The Granger causality of income on health using a microsimulation approach

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Abstract

Socio-economic status and health status are positively related. However, one must be careful in considering the causal impact of income on health, since the reverse causality might be at play. Since income inequalities are an important factor in health inequality, policy makers who aim at improving general health or narrowing health inequalities using public policies, need to understand the sources and the true direction of the causality between income and health. We thus implement an original method in order to assess the Granger causality of income on the self-perceived health status. Using the Survey of Health, Aging and Retirement in Europe (SHARE), we exploit the panel dimension of the data. We use a microsimulation method to tackle the endogeneity issues of the factors which might influence the relationship between health and income, by incorporating lagged values of the variables of interest. Once these other factors are controlled, we then apply an instrumental variables method, as well as exogenous income shocks, to solve the income endogeneity issues. We find evidence of a strong positive and significant effect of income on self-assessed health, implying the Granger causality of income on health. Thus, public policies, such as redistribution, are efficient to reduce income-related health inequalities.

Keywords: Granger causality; microsimulation; income; self-assessed health; Europe.

JEL Classification: C15; C23; D31; I10; J14.

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1 Introduction

A topic at the center of health economics is the relationship between health and individual income, with the consensus view among researchers being that higher socioeconomic status is associated with better health (Preston [1975]). This relationship has been reviewed using many health outcomes in different countries (e.g. Van Doorslaer et al. [1997] utilizing self-assessed health). While this relationship appears to be well-known, this is not the case concerning its causal interpretation. There are many possible pathways through which earnings can impact health. Indeed, there is a causal relationship between socioeconomic status, or more specifically income, and health of the former on the latter (Frijters et al. [2005] or Apouey and Clark [2015]). However, we can also think of the reverse association, for instance stating that poor health status may influence income, by reducing the ability to work (Michaud and Van Soest [2008]). This lack of a clear understanding of causality is an important omission, and the direction of the causal effect of income on health does not seem obvious. Since income inequalities are an important factor in health inequality (e.g. Carrieri and Jones [2016]), policy makers who aim at improving general health or narrowing health inequalities in a society, need to understand the sources and the true direction of the causality between income and health. The difficulty in disentangling cause and effect is due to endogeneity, more specifically whenever health and income mutually determine one another, there are simultaneity issues. Since simultaneous causality in both directions may exist, testing the causal impact of income on health requires assessing the exogeneity of income. In this context, considering that randomized controlled experiments are not really feasible, this can lead to errors and inefficiency (Deaton and Cartwright [2016]) and this is why other approaches need to be employed.

In the relationship between health and income, various mechanisms can occur at the same time, affecting the impact of income on the self-perceived health status. To this extent, identifying the factors which influence the age profile of the self-perceived health is of importance, but remains a difficult undertaking, justifying further investigation. In this paper, we intend to perform a microsimulation analysis following the methodology of Dormont et al. [2006], in order to analyze health changes over time. This methodology permits us to separately identify changes due to alterations in morbidity, or due to the technological trend on the one hand, and changes due to individual characteristic,s on the other hand. Thus, the microsimulation method aims to identify the impact of income changes, while controlling for morbidity, technological progress and individual characteristics on self-perceived health status.

To correctly identify these factors, one needs to control for their possible endogeneity towards the self-perceived health status. Indeed, individuals take into account several elements of their health when assessing their subjective measure of health. Diseases, diagnosed health problems, as well as interactions with health professionals are factors which influence the self-rated health (Tubeuf et al. [2008]). This measurement, even if it is subjective, is a good predictor of an individual's health (Benitez-Silva et al. [2004]). Thus, it incorporates factors which are not always observed by health professional,s because it integrates personal expectation of the level of health.

This paper contributes to these subjects by bringing the Granger causality of income on health to the forefront. In this paper, we use European dynamic micro data, where the temporal dimension of the data is employed to evaluate and predict changes in self-perceived health status according to income. Thus, a microsimulation method is implemented to control for the factors which could influence the impact of income on health. Moreover, instrumental variables, as well as exogenous income shocks, are used to get rid of the endogeneity issues related to income. With these methods, we ensure the direction of the causality from income to health.

