical probability is a physical property of the world, e.g. the probability that a coin will land heads, while the Bayesian probability is a property of the person who assigns the probability, e.g. the degree of a person's belief that the coin will land heads. In the traditional statistical modelling, prior knowledge may not be desirable, since the data introduced can be irrelevant to the main outcome of interest. However, sometimes including prior information can be useful, since an event may depend on the probability of an event that took place before and it allows the evaluation of its impact on a specific event. Bayesian networks have been developed based on Bayes' theorem of probability theory to propagate information between nodes-variables. Bayes' theorem describes how prior knowledge about hypothesis *A* is updated by the observed evidence *B*. The theorem relates the conditional and marginal probabilities of *A* and *B* as:

$$P(A\mid B)=\frac{P(A)\cdot P(B\mid A)}{\int P(A)\cdot P(B\mid A)\cdot dB} \tag{2}$$

P(*A*) is the prior probability to the hypothesis or the likelihood that A will be in a particular state, prior to consideration of any evidence. P(*B*|*A*) is the conditional probability or the likelihood of the evidence, given the hypothesis to be tested and P(*A*|*B*) is the posterior probability of the hypothesis or the likelihood that *A* is in a state, conditional on the evidence provided. The integral in (2) represents the likelihood that the evidence is observed, given a probability distribution. Relation (2) refers on a simple problem where only two variables are incorporated. However, in real learning problem applications, the main interest is to explore the relationships among numerous variables. Bayesian network is an appropriate representation tool for this task, which encodes the joint probability distribution, physical or Bayesian, for a large set of variables. DAGs were primarily developed in computer science by Judea Pearl (1988; 2000; 2009) and Spirtes et al. (2000). DAGs consist of three elements: variables (nodes, vertices), arrows (edges), and missing arrows. *Arrows* represent possible *direct causal effects* between pairs of variables and order the variables in time. We present an example of a DAG in figure 1.

(Insert figure 1)

The arrow between *T* and *F* in figure 1 means that *T* may have a direct causal effect on *F*. Similarly, for the arrow between *B* and *T* or *A* and *C* or *B* and *C*. Where there are *missing arrows*, the strong assumption of no direct causal effect between two variables is rejected, which is the so-called "strong null" hypothesis of no-effect. In figure 1 the *missing arrow* between *T* and *Y* or *B* and *F,* implies the complete absence of a direct causal effect of *T* on *Y* or of *B* on *F*. The variables that are directed caused by a given variable are called *children*. Given figure 1 the only child of *F* is *Y* and so on. A parent may have more than one child. For example, *B* has three children, *C*, *D*, and *T*. All variables directly or indirectly caused by a given variable are called its *descendants*. The descendants of *T* are *F* and *Y*, while the *descendants* of *B* are *C, D, T* (B's children), *E* (D's and T's child), *F* (T's child) and *Y* (child of *A*, *C*, *D*, *E*, *F*). On the other hand, *parents* are the variables that direct cause another variable. Coming back to figure 1 the only parent of *F* is *T*, while the parent of *T* is *B.* A similar definition to *descendants*, working on the opposite way, is given for the variables that directly and indirectly cause of another variable and are called *ancestors.* For instance, the *ancestors* of *F* are *T* and *B*, while the *ancestors* of *E* are *B, D*, and *T*. *Paths* are sequences of adjacent arrows that traverse any given variable at most once. The arrows along a path may point in any direction. For example if *B* is the treatment and *F* is the outcome *then* $B \rightarrow T \rightarrow F$ is the only causal path. Denoting the parents as par_i and given the structure in *G*, the joint probability for *V* is defined as: (see definition 1 in appendix)

$$p(x) = \prod_{i=1}^{m} p(x_i \mid par_i) \tag{3}$$

Applying the chain rule of probability, we have:

$$p(x) = \prod_{i=1}^{m} p(x_i \mid x_1, ..., x_{i-1}) \tag{4}$$

The Markov blanket condition is the main important assumption of the Bayesian Networks. This is the condition where a node *X* is a set of nodes composed of the parents and children of *X* and the children's other parents (Pearl, 2000). The Markov blanket contains the variables that shield the node *X* from the rest nodes of the network. This means that the Markov blanket of a node is the only knowledge and information needed to predict the behaviour of that node (see definitions 1-2 in appendix). Coming back to figure 1 the Markov condition entails the following conditional independence relation for *F* to *B* and similar for the other relations.

$$F \perp B \mid T \tag{5}$$

Therefore, *F* is independent of *B* given *T*, where $\perp$ stands for statistical independence. This definition allows us to start with the complete graph, where each node is connected to all other nodes. The next step involves the removal of the edges between X_i and X_j iff $X_i \perp X_j | rest$, where *rest* denotes the rest of the variables. Based on the definition 3 in appendix we have that $X_i \perp X_j | X_r \Leftrightarrow \rho_{i,j|k}$. A test for conditional independence is therefore a test for partial correlation between the variables. In that case, we can estimate the partial correlations via regression analysis. Then we use the Fisher's Z-Transform test for the conditional independence (Spirtes et al. 2000; Kalisch and Buhlmann, 2007):

$$Z(i.j \mid k) = \frac{1}{2} \frac{(1 + \hat{\rho}_{i,j|k})}{(1 - \hat{\rho}_{i,j|k})} \tag{6}$$

Then it will be:

$$\sqrt{n - |k| - 3} \, | Z(i.j \mid k) | \, N(0,1) \tag{7}$$

For the independence test, we use the significance level α=0.05. We estimate the DAG using the PC algorithm, and we present the pseudo-code in box 1 in appendix (Spirtes et al., 2000). The *d*-separation condition is very important and useful in the construction of a BN, because it controls for possible confounders, as in the form of S described here (see definition 4 and more details on causation or over-control bias, selection and confounding bias in the appendix). Graphically, *d*-separation usually exhibits two main cases: first is $X \rightarrow S \rightarrow Y$ and second, $X \leftarrow S \rightarrow Y$. The intuition in this graphical representation is that X and Y are independent from each other conditioned on S. In the first case X causes Y through S, while in the second case X and Y have a common cause S. In addition, given the edge $X \rightarrow S$ it is said that the tail of the edge is at X, while the head over the edge is at S.

However, Bayesian Networks as every other statistical model is not without drawbacks. First, while Bayesian models are a useful way to model knowledge, it may be difficult to find an agreement on the structure of the model and the nodes important to include in the analysis. Following the previous literature, we consider the control variables that can be related to health status and wealth. Second, it can be a challenge to express the knowledge in the form of the probability distribution (Uusitalo, 2007). Another issue, common to natural and randomised trial experiments, is the plausible unobservable variables.

5. Empirical results

5.1 Ordered Probit and Logit regressions

In this section, we report and discuss the empirical estimates. The main coefficient of interest is the dummy indicating whether the household receives survivor benefits. The coefficient is significant and equal to 0.0532, based on the Probit model in Table 2. The concluding remarks stay the same when we apply the ordered Logit model, and the coefficient equals 0.1086. We should note that the magnitude of the coefficients is different, since the Logit and Probit models follow a distinct distribution. The marginal effects of the coefficients range between 0.093-0.101, implying the widows that receive survivor benefits report better health status levels by 0.1 units, on a scale measured from 1 to 5.