In section 2 we present the theoretical framework of the causal relationship between income and health. Section 3 describes the econometric framework, as well as the microsimulation approach. Then in section 4, we detail our data. Section 5 reports on the results of the empirical analysis. Section 6 concludes the paper.

2 The causal relationship

2.1 Literature review

The relationship between self-perceived health status and individual income is heavily documented in health economics. Self-perceived health status assesses the general perceived health of an individual. In order to collect this information, individuals are asked: "Would you say your health in general is..." and they have to choose between five answer categories ("excellent", "very good", "good", "fair" or "poor"). Self-perceived health status is an important predictor of an individual's health since it combines different elements that an individual knows about his own health. This subjective measure also integrates factors which are not always considered by health professionals such as individuals' beliefs and attitudes towards the health commodity. Thus, this indicator, despite its subjective nature, is a good predictor of people's actual health status (Benitez-Silva et al. [2004]; DeSalvo et al. [2005] ; Bond et al. [2006]). Recent studies modeling the dynamics of this relationship question the existence of a causal effect of income changes on health. The direction of causality

is considered to be an important issue much debated among economists, since the lack of a clear and true understanding constitutes a major shortcoming for policy makers, who aim to narrow health inequalities and improve health. The difficulty in disentangling cause and effect is due to endogeneity because in such investigation, researchers are not able to run randomized controlled experiments. In this paper, we want to investigate the direction of the causality by tackling the question of what happens to a person's health when they experience a shock to their income. In the literature, some papers have already used instrumental variables methods or exogenous income shocks to investigate a causal link between health and income.
Ettner [1996] examines the effect of income on different health proxies, such as self-assessed health, daily activity limitations, proxies for alcohol abuse and others. She uses cross-sectional data from a number of US surveys collected in the 1980s. Depending on the health outcome, she uses ordered probit, probit or two-part models. The problem of reverse causality is addressed via an instrumental variables method, using parental education, work experience, spousal characteristics and unemployment rate as instruments. In each case, Ettner finds that income still has a significant impact on health.
Meer et al. [2003] also use an instrumental variables method on American data in order to deal with the income endogeneity issue. As income variable, they use change in wealth, which is instrumented by the amount of inheritances and gifts received over the last five years (amounts larger than US $10,000). In the instrumental variable estimation, wealth does not have a significant effect on health. Moreover, the validity of inheritance information as an instrument is also open to debate, as noted by the authors.
Lindahl [2005] uses Swedish longitudinal data to account for the health-income relationship. In this paper, lottery prizes are used to provide exogenous variations in income. However, the identification of lottery winners is not ideal since it is not possible to establish when the individual wins in his lifetime. Lindahl runs the estimation on different aspects of health and the results are varied. He finds that lottery winnings have a positive impact on mental health imply lower body mass index. However, lottery winnings have no effect on other physical health problems.
Frijters et al. [2005] analyze the association between self-assessed health and income using German data. Their instrumental method is to use an exogenous change in income due to the fall of the Berlin wall. In other words, they investigate whether there was a causal effect of income changes on the health satisfaction of East and West Germans in the years following reunification. Results show a positive impact of income on health.
Using British data, Gardner and Oswald [2007] explore the causality issue using medium-sized lottery wins (£1000+) as their instrument. They use medium-sized lottery wins because individuals who get no win are almost indistinguishable in

their responses from individuals with a small win. They find that mental health is positively affected by income.

Michaud and Van Soest [2008] investigate the pathways of the health-wealth gradient using six waves of the Health and Retirement Study (U.S.), implemented in a GMM framework. They instrument wealth using inheritances but do not find any causality from wealth to health. They also investigate the causality from health to wealth and the results are significant.

Work by Adda et al. [2009] has modelled income and health as a stochastic process evolving over the life cycle, created using a synthetic cohort dataset which is based on successive years of micro data from several English cross-sectional surveys. They exploit the fact that, at the cohort level, over the eighties and nighties, there were sizeable changes in income, mainly due to changes in the macroeconomic environment. Their results imply that income variations have little effect on health, but do affect health behaviors and mortality.

Economou and Theodossiou [2011] use European data to investigate the socioeconomic status-health relationship, and control for the income endogeneity using inheritance, children's education and art collection as instruments. The results indicate a strong and positive relationship between household income and health. However, the use of cross-sectional data weakens the causal statement.

Moreover, some researchers have also investigated the impact of household income on children's health by using an instrumental variables approach to get rid of the endogeneity of income (e.g. Case et al. [2002]; Kuehnle [2014]). They instrument income using labor characteristics of workers in the households. The results vary depending on the database (US and UK datasets).

Apouey and Clark [2015] determine the exogenous impact of income on different health outcomes with English data, using lottery winnings to make causal statements. They find that positive income shocks do not have a significant effect on general health, but do have an effect on mental health.

Finally more recently, Halliday [2016] employs data from the Panel Study of Income and Dynamics (U.S.) to investigate the causal link of income on health. He implements a GMM procedure on a model in first-differences, and uses further lag variables as instruments. His results establish a causal link running from income to health in the case of married individuals.

Moreover, we should be aware that in the causal relationship between health and income, there are likely to be effects which need to be controlled. In graph 1, we notice that health status is a decreasing function of age.[1] When people get older,

[1]Graph 1 comes from data of the Survey of Health Ageing and Retirement in Europe. In this survey, people are interviewed each two years (wave one: 2004-2005; wave two: 2006-2007; wave four: 2010-2011; wave five: 2013-2014; see section 4.1 for further information).

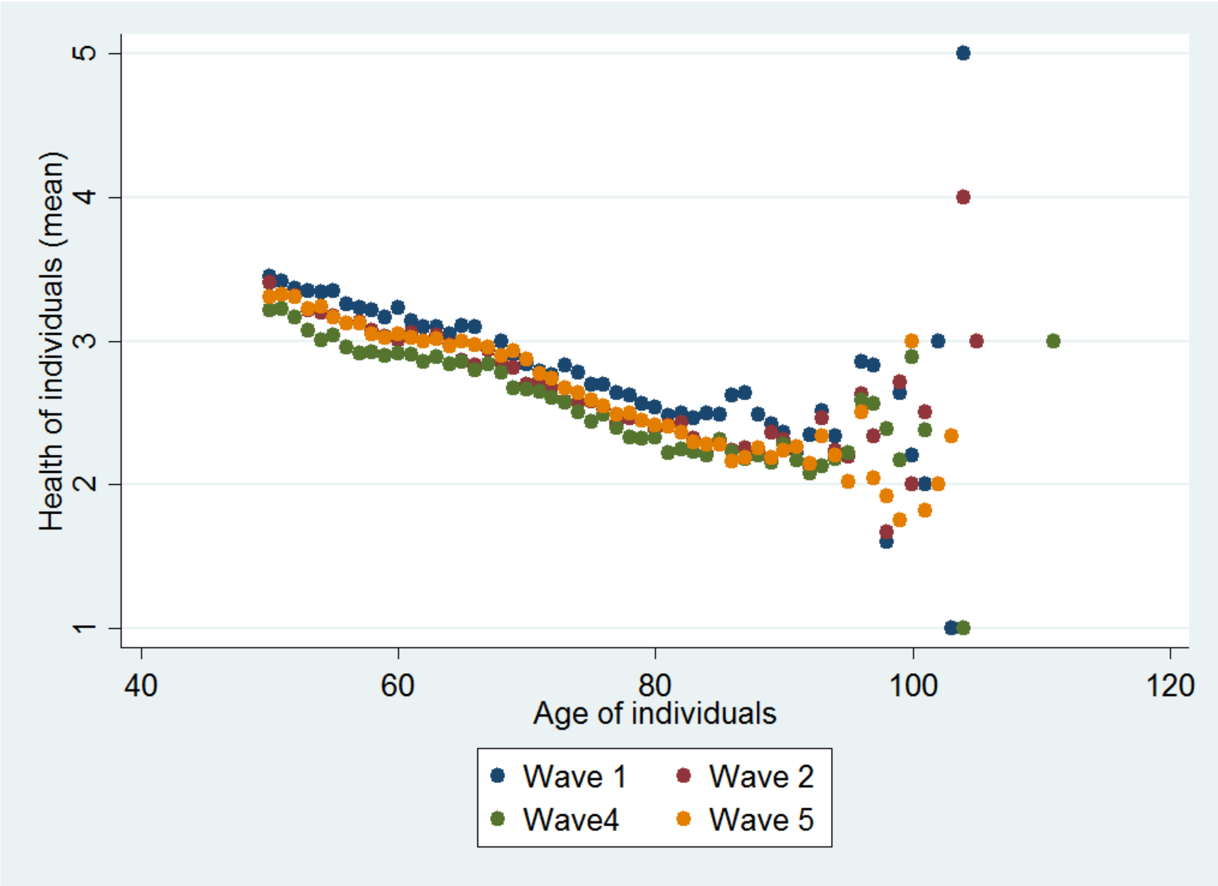

Figure 1: Health of individuals - SHARE survey

they tend to consider themselves as being less healthy. Changes in health status are thus partly due to the age. As a result, researchers need to control for this factor if they want to establish a causal link between income and health. We also see that the dotted lines, corresponding to the four time-periods, are almost identical, though they do not entirely coincide. This could be due to changes in behaviors on the one hand or changes in age, morbidity or technological progress, on the other. These last two effects are likely to be important explanatory factors in the relationship, but they might be endogenous to the self-perceived health status. Indeed, self-rated health assimilates morbidity, which in turn depends on diagnosed health problems, interactions with health professionals, as well as diseases (Tubeuf et al. [2008]). Traditional measures of morbidity provide important information about levels of health. Morbidity corresponds to the incidence of diseases. It seems that morbidity is a good predictor of the self-assessment of health status, and this is why we will control for its effect in the health-income relationship. Indeed, when assessing the health gap between individuals, it is important to measure health status in terms of non-fatal health outcomes. We model for morbidity thanks to indicators characterized by chronic illnesses and disability.