On the socio-economic characteristics, the results show no difference in the health status between age groups 25-29 and the reference category group of 20-24 years old. A monotonic negative relationship between health status and the age groups of 30 years and older is noted. Earlier studies support that age is negatively associated with health status, implying that a higher probability of health problems is present in old-aged people (Getzen, 1992). However, this does not imply that the decline in health with age is experienced at the same rate, and neither implication is homogeneous. Nevertheless, people do not respond the same on the loss of a spouse at all ages. Young women who become widows are less emotionally prepared than their older counterparts. Furthermore, young widows feel lonelier, as the peer group range is smaller. The death of a spouse causes major financial distress to young widows, when the savings and wealth are low at a young age (Scannell, 2003). Sevak et al. (2003) share the same opinion where they found that the young widows face greater risks of economic hardship after widowhood. They conclude that the widowed, especially young women, are less financially prepared.

A strong relationship between socio-economic status (SES) and health status is found in earlier research studies. SES is important to health, not only for those in poverty and low-education levels, but at all levels of SES. On average, the more advantaged individuals are, the better their health is, as the social groups are closer to the top of the socio-economic status. Well-educated and higher-income classes have lower rates of morbidity and mortality and better rates of health status. We confirm these findings from the results in Table 2.

Individuals with higher education levels and higher income are more likely to report better levels of health status than the less educated and those with low-income levels.

Education is an important factor, and it has a positive relationship with health status, as is associated with health knowledge and certain health behaviours. For instance, well-educated people have greater knowledge of health conditions, better self-management skills and higher participation rates in prevention programmes, such as cancer screening (Katz, 1997; Van der Meer and Mackenbach, 1999; Sabates and Feinstein, 2006). A study exploring the relationship between education and obesity found that obese people with a low education level were likely to believe it unnecessary to lose weight (Kennen et al., 2005). Individuals having low educational qualifications are ignorant of the adverse health effects of smoking and of its effects during pregnancy (Logan and Spencer, 1996; Arnold et al., 2001).

The positive relationship between income and health is well documented in the literature. The argument behind this finding is that higher income levels allow individuals to have better access to health care and to purchase health inputs of higher quality. Another argument is that healthy individuals can work extra hours and can be productive and thus able to earn higher wages in the labour market.

Employment status is another important determinant of health status. Based on the results, those who work part time, the retired, students, disabled people and those who fulfil domestic tasks present significantly lower levels of health status. This can be explained because full-time employed people earn extra money and enjoy higher levels of physical and mental health. Furthermore, well-educated people may have more opportunities in the labour market and can find employment in better jobs, earning more, suggesting interdependence among those factors. Stronks et al. (1997) explored the interrelationship between education, employment status and health. In particular, when their analysis controls for other socio-economic factors, the association between income and health is higher than education or employment status and health. Fone et al. (2006) examined the relationship between economic inactivity and mental health problems at the ward level utilising the Welsh Health Survey. They found that ward deprivation score is associated with mental health. The effect becomes stronger for the economically inactive people. Overall, the relationship between employment status, socio-economic status and health can be complex. The employment status is found to be associated with health, as the unemployed and housewives are less healthy than those in paid employment (Bartley et al., 1992; Stronks, 1997; Brown et al., 2012). Employment status is related to SES, where people from lower socio-economic groups have a higher risk of losing their jobs (Stronks, 1997; Brown et al., 2012). For this reason, we apply the proposed Bayesian Network in the next section of the study. Those who have not reported problems related to a leaking roof, damp walls or rot in the window frame, heating problems in the dwelling, and those that they are not exposed to pollution or other environmental problems are likely to present significantly higher levels of health status (Ozdamar and Giovanis, 2014). The results show an insignificant association between monthly expenses, tenure status and health. We find no significant differences for the fuel type of the heating system, including the gas fuel-oil, electricity, natural gas and the reference category – wood. The exceptions are coal and dried cow dung, where the findings show that the relationship between those types of fuel for heating and health is significant and negative (Ozdamar and Giovanis, 2014).

Those who locate in urban areas are likely to report lower health levels. We could expect that these areas offer more opportunities in the labour market, higher income, and centralised health services. But the benefits can be partially offset by other factors, such as higher unemployment, air and noise pollution, higher crime rates, depression and stress, among others. For instance, 30 per cent of the sample that live in urban areas reported being exposed to air and other environmental problems. In rural areas, it is 10 per cent. However, rural residents may face significant challenges in accessing health care and necessary support services, difficulties related to accessibility due to distance from health centres and the lack of proper infrastructure (Arcury et al., 2005; Beck et al., 2009). Furthermore, the majority of the rural residents are poor, low educated, older, less likely to have health coverage and more likely to encounter transportation challenges (Glover et al., 2004; Laditka, 2009).

In Table 2, columns (3) and (4), we report the results when the level of survivor benefits is considered. We should note that we include in the regression analysis only widows who receive survivor benefits. The concluding remarks remain the same, suggesting that survivor benefits can improve health and wealth of the widowed mother households.

(Insert Table 2)

One issue with the estimates discussed so far is the possible selection bias among those who receive survivor benefits – the treatment group – and those who do not – the control group. According to the Heckman selection model (Heckman, 1979)[2], both groups share similar socio-economic and household characteristics. In the control group, widow women are uninsured and not eligible for survivor benefits. In addition, endogeneity is not a major issue, as the death of the spouse is an exogenous event. Furthermore, the propensity score matching presented in Table 3 shows that there was no systemic difference in the characteristics between treated and untreated. The exception is house size, which is significant before and after matching. We should mention that we applied propensity score matching for household income, excluding the amount of survivor benefits. This allows us to use this income as a baseline and then to explore the additional effect of the survivor benefits.

(Insert Table 3)

Next, in Table 4, we present the ordinary least squares estimates, considering as dependent variable the wealth index, which we constructed based on the items mentioned

[2] The study applied a Heckman selection model, but the results are not presented. However, the ρ is insignificant, indicating that there are not unobservables that co-occur with the health status improvement and the claiming of the survivor benefits. So, the treatment and control groups examined in this study are well chosen.

above (for more details, see Guio, 2009). We observe a positive relationship between survivor benefits and wealth. Age and education level are associated with wealth in a positive direction, showing that older widows are richer, which may result from long-term savings and plausible investments on properties. Also, well-educated people are more likely to be wealthier and associated with better labour opportunities and higher wages. For employment status, the coefficients present the expected signs, where the old and disabled individuals, seasonal workers, the unemployed and those who fulfil domestic tasks are less wealthy than those who work full time. Those who live in urban areas and are exposed to better air quality face a lower risk of poverty. This shows that people in urban areas have additional labour opportunities and access to health services, which may lead to improved well-being. Household size is negatively correlated with wealth. This is because, as the number of household members increases, widowed mothers face a higher financial burden. In column (2), we report the same estimates, where the treatment dummy is whether the household receives survivor benefits. In addition, we include household income in the regressions. Overall, the results in column (2) show that those who receive survivor benefits increase their wealth by 0.18 units more, corresponding to a poverty gap of 23 per cent. The results remain the same, except for the age, where we found an insignificant relationship to poverty. We should note that the number of observations is smaller, when we consider the poverty index. This results from the construction of the index which is based on whether the household owns an item and whether it has specific financial and dwelling problems. Thus, the reported households that have no reason to possess a specific item are not considered, avoiding the measurement error followed by Townsend (1979). The findings are consistent with the study by Holden and Zick (2000), who found that survivor benefits are beneficial for wealth.