The last impact we need to be careful about the technological progress. Technology has nestled into daily life at a rapid pace. In the sixth edition of the "Public Health Status and Foresight Report: A Healthier Netherlands" (Hoeymans et al. [2014]), the authors argue that technological applications arise in prevention, treatment and care. The benefits range from improved diagnostic skills to regenerative medicine facilitating the independent living. For example, research enables more targeted prescription of medicines, and sensor technology enables instruments that monitor health status and home automation devices. As a result, one anticipates self-perceived health status will increase across the board in the future, thanks to technological and societal trends allowing an improvement in medical care. Technological trends can be modelled with longevity as a proxy. Examining trends and patterns in mortality can help to explain changes and differences in health status, permitting evaluation of health strategies. In addition, technological trends can also be modelled using a variable which is homogeneous across individuals in a given year. The pattern of these causes reflect changes in behaviors, as well as the effects of medical and technological advances.

In order to establish a causal relationship between health and income, the goal of this paper is to take into account all the previously enumerated effects.

2.2 Endogeneity issues

To formulate a causal relationship between self-perceived health status and income, one has to be careful about the endogeneity issues which can arise. Indeed, as explained earlier, we need to think of the opposite direction of causality between health and income. In order to assess the real impact of income on health, we focus on the concept of Granger causality, which takes into account the temporal dynamic of the relationship.[2] The definition of causality by Granger [1969] distinguishes lag causality from instantaneous one. As a result, we investigate the causal impact of past income on current health status. This approach includes the phenomenon of persistence of the health status in the relationship. We estimate the following health equation using a dynamic panel data approach to highlight a permanent causality from income to health :

$$h_{it} = \alpha_0 + \lambda h_{i,t-1} + \delta inc_{i,t-1} + X_{it}\beta + Z_{it}\Omega + c_{jt} + \epsilon_{it} \qquad \forall i = 1...N \quad \& \quad \forall t = 1...T_i \tag{1}$$

[2] In comparison with the Rubin causality, mainly used in microeconomics to assess the impact of public policies on an output between a treatment group and a control one, but without any temporal dimension theoretically.

where T_i corresponds to the number of observations for an individual i; h_{it} is the self-perceived health status of individual i at date t; inc_{it} is the income of individual i at date t; c_{jt} represents the technological trend of a country j at date t, thus corresponding to cross-country and time fixed effects; and ϵ_{it} is an error term. We consider two sets of observed variables, X_{it} and Z_{it}, for which we have to control for their exogeneity. Thus, they can be either exogenous or endogenous, depending on their respective impacts on health. These variables representing, on one hand, age, gender, marital status, as well as schooling, and on the other hand, morbidity indicators, are, respectively, exogenous and endogenous according to their different impacts on health. Hereafter, we detail our approach concerning the endogeneity status of the different variables.

The first thing to notice is the auto-regressive form of equation 1, which comes from the data generating process underlying the Granger causality of income on health. This auto-regressive form implies a biased estimation if we have:

$$E(h_{i,t-1}.\epsilon_{it}) \neq 0 \quad \forall t$$

However, here we assume that ϵ_{it} is a white noise such that:

$$E(h_{i,t-1}.\epsilon_{it}) = 0 \quad \forall t$$

Then, there is no endogeneity issue if the preceding assumption holds true, with the lag variable being controlled.

Concerning the income variable, the Granger causality involves a delayed causality of income on health in a manner such that income creates disparities throughout time. In other words, lagged income always has an impact on current health such that a permanent variation in individuals income will have a permanent impact on health. Moreover, income affects health and might also affect other unobservable variables (such as the lifestyle or the food expenditures) which in turn might influence health status. This income might be endogenous in the relationship, implying the following :

$$E(inc_{it'}.\epsilon_{it}) \neq 0 \quad \forall t' \leq t$$

As a result, in order to solve this endogeneity issue, we are going to implement an instrumental variables approach as well as exogenous income shocks to the estimation. In the case of such endogeneity, standard estimation procedures which assume that income is exogenous will produce biased estimates of the parameters. The instrumental variables approach allows to implement an unbiased estimation method. To use this method, we need a variable, x^k_{it}, which is not in equation 1 and which satisfies two conditions:

1. x_{it}^k is uncorrelated with ϵ_{it} in order to be exogenous: $Cov(\epsilon_{it}, x_{it}^k) = 0$;
2. x_{it}^k is correlated with the income variable: $Cov(x_{it}^k, inc_{i,t-1}) \neq 0$.

By using this method, we intend to correctly identify the causal relationship between self-perceived health status and income. In the literature, authors use instrumental variables methods or exogenous income shocks to set up a causal link between health and income (see section 2.1 for a review of such studies).

In the estimation of equation 1, we need to control for the exogeneity status of the two sets of variables X_{it} and Z_{it}. We have decided to separate the morbidity indicators from the other variables in order to see the specific impact of morbidity on health. Thus, we consider the exogeneity of what we are calling, hereafter, the covariates (age, gender, marital status and schooling) where then:

$$E(X'_{it}.\epsilon_{it}) = 0 \quad \forall t$$

Concerning gender, we note that this is fixed across waves. Then, for the other variables, each component provides different resources and displays different relationships to various health outcomes. As a result, concerning schooling, a higher level will allow an individual to have better access to health systems and therefore one's subjective health should improve. Education shapes future occupational opportunities and earning potential. Thus, it also provides knowledge that allows better-educated persons to readily gain more access to information, which in turn promotes health. Grossman [1972] proposes, in addition, that variables such as age and education will influence the optimum level of health. As a result, if one decides to control for age, then we should also control for education. The only role of the above covariates is to control for effects, across individuals, other than income, morbidity or technical progress, which influence self-perceived health. Thus, we do not apply a causal interpretation to their coefficients.

Moreover, we need to focus on the possible endogeneity of the morbidity indicators which could bias our estimation. All the morbidity indicators are self-reported and are therefore, essentially subjective. Indeed, there might be an instantaneous correlation such that:

$$E(Z'_{it}.\epsilon_{it}) \neq 0 \quad \forall t$$

For example, we can think of the following: an individual is hit by a car and breaks his leg as a result of this accident. This may then limit the person's usual activities. Thus, this person asserts to being limited due to health problems (part of the morbidity indicators), which in turn impacts the self-perceived health status. However, once they recover, they may feel better, and won't be so limited henceforth. Furthermore, Cabrero-García and Juliá-Sanchis [2014] explain "the greater the reported morbidities, the more limited is the subject's activity and the poorer his health". We intend to rid ourselves of this bias using our microsimulation approach, in which we control for each factor which can influence the health status. We consider lagged values of the morbidity indicators in order to remove this instantaneous correlation that makes our estimation biased. In other words, the error term remaining after the microsimulation will no longer be corrupted. Finally, in this paper we choose to only focus on the instrumentation of income and not the one of morbidity. Indeed, we think that morbidity only has an instantaneous endogeneity effect on self-perceived health, implying that, with lagged values of morbidity, we no longer face an endogeneity issue. Since, finding good instruments is a complicated task in general, we focus on the health and income relationship, restricting ourselves only to the search for appropriate income instruments.