(Insert Table 4)

5.2 Bayesian Networks (BN)

In this section, we discuss the results of the BN DAG using the PC algorithm. We present the DAG output in figure 2, and we report the effects of the survivor benefits in table 5. We do not present the remained estimated coefficients since is not the main subject of interest. The results confirm the causal effects of the survivor benefits on health status and wealth. In figure 2, we present the Bayesian Network in a DAG using the dummy of the survivor benefits. Based on table 5 the causal effect on health is equal to 0.123 higher, but close, with the one found applying the Ordered Logit, and is 0.109. Thus, the BN shows that the households that receive the survivor benefits report higher levels of health status. The effect on wealth is 0.1370 showing that those who receive the survivor benefits increase their wealth by 0.14. Second, it is possible, using graphs, to confirm the determinants of survivor benefits eligibility, which include the education level, urban location, employment status and the household size. Age has no direct causal effects on survivor benefits, but the effects go through the employment status and the causation is: *age* $\rightarrow$ *employment status* $\rightarrow$ *survivor benefits.* The causal effect of age is blocked-off from employment status. Therefore, we use the factorisation relation (4), to identify the effect of age. Also, using the same relation (4), to identify the effect of the employment status on the survivor benefits, the regression should condition on age, the urban area, the house tenure status, and the education level. Consequently, knowing the age, the education level, the house tenure and the area-location of the respondent, we can identify the effect of the employment status on the survivor benefits. The effect of tenure status goes through the employment status and the urban area, and the air pollution problems go through the urban area.

Third, various other causal paths can be derived. As we discuss in the appendix, the forks $X \leftarrow S \rightarrow Y$ show that the variables X and Y can be associated if they share a common cause.

This is the case of the fork $X \leftarrow S \rightarrow Y$, and is known as *confounding* bias. In the estimated DAG the fork can be represented: *health* ← *survivor benefits* → *wealth*. In other words, the confounding bias or omitted variable bias takes place when a variable which causes both independent and the dependent variable is omitted. The DAG graph reveals that a direct causation from health to wealth is present, avoiding the *confounding* bias. Fourth, the endogenous bias refers to the inverted fork relationship $X \rightarrow S \leftarrow Y$. in this case, X and Y are marginally independent, because they do not cause each other and do not share a common cause (see appendix). Consequently, conditioning on the common outcome S of the two variables X and Y, we cannot identify the causal effect of X on Y, and this is the *endogenous* or *selection bias.* Let us consider, for example the following relation or the following inverted fork in figure 2: *urban area→survivor benefits←employment status*. In this case, we are not able to identify the effect of *urban* on *employment status* using the single equation modelling. However, figure 2 reveals a causal effect from the *urban area* to *employment status*. We expect this result, since the area classification can determine the employment status, i.e. in urban areas the competition in the labour market may lead to higher unemployment. Nevertheless, urban areas offer additional options and possibilities for women to find employment, while the women in the rural areas are more likely to stay housekeepers. The effect can be mixed because both area of the location and the employment status, share common causes, such as the education level and tenure status (*edu* and *tenure_st* respectively in figure 2). Thus, Bayesian Network framework can overcome the issues with the conventional single equation econometric modelling. Moreover, it is possible to examine whether there is a causal effect of the variable of interest on the dependent variable and whether we should control for specific variables.

(Insert figure 2)

(Insert table 5)

The causal effect of survivor benefits is the regression of the survivor benefits dummy and its parents on health status. Therefore, we identify the effect on health given whether the household receives the survivor benefits, given the employment status (*emp*), the urban location (*urban*), education level (*edu*), household size (*num_member*) and the household income. When we take the logarithm of the survivor benefits levels, the estimated DAG Bayesian Network is similar. We find that the causal effect of the survivor benefits on health status is 0.1190, while their effect on wealth is equal to 0.49. More specifically, as the survivor benefits are expressed in natural logarithms, the effect on health is 6.21 per cent, indicating that the benefits improve the health status by 6.21 per cent. For wealth, a 1 per cent increase in survivor benefits increases wealth or decreases poverty by 2.2 per cent.

6. Conclusions

In this study, we examined two main hypotheses. First, whether the widowed mothers eligible for survivor benefits present better health status. Second, whether are more likely to be at risk of poverty than the widowed mothers who do not claim benefits. Overall, the results are classified into two main categories. The first includes the single equation modelling, and we applied the ordered Logit and Probit models. We found a significant association between health status, wealth and survivor benefits. The second framework was a Bayesian Network which we proposed, with purpose to examine the causal effects of survivor benefits on health status and wealth. We conclude that the survivor benefit is a valuable social assistance that improves the health status and reduces the risk of poverty of households. We argue that the results are important, as they imply that the social security and survivor benefits are beneficial for wealth and health outcomes. The consequences of the health gains and wealth improvement may lead to economic growth and to the reduction of ill-health traps in poverty.

Based on the findings of this study, the policy implications are various. Information on an optimal consumption plan should be developed to help families to save enough to smooth the standard of living for surviving family members when the major breadwinner dies. This is often a result of myopia and risk misestimates, leading to a significant drop in the standard of living, and some households might end up in poverty. Mandatory survivor benefit programmes intend to limit these outcomes. Another option is the incentives for elimination of the mandatory benefits for survivors. This is based on the increasing labour participation of women and where each partner can provide for himself or herself. However, this setup ignores the children and the fact that women still work less, since men are the major breadwinners in Turkey. In addition, this setting ignores the household economies of scale, where the costs do not fall by the same proportion when one family member dies. Therefore, this is the main reason survivor insurance is necessary as a mutual protection for both spouses rather than a simple protection for the wife when the husband dies.