3 Econometric framework

The objective of this paper is to formulate a causal relationship between self-perceived health status and income. As a result, the Granger causality is highlighted in order to establish this link while controlling for other factors that can influence the health. Because of the endogeneity issues in equation 1, we could use popular methods, such as the one of Arellano and Bond [1991], which takes into account the lagged values of the dependent variable and other explanatory variables. Due to the data availability (only four waves), we choose instead another strategy. In this way, we combine two approaches. First, a microsimulation method is used to make the morbidity variables exogenous. This microsimulation approach entails several steps. The first step estimates the health equation (equation 1). Then, we identify the impacts of each factors by using the estimated coefficients obtained from the previous regression. Secondly, instrumental variables techniques and exogenous income shocks are used to assess the endogeneity of income.

3.1 Microsimulation approach

Microsimulation models are useful to establish the effectiveness of health policies in order to understand their value in improving health and reducing inequalities in health. Accounting for issues such as population heterogeneity and the capacity to capture the long run effects of an intervention have hindered traditional methods seeking to identify th effects of a policy. An advantage of microsimulation models is that they correspond to an ex-ante evaluation which has the ability to predict the potential impact of a specific policy under different scenarios. There exists different types of microsimulation models (see Zucchelli et al. [2012] for a review). In this paper, we intend to develop our microsimulation method, following the methodology of Dormont et al. [2006].

In order to implement the microsimulation approach, we first specify and estimate a model explaining the relationship between self-perceived health status and income, in order to get the contributions of each factors on the health of individuals. We use an ordered probit model since our variable of interest was initially qualitative, then transformed into a categorical variable by us. With the self-perceived health status outcome being denoted as h_{it}, the model can be stated as

$$h_{it} = j \quad \text{iff} \quad \mu_{j-1} < h^*_{it} \leq \mu_j, \quad \text{for} \quad j = 1, 2, 3, 4, 5$$

The latent variable specification of the model that we estimate corresponds to equation 1:

$$h^*_{it} = \alpha_0 + \lambda h^*_{i,t-1} + \delta inc_{i,t-1} + X_{it}\beta + Z_{it}\Omega + c_{jt} + \epsilon_{it}$$

where h^*_{it} is a latent variable which underlies the self-reported health status[3] and ϵ_{it} is an error term which can be decomposed into two terms, η_i and ζ_{it}, and assumed to be normally distributed since we are using a dynamic fixed-effect panel framework. The other variables are the ones of equation 1. In this study, the latent outcome h^*_{it} is not observed. Instead, we observe an indicator of the category in which the latent indicator falls. As a result, the observed variable is equal to 1, 2, 3, 4 or 5 for "fair", "poor", "good", "very good" or "excellent" with probabilities:

$$P(y = j|x) = F(\mu_j - x_i\beta) - F(\mu_{j-1} - x_i\beta)$$

with the interval decision rule being[4]:

1. $h_{it} = 1$ if $h^*_{it} \leq \mu_1$;
2. $h_{it} = 2$ if $\mu_1 < h^*_{it} \leq \mu_2$;
3. $h_{it} = 3$ if $\mu_2 < h^*_{it} \leq \mu_3$;
4. $h_{it} = 4$ if $\mu_3 < h^*_{it} \leq \mu_4$;
5. $h_{it} = 5$ if $h^*_{it} > \mu_4$.

Once this is estimated, we can focus on the changes in health while controlling for other factors. The different steps of the microsimulation are the following: we control for each aspect that could bias the causal relationship of income and health by considering the values of variables at their previous dates ($t-1$ rather than t), while taking into account the estimated coefficients of equation 1. As a result, in the microsimulation approach, we set the morbidity indicators, the technical progress,

[3] Once h^*_{it} crosses a certain value you report fair, then poor, then good, then very good, then excellent health.