To summarise, we suggest various policy measures to protect the widows and their households that do not have insurance and are not eligible for survivor benefits. One option is to widen the health coverage to the uninsured individuals, either by covering the financial contributions for the poor or providing services for them. Another policy is to extend tax-based systems and to improve tax collection efficiency. This will result in extra funds that can be used in a more effective way for non-eligible widowed mothers. Also, for a family to be eligible for survivor benefits, a minimum of 900 contributory days and five qualifying years is required. The required period for civil servants and self-employed people is 1,800 days. Therefore, another policy option could be the reduction in the period of contributory days. Attention should be paid to young widows with preschool children, who experience in a temporary period high childcare expenses. Elder widows is another case group whose benefits, if not partially indexed to wages, will fall far behind that of the average current employee. A flat benefit or minimum pension guarantee requires inter-family transfers through public funds. Furthermore, the changing role and increasing labour force participation rates of women should be recognised to adjust the survivor benefits in a proper way. More specifically, in the cases where both spouses work and have their own pensions, survivor benefit rates should be less than the unemployed widows. For instance, women who became widowed at a young age and do not have young children can work. So, it is no longer necessary to give them a higher benefit rate for life. Costs should be measured based on the expected present value of lifetime benefits that take the number of years of benefits and not the annual amounts. Thus, the above-mentioned policies have a twofold target: First, decreasing the probability of being in poverty by dividing the funds and, second, in an indirect way by reducing the risk of poverty and increasing the households' wealth through health status improvement.

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References

Arcury, T.A., Preisser, J.S., Gesler, W.M., Powers, J.M., 2005. Access to transportation and health care utilization in a rural region. Journal of Rural Health, 21(1), 31–38.

Arnold, C.L., Davis, T.C., Berkel, H.J., Jackson, R.H., Nandy, I., London, S., 2001. Smoking status, reading level and knowledge of tobacco effects among low-income pregnant women. Preventive Medicine, 32, 313-320.

Assaad, R., Rouchdy, M., 1999. Poverty and Poverty Alleviation Strategies in Egypt, Cairo Papers in Social Science, 22(1).

Avis, N. E., Brambilla, D. J., Vass, K., McKinlay, J. B., 1991. The Effect of Widowhood on Health: A Prospective Analysis From The Massachusetts Women's Health Study Social Science and Medicine, 33(9), 1063-1070.

Bartley, M., Popay, J., Plewis, I., 1992. Domestic conditions, paid employment and women's experience of ill health. Sociology of Health and Illness, 14, 313–343.

Beck, S.L., Towsley, G.L., Caserta, M.S., Lindau, K., Dudley, W.N., 2009. Symptom Experiences and Quality of Life of Rural and Urban Older Adult Cancer Survivors. Cancer Nurs. 32(5), 359–369.

Bennet K.M., Smith, P.T., Hughes, G.M., 2005. Coping, depressive feelings and gender differences in late life. widowhood Aging and Mental Health, 9(4), 348–353.

Bromley, J., Jackson, N.A., Clymer, O.J., Giacomello, A.M., Jensen, F.V., 2005. The use of Hugin to develop Bayesian networks as an aid to integrated water resource planning. Environmental Modelling and Software, 20, 231-242.

Brooks-Gunn, J., Duncan, G.J., 1997. The effects of poverty on children. Future of Children, 7(2), 55-71.

Brown, J., Tristram, A.M., Gilmour, H., Sanati, K.A., Macdonald, E.B., 2012. Employment status and health: understanding the health of the economically inactive population in Scotland. BMC Public Health, 12, 327.

Brown, S., Risa A., Kilic, D., 2014. Out-of-pocket health care expenditure in Turkey: Analysis of the 2003–2008 Household Budget Surveys. Economic Modelling, 41, 211-218.

Chakraborty, S., 2009. Europe & Central Asia: Knowledge Brief. Volume 12, December 2009. The World Bank.

Duncan, G.J., Hoffman, S.D., 1985. Economic Consequences of Marital InstabilityIn Horizontal Equity, Uncertainty, and Economic Well-Being, edited by David M. and Smeeding, T. University of Chicago Press, pp. 427-470.

Erus, B., Aktakke, N., 2012. Impact of healthcare reforms on out-of-pocket health expenditures in Turkey for public insures. The European Journal of Health Economics, 13(3), 337-346.

Fasoranti, O.O., Aruna, J.O., 2007. A Cross-Cultural Comparison of Practices Relating to Widowhood and Widow-Inheritance among the Igbo and Yoruba in Nigeria. Journal of World Anthropology: Occasional Papers, 3(1), 53–73.

Filmer, D., Pritchett, L., 2001. Estimating Wealth Effects Without Expenditure Data—Or Tears: With an Application to Educational Enrollments in States of India. Demography, 38(1), 115-132.

Fone, D. L., Dunstan, F.D., Christie, S., Jones, A., West, J., Webber, M., Lester, N., Watkins, J., 2006. Council tax valuation bands, socio-economic status and health outcome: a cross-sectional analysis from the Caerphilly Health and Social Needs Study. *BMC Public Health*, 6, 115.

Getzen, T.E., 1992. Population aging and the growth of health expenditure. Journal of Gerontology, Social Sciences, 47, 98–104

Glover, S., Moore, C.G., Samuels, M.E., Probst, J.C., 2004. Disparities in access to care among rural working-age adults. Journal of Rural Health, 20(3), 193–205.
Grütjen, D. 2006. The Turkish Welfare Regime: An Example of the Southern European Model? The Role of the State, Market and Family in Welfare Provision. Turkish Policy Quarterly, 7(1), 111-129.
Guio, A.-C. 2009. What can be learned from deprivation indicators in Europe? Paper presented at the Indicators Sub-Group of the Social Protection Committee, Eurostat Methodological Working Papers http://www.bristol.ac.uk/poverty/downloads/keyofficialdocuments/Deprivation%20indicators%20in%20Europe.pdf. Luxembourg: Office for Official Publications of the European Communities.
Haveman, R., Wolfe, B., Spaulding, J. 1991. Child events and circumstances influencing high school completion. Demography, 28(1), 133-158.
Heckman, J. 1979. Sample selection bias as a specification error. Econometrica, 47(1), 153–161.
Holden K. C., Smock, P. J., 1991. The Economic Costs of Marital Dissolution: Why Do Women Bear a Disproportionate Cost? Annual Review of Sociology, 17, 51–78.
Holden, K. C., Zick, C., 2000. Distributional Changes in Income and Wealth upon Widowhood: Implications for Private Insurance and Public Policy. In Retirement Needs Framework. SOA Monograph M-RS00-1. Schaumburg, Ill.: Society of Actuaries.
Huang, R, Yang, M., 2014. Paid maternity leave and breastfeeding practice before and after California's implementation of the nation's first paid family leave program. Economics and Human Biology 16, 45–59.
Hungerford, T. L., 2001. The Economic Consequences of Widowhood on Elderly Women in the United States and Germany. The Gerontologist, 41(1), 103-110.
Huston, A.C., McLoyd, V.C., Garcia Coll, C.T., 1994. Children and poverty: Issues in contemporary research. Child Development, 65(2), 275-282.
Iams, H. M., Sandell, S. H., 1998. Cost-neutral policies to increase Social Security benefits for widows: A simulation for 1992. Social Security Bulletin, 61(1), 34-43.
Kalisch, M., Buhlmann, B., 2007. Estimating high-dimensional directed acyclic graphs with the PC-Algorithm. Journal of Machine Learning Research, 8, 613-636.
Katz, P.P., 1997. Education and self-care activities among persons with rheumatoid arthritis. Social Science and Medicine, 46(8), 1057-1066.
Kennen, E.M., Davis, T.C., Huang, J., Yu, H., Carden, D., Bass, R., et al., 2005. Tipping the scales: The effects of literacy on obese patients' knowledge and readiness to lose weight. Southern Medical Journal, 98(1), 15-18.
Khanam, R., Nghiem, S., Connelly, L. 2016. The effects of parental leave on child health and postnatal care: Evidence from Australia. Economic Analysis and Policy, (49), 17-29.
Kinnear, K. L., 1999. Single parents: A reference handbook. Abc-Clio Inc.
Laditka, J.N., Laditka, S.B., Probst, J.C., 2009. Health care access in rural areas: evidence that hospitalization for ambulatory care-sensitive conditions in the United States may increase with the level of rurality. Health and Place, 15(3), 731–740.
Lee, G.R., Demaris, A., Bavin, S., Sullivan, R., 2001. Gender Differences in the Depressive Effect of Widowhood in Later Life. Journal of Gerontology: Social Sciences, 56(B), 556–561.
Logan, S., Spencer, N., 1996. Smoking and other health related behaviour in the social and environmental context. Archives of Disease in Childhood, 74(2), 176-179.
Morgan, L. A., 1989. Economic Well-Being Following Marital Termination A Comparison of Widowed and Divorced Women. Journal of Family Issues, 10(1), 86-101.

Myers, D. A., Burkhauser, R. V., Holden, K. C. 1987. The transition from wife to widow: The importance of survivor benefits to widows. Journal of Risk and Insurance 54, 752-759.
Neapolitan, R.E., 2003. Learning Bayesian Networks. Prentice Hall Series in Artificial Intelligence, Pearson Education: New Jersey.
Nestel G., Mercier, J., Shaw, L. B., 1983. Economic Consequences of Midlife Change in Marital Status. In Unplanned Careers: The Working Lives of Middle-aged Women, edited by Shaw L. B. Lexington Books, Lexington, MA, 113-135.
Ozdamar, O., Giovanis, E., 2014. Valuing the Effects of Air and Noise Pollution on Health Status in Turkey. MPRA Paper No. 67926. Online at https://mpra.ub.uni-muenchen.de/67926/
Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems. San Mateo, California, Morgan Kaufmann.
Pearl, J., 2000. Causality. Models, Reasoning, and Inference. Cambridge University Press, Cambridge.
Pearl, J., 2009. Causal inference in statistics: An overview. Statistical Surveys, 3, 96–146.
Rosenbaum, P. R., Rubin, D.B. 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70(1), 41–55.
Sabates, R., Feinstein, L., 2006. The role of education in the uptake of preventative health care: The case of cervical screening in Britain. Social Science and Medicine, 62, 2998-3034.
Sandell, S. H., Iams, H. M., 1996. Reducing Women's Poverty by Shifting Social Security Benefits from Retired Couples to Widows. Journal of Policy Analysis and Management, 16(2), 279–297.
Scannell, D.E., 2003. Women's adjustment to widowhood. Theory, research, and interventions. Journal of Psychosocial Nursing and Mental Health Services, 41(5), 28–36.
Sevak, P., Weir, D.R., Willis, R.J., 2003. The Economic Consequences of a Husband's Death: Evidence from the HRS and AHEAD. Social Security Bulletin, 65(3), 31-44.
Siegenthaler, J. K., 1996. Poverty among single elderly women under different systems of old-age security: A comparative review. Social Security Bulletin, 59(3), 31-44.
Smock, P. J., Manning, W. D., Gupta, S., 1999. The Effect of Marriage and Divorce on Women's Economic Well-Being. American Sociological Review, 64(6), 794-812.
Spirtes, P., Glymour, C., Scheines, R., 2000. Causation, Prediction, and Search. 2nd ed, MIT Press, Cambridge, MA.
Springer, P.B., 1984. Health Care Coverage of Survivor Families with Children: Determinants and Consequences. Social Security Bulletin, 47(2), 3-16.
Stronks, K., van de Mheen, H., van den Bos, J., Mackenbach, J.P., 1997. The interrelationship between income, health and employment status. International Journal of Epidemiology, 26(3), 592-600.
Townsend, P., 1979. Poverty in the United Kingdom, London: Allen Lane and Penguin Books.
Turkish Statistical Institute, 2013. Income and Living Conditions Survey Micro Data Set (Cross Sectional. 2006-2012. Ankara.
Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecological Modelling, 203, 312-318.
Van der Meer, J.B.W., Mackenbach, J.P., 1999, The care and course of diabetes: Differences according to level of education. Health Policy, 46, 127-141.

Waldron, I., Hughes, M. E., Brooks, T. L., 1996. Marriage Protection and Marriage Selection—Prospective Evidence for Reciprocal Effects of Marital Status and Health. Social Science and Medicine, 43(1), 113-123.

Wilcox, S., Evenson, K. R., Aragaki, A., Wassertheil-Smoller, S., Mouton, C. P., Loevinger, B. L., 2003. The effects of widowhood on physical and mental health, health behaviors, and health outcomes: The Women's Health Initiative. Health Psychology. 22(5), 513-522.

APPENDIX

The causal Markov assumption is the central assumption that defines BN. According to this assumption, each node is independent of its non-descendants in the graph, conditional on its parents in the graph. In other words, given a node's immediate cause, we can disregard the causes of its ancestors

Definition 1. (Markovian parents) (Pearl, 2000): *Let $V = \{X_1, X_2, . . . X_v\}$ be set of variables, and let P(v) be the joint probability distribution on these variables. A set of variables PA_j is said to be Markovian parents of X_j if PA_j is a minimal set of predecessors of X_j that renders X_j independent of all its other predecessors.*

Definition 2. (Conditional Independence Graph): *The conditional independence graph of X is the undirected graph G = (V,E) where $V = \{X_1, X_2, . . . X_v\}$ and (i, j) is not in the edge set E iff $X_i \perp X_j \mid X_{v\setminus\{I,j\}}$.*

Definition 3. (Partial Correlation): *For $i \neq j \in 1, . . . , p$, $k \in rest$, let $\rho_{i,j|k}$ be the partial correlation between X_i and X_j given X_r ;$r \in k$.*

Definition 4. (d-separation) (Pearl, 1988; Spirtes et al., 2000; Neapolitan, 2003): *Let G= (V,E) be a DAG*, a path *p* is said to be d-separated (or blocked) by a set of nodes S iff:

(i) p contains a chain $i \rightarrow j \rightarrow k$ or a fork $i \leftarrow j \rightarrow k$ such that the middle node *j* is in S, or

(ii) (ii) p contains an inverted fork $i \rightarrow j \leftarrow k$ such that neither the middle node *j* nor any of its descendants (in *G*) are in S

Box 1. PC algorithm for the estimated DAG

Step 1:

Start with the complete undirected graph, $C^{\sim}$ with vertices $V = X_1, . . . ,X_p$. Then:

Step 2:

Set $l = -1$ and $C = C^{\sim}$

Step 3:

Increase *l* by one. For all pairs of adjacent nodes:

- Check for conditional independence
- Remove edge (X_i, X_j) if $X_i \perp\!\!\perp X_j | rest$

Step 4:

Repeat step 2 until $l = m$ or until each node has fewer than $l - 1$ neighbours

And let *mr* each $\in$ max *l*, *m* denote the stopping level of the algorithm and *q* be the maximum number of neighbours

The steps for calculating DAG using the PC algorithm are (for more details on PC algorithm see also Spirtes et al., 2000):

- For each X and Y, see if X Y; if so, remove their edge.
- For each X and Y which are still connected, and add third variable Z_1, see if X $Y|ZZ_1$; if so, remove the edge between X and Y.
- For each X and Y which are still connected, and add third and fourth variables
- Z_1 and Z_2, see if X $Y|Z_1,Z_2$; if so, remove their edge. For each X and Y which are still connected, see if X $Y|$ all the p − 2 other variables; if so, remove, their edge

In more details it will be:

Step 1. Form the complete undirected graph G on the set of variables V;

Step 2. For each pair of variables X and Y that are adjacent in the current G such that adj(G, X)\{Y} or adj(G, Y)\{X} has at least n elements, check through the subsets of adj(G, X)\{Y} and the subsets of adj(G, Y)\{X}that have exactly n variables. If a subset S is found conditional on which X and Y are independent, remove the edge between X and Y in U, and record S as separation set- Sepset(X, Y) and repeat until for each ordered pair of adjacent variables X and Y , adj(G, X)\{Y} has less than n elements.

Step 3. Let P be the graph resulting from step 2. For each unshielded triple {A, B, C} in P, orient it as A → B ← C iff. B is not in Sepset(A, C).

Step 4. Execute the following orientation rules until none of them applies:

a If A → B −C, A and C are not adjacent, orient as B → C.

b If A → B → C and A −C, orient as A → C.

c If A → B ← C, A−D −C, D −B, and A and C are not adjacent, orient D −B as D → B.

Figure 1. An example of a Directed Acyclic Graph (DAG)

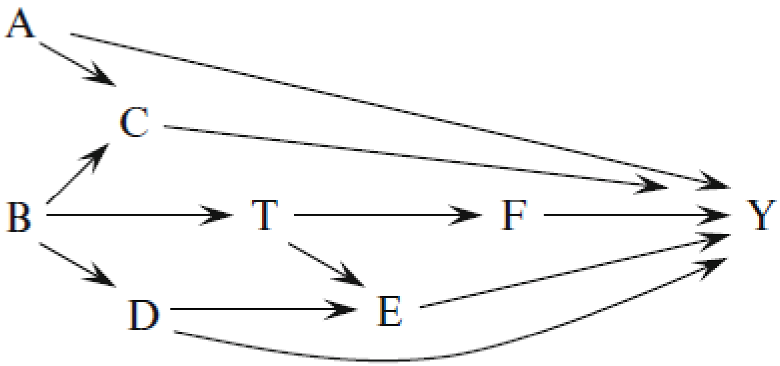

Figure 2. Estimated DAG with PC Algorithm for the Treatment Group of Survivor Benefits

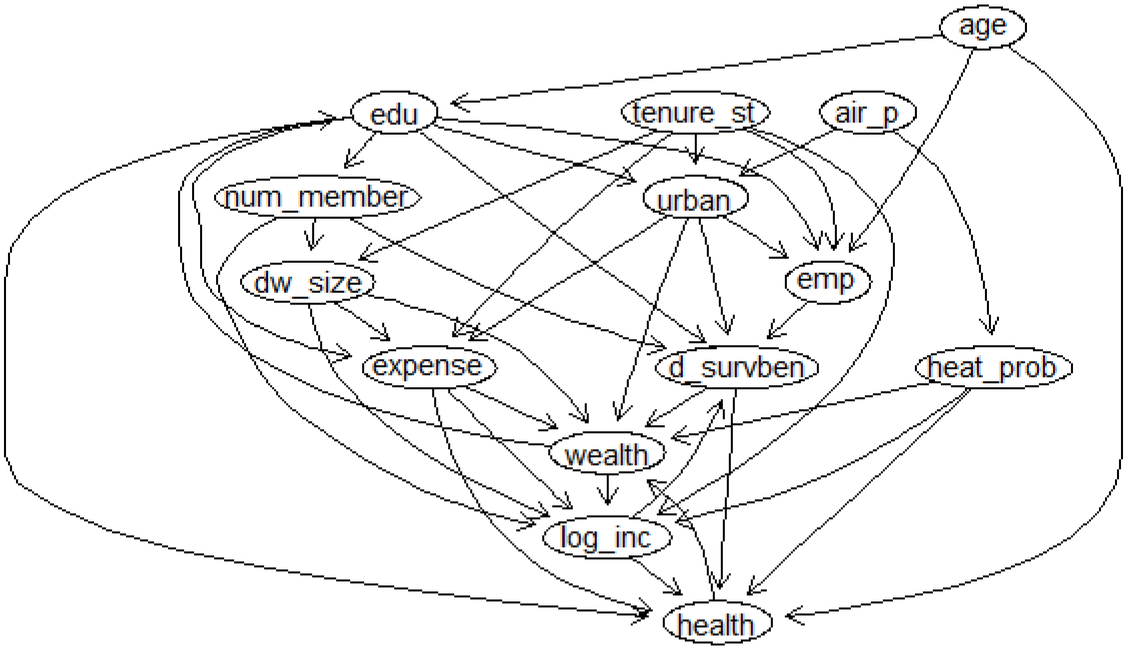

Table 1. Summary Statistics of the Dataset for Widowed Women

Continuous Variables	(1) N	(2) mean	(3) sd	(4) min	(5) max
Monthly expenses	11,389	164.7	152.0	0	2,208
Dwelling Size	11,389	96.02	32.02	25	400
Number of members in Household	11,389	2.696	1.559	1	16
Log (Income)	11,389	9.492	0.729	5.938	13.20
Log (Survivor Benefits)	6,721	8.582	0.475	5.298	12.03
Log (Other Income)	6,621	9.041	1.062	2.463	13.19
Categorical Var.	**Percentage**	**Categorical var.**	**Percentage**	**Categorical Var.**	**Percentage**
Health (very bad)	8.60	Fuel type (wood)	20.75	Tenure status (owner)	75.26
Health (bad)	39.04	Fuel type (coal)	50.18	Tenure status (tenant)	11.03
Health (fair)	35.48	Fuel type (natural gas)	17.65	Tenure status (lodging)	0.30
Health (good)	16.05	Fuel type (fuel-oil)	0.60	Tenure status (rent-free)	13.42
Health (very good)	0.83	Fuel type (diesel oil-gasoil)	0.25	Employment St. (Full-Time)	6.57
Gender (Female)	100.0	Fuel type (electricity)	4.43	Emp.St.(Part-Time)	10.51
Age (20-24)	0.09	Fuel type (dried cow dung)	5.53	Emp.St.(Looking for a job)	10.70
Age (25-29)	0.40	Fuel type (other)	0.61	Emp.St.(Student or unpaid work experience)	10.72
Age (30-34)	0.81				
Age (35-39)	1.67	Education (Illiterate)	57.05	Emp.St.(Retirement/giving up business)	5.66
Age (40-44)	2.90	Education (Literate but not a graduate)	12.86	Emp.St.(Seasonal)	0.11
Age (45-49)	4.98	Education (Primary Sch.)	24.56	Emp.St.(old, permanently disabled)	42.22
Age (50-54)	7.84	Education (Secondary Sch.)	2.20	Emp.St.(Fulfilling domestic tasks)	40.29
Age (55-59)	9.60	Education (High Sch.)	1.39	Emp. St.(Other inactive person)	1.00
Age (60-64)	11.45	Education (Vocational high Sch.)	1.10	Unmet need for medical examination or treatment (No)	75.31
Age (65 +)	60.28	Education (Higher edu)	0.85	Pollution, grime or other environmental problems (No)	78.40
Urban Area	56.71				
Leaking roof, damp walls or rot in window frames problems (No)	51.72	Heating problems because of insulation (no)	53.46		
Receipting Survivor Benefits	59.01				

Table 2. Ordered Probit and Logit Estimates for the Survivor Benefits and Health Status

Variables	(1) Ordered Probit	(2) Ordered Logit	(3) Ordered Probit	(4) Ordered Logit
Log(Income)	0.1555***	0.2667***		
	(0.0277)	(0.0403)		
Receipting survivor benefits	0.0532**	0.1086**		
	(0.0248)	(0.0439)		
Log (Other Income)			0.0807***	0.1412***
			(0.0190)	(0.0335)
Log (Survivor Benefits)			0.0620**	0.1234**
			(0.0312)	(0.0547)
Age (25-29)	-0.1818	-0.3364	-0.1809	-0.4074
	(0.2292)	(0.4639)	(0.2940)	(0.5441)
Age (30-34)	-0.8342***	-1.6257***	-0.7286***	-1.4407***
	(0.2305)	(0.4601)	(0.2772)	(0.4971)
Age (35-39)	-0.7556***	-1.5028***	-0.6546***	-1.3877***
	(0.2118)	(0.4290)	(0.2447)	(0.4395)
Age (40-44)	-1.0276***	-2.0338***	-0.9424***	-1.9052***
	(0.2047)	(0.4187)	(0.2286)	(0.4135)
Age (45-49)	-1.2606***	-2.4156***	-1.1642***	-2.2749***
	(0.2015)	(0.4123)	(0.2209)	(0.3973)
Age (50-54)	-1.3655***	-2.6447***	-1.2790***	-2.5070***
	(0.2003)	(0.4104)	(0.2200)	(0.3956)
Age (55-59)	-1.4739***	-2.8293***	-1.4446***	-2.8026***
	(0.1993)	(0.4088)	(0.2186)	(0.3930)
Age (60-64)	-1.5538***	-2.9559***	-1.5112***	-2.9006***
	(0.1992)	(0.4084)	(0.2184)	(0.3921)
Age (65+)	-1.7557***	-3.2863***	-1.7108***	-3.2226***
	(0.1982)	(0.4069)	(0.2172)	(0.3900)
Education (Illiterate)	0.0151	0.0267	-0.0117	0.0003
	(0.0333)	(0.0584)	(0.0411)	(0.0722)
Education (Literate but not a graduate)	0.1194***	0.2067***	0.1208***	0.2238***
	(0.0295)	(0.0517)	(0.0369)	(0.0648)
Education (Primary Sch.)	0.0929	0.1467	0.0709	0.1360
	(0.0715)	(0.1227)	(0.0835)	(0.1446)
Education (Secondary Sch.)	0.2612***	0.4914***	0.2050**	0.4029**
	(0.0880)	(0.1553)	(0.1006)	(0.1787)
Education (High Sch.)	0.3974***	0.6807***	0.5135***	0.9021***
	(0.1022)	(0.1777)	(0.1183)	(0.1985)
Education (Vocational High Sch.)	0.1966	0.3247	0.3166**	0.5356**
	(0.1206)	(0.2110)	(0.1489)	(0.2635)
Leaking roof, damp walls or rot in window frames problems (No)	0.1581***	0.2639***	0.1837***	0.3088***
	(0.0363)	(0.0643)	(0.0475)	(0.0839)
Fuel type (coal)	-0.0582*	-0.0981*	-0.0603	-0.1199
	(0.0299)	(0.0524)	(0.0426)	(0.0744)
Fuel type (natural gas)	0.0487	0.0890	0.0454	0.0537
	(0.0490)	(0.0859)	(0.0627)	(0.1099)
Fuel type (fuel-oil)	-0.0549	-0.0744	-0.1986	-0.4126
	(0.1380)	(0.2368)	(0.1521)	(0.2579)
Fuel type (diesel oil), gasoil	0.1646	0.2925	0.3168	0.5340
	(0.2143)	(0.3906)	(0.2609)	(0.4932)
Fuel type (electricity)	-0.0769	-0.1239	-0.0504	-0.1097
	(0.0608)	(0.1052)	(0.0757)	(0.1317)
Fuel type (dried cow dung)	-0.1123**	-0.2328**	-0.1270	-0.2722
	(0.0548)	(0.0956)	(0.0989)	(0.1806)
Fuel type (other)	0.0394	0.0309	-0.0889	-0.2378
	(0.1438)	(0.2479)	(0.1952)	(0.3354)

Table 2 (cont.) Ordered Probit and Logit Estimates for the Survivor Benefits and Health Status

Variables	(1) Ordered Probit	(2) Ordered Logit	(3) Ordered Probit	(4) Ordered Logit
Tenure status (tenant)	0.0040	0.0170	0.0215	0.0481
	(0.0471)	(0.0836)	(0.0629)	(0.1105)
Tenure status (lodging)	-0.1538	-0.3957	-0.1569	-0.4447
	(0.2154)	(0.3285)	(0.2453)	(0.3704)
Tenure status (rent-free)	-0.0497	-0.0668	-0.0318	-0.0276
	(0.0305)	(0.0531)	(0.0408)	(0.0707)
Emp.St.(Part-Time)	-0.1336**	-0.2350**	-0.1811**	-0.3206**
	(0.0647)	(0.1130)	(0.0871)	(0.1498)
Emp.St.(looking for a job)	0.1132	0.1756	-0.0993	-0.2625
	(0.2331)	(0.4402)	(0.3029)	(0.5620)
Emp.St.(Student or unpaid work experience)	-1.1862***	-2.2240***	-0.9424***	-1.8142***
	(0.3732)	(0.7763)	(0.3085)	(0.6080)
Emp.St.(Retirement/giving up business)	-0.2766***	-0.4605***	-0.2105***	-0.3455**
	(0.0620)	(0.1091)	(0.0787)	(0.1387)
Emp.St.(Seasonal)	0.3365	0.6208	-0.0847	-0.7946
	(0.3712)	(0.7359)	(0.7824)	(1.7235)
Emp.St.(old, permanently disabled)	-0.7373***	-1.2968***	-0.7006***	-1.2526***
	(0.0473)	(0.0837)	(0.0623)	(0.1103)
Emp.St.(Fulfilling domestic tasks)	-0.1835***	-0.3303***	-0.1312**	-0.2496**
	(0.0441)	(0.0781)	(0.0571)	(0.1011)
Emp.St.(other inactive person)	-0.4814***	-0.8068***	-0.3642***	-0.6442***
	(0.1180)	(0.2060)	(0.1393)	(0.2425)
Number of member in Household	0.0130	0.0248	0.0163	0.0286
	(0.0092)	(0.0160)	(0.0137)	(0.0241)
Dwelling Size	0.0005	0.0014**	0.0009*	0.0020**
	(0.0004)	(0.0007)	(0.0005)	(0.0008)
Monthly expenses	0.00076*	0.0001	0.0001	0.0001
	(0.00039)	(0.0002)	(0.0001)	(0.0002)
Heating problems because of insulation (no)	0.0976***	0.1797***	0.0960**	0.1803**
	(0.0349)	(0.0620)	(0.0455)	(0.0788)
Pollution, grime or other environmental problems (No)	0.0993***	0.1765***	0.1027**	0.1872***
	(0.0260)	(0.0455)	(0.0333)	(0.0586)
Urban Area	-0.0614**	-0.1172**	-0.0559*	-0.1088*
	(0.0271)	(0.0478)	(0.0282)	(0.0633)
Wald Chi-Square	2,830.01	2,764.42	1,523.03	1,503.21
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	11,389	11,389	6,621	6,621

Robust standard errors within brackets, p-values within square brackets, ***, ** and * indicate significance at 1%, 5% and 10% level.

Table 3. Propensity Score Test Before and After Matching

Variables	t-test Before matching	t-test After matching	Variables	t-test Before matching	t-test After matching
Age	0.583	0.281	Heating problems in the house	1.29	-0.83
	(0.463)	(0.782)		(0.129)	(0.421)
Education Level	1.57	1.26	Fuel Heat Type	1.77	1.37
	(0.147)	(0.179)		(0.123)	(0.172)
Employment Status	1.80	0.84	House size	10.45***	-5.03***
	(0.121)	(0.345)		(0.041)	(0.533)
Household Income	1.11	-0.85	Monthly household expenses	2.15	-0.02
	(0.231)	(0.461)		(0.0034)	(0.983)
Tenure Status	-1.03	-0.32	Unmet doctor needs	16.69***	-2.09**
	(0.232)	(0.748)		(0.000)	(0.037)
Household Size	-1.23	-1.06	Urban and Rural Area	1.58	1.00
	(0.216)	(0.237)		(0.104)	(0.231)
Self-reported Air Pollution	11.58	-1.49	Region	-1.76	-1.54
	(0.094)	(0.137)		(0.105)	(0.124)
Number of Leaking problems in the house	1.24	0.78			
	(0.175)	(0.546)			

p-values within square brackets, *** indicate significance at 1% level

Table 4. Poverty-Deprivation OLS Estimates

Variables	(1)	(2)
Dummy of Survivor		0.1790**
		(0.0840)
Logarithm of Household Income		2.0646***
		(0.0625)
Logarithm of Survivor Benefits	0.5908***	
	(0.0850)	
Logarithm of Household Income-Survivor Benefits	1.2340***	
	(0.0688)	
Age (reference category= age group 20-24)		
Age group 25-29	2.5965***	0.5038
	(0.4037)	(0.8149)
Age group 30-34	2.7500***	0.4632
	(0.4498)	(0.7584)
Age group 35-39	2.8821***	0.8241
	(0.4354)	(0.7473)
Age group 40-44	2.7236***	0.9736
	(0.3895)	(0.7362)
Age group 45-49	2.3243***	0.7561
	(0.3779)	(0.7351)
Age group 50-54	2.3559***	0.7577
	(0.3708)	(0.7322)
Age group 55-59	2.4219***	0.8172
	(0.3670)	(0.7331)
Age group 60-64	2.7153***	0.9713
	(0.3821)	(0.7325)
Age group 65+	2.7520***	0.9392
	(0.3664)	(0.7305)
Education Level (Reference category= Illiterate)		
Literate but not a graduate	0.5779***	0.3247***
	(0.1140)	(0.0886)
Primary School	0.8270***	0.7288***
	(0.1035)	(0.0821)
Secondary School	1.0076***	0.9256***
	(0.2203)	(0.1758)
High School	2.0208***	1.6967***
	(0.2882)	(0.2297)
Vocational/Technical school	1.1731***	0.9626***
	(0.2848)	(0.2454)
Higher Education	1.2101***	1.1812***
	(0.3458)	(0.3230)
Tenure Status (reference category=Owner)		
Tenure Status (Tenant)	0.1606	-0.2326***
	(0.1033)	(0.0790)
Tenure Status (Lodging)	1.1332	-1.1117***
	(0.7888)	(0.3902)
Tenure Status (Other free-rent accommodation)	-0.3653***	-0.0999
	(0.1083)	(0.0864)

Table 4 (cont.) Poverty-Deprivation OLS Estimates

Variables	**(1)**	**(2)**
Employment Status (reference category=Full-Time)		
Employment Status (Part-Time)	-0.0270	-0.1704
	(0.2441)	(0.1752)
Employment Status (Unemployed)	-0.0346	-0.7624
	(0.4769)	(0.4997)
Employment Status (Student or unpaid work experience	0.1643	0.8100
	(0.3781)	(0.5184)
Employment Status (Retired)	0.4892	0.4157
	(0.4029)	(0.3603)
Employment Status (Seasonal)	-0.2408***	-0.7434***
	(0.0784)	(0.1889)
Employment Status (Old, permanently disabled)	0.2356	0.0326
	(0.1584)	(0.1265)
Employment Status (Fulfilling domestic tasks)	-0.3588***	0.1597
	(0.1363)	(0.1131)
Employment Status (Other inactive)	0.1658	-0.0570
	(0.3157)	(0.2631)
Household Size	-0.0965**	-0.0640***
	(0.0375)	(0.0237)
Pollution, grime or other environmental problems (No)	0.0383	0.0767
	(0.0794)	(0.0626)
Urban Area	0.4489***	0.5141***
No. Observations	1,565	3,044
R-squared	0.5619	0.5913

Robust standard errors within brackets, *** and ** indicate significance at 1% and 5% level.

Table 5. Bayesian Network Estimates

	DV: Health Status (1)	**DV: Wealth (2)**
Dummy of Survivor Benefits	0.1238**	0.1370***
	(0.0576)	(0.0139)
Logarithm of Survivor Benefits	0.1190***	0.4905***
	(0.0239)	(0.0205)

Standard errors within brackets, *** and ** indicate significance at 1% and 5% level.