[4] In this model, the threshold values $(\mu_1, \mu_2, \mu_3, \mu_4)$ are unknown. We do not know the value of the index necessary to go from very good to excellent.

as well as the socioeconomic characteristics of individuals, at their previous values, such that we have the following formula:

$$\tilde{h}_{it} = \hat{\lambda} h_{i,t-1} + \hat{\delta} inc_{i,t-1} + X_{i,t-1}\hat{\beta} + \hat{\Omega} Z_{i,t-1} + \hat{c}_{j,t-1} \tag{2}$$

where Z_{it} is replaced by $Z_{i,t-1}$, c_t is replaced by c_{t-1}, X_{it} is replaced by $X_{i,t-1}$, and $\hat{\lambda}$, $\hat{\delta}$, $\hat{\beta}$, $\hat{\Omega}$, $\hat{c}$ correspond to the estimated coefficients obtained from equation 1, and are assumed to be time-invariant.
Estimating the health in t with the morbidity of individuals in $t-1$ shows the different impacts on health while keeping morbidity constant. As a result, this gives us the health effects that are not due to morbidity changes. Concerning technological trend, which we assume to be a homogeneous factor for all individuals for a given year and for a given country, the same principle applies. Since technological trend is a variable which is country and time-specific, it can be considered to be a fixed-effect. By doing this, we control for the unobserved heterogeneity across year and country. Finally, we add a control for individual demographic characteristics. Individual characteristics correspond to age, gender, schooling and marital status. We consider these individual socioeconomic characteristics as exogenous since their roles in the estimates are to be variables of control. As a result, fixing all these variables at the previous date informs us as to the sole impact of income on the self-perceived health status of individuals in t, excepting morbidity, technological trend and individual socioeconomic characteristics. This estimate gives us the effects that are only due to the individual income (including the phenomenon of persistence of the health status).

Thus, keeping these variables constant helps us to establish a permanent causal link between health and income. Indeed, the goal of this paper is to establish a causal relationship between self-perceived health status and individual income without the effect of the increase in the age of individuals or of changes associated to the other variables. After this last step we end up with a continuous health variable which can be used to re-estimate the health-income relationship using an ordinary least square method:

$$\tilde{h}_{it} = \kappa_0 + \lambda \tilde{h}_{i,t-1} + \delta inc_{i,t-1} + X_{it}\beta + \Omega Z_{it} + c_{jt} + \nu_{it} \tag{3}$$

where κ_0 is a constant term and ν_{it} is the error term.
The microsimulation approach allows us to get rid of the endogeneity issue associated with the morbidity indicators, since $\tilde{h}_{it}$ does not include unobservable components which might explain the morbidity in t and the health status in t. This health status is derived from the lagged explanatory variables, including the lagged

morbidity indicators, such that we have the following:

$$E(Z_{it}.\nu_{it}) = 0$$

We thus assume that we get rid of the endogeneity issue associated with the morbidity indicators once we have introduced their lagged values into our microsimulation approach. Finding instruments for the morbidity is a complicated task and researchers need to be conscientious in the choice of instruments. As our principle objective is to assess the causality of income on health, we focus our study on the instrumentation of income. This method enables us to proceed to the establishment of a causal link between income and health.

3.2 Instrumentation of the income

In the health economics literature concerning causality, due to endogeneity issues, the difficulty is distinguishing the cause and the effect. Wooldridge [2002] brings two issues to the forefront which need to be taken into accountin solving the endogeneity problem:

1. The issue of reverse-causality is a concern when one studies the income-related health relationship: a positive income shock can lead to an improvement in the health status through, for example, better access to medical services. However, we can also think of the reverse relationship where people in good health are likely to be more economically productive and thus have higher incomes.

2. Some individual characteristics which are not identified by the researcher may determine both income and self-assessed health status. A biased estimation between income and health results from a failure to control for these effects.

From an early stage in the debate, it was argued that higher income causes better health (Preston [1975]). Smith [1999] explains that this positive relationship leads to a number of interpretations: causality may go from income to health (high economic resources lead to better health status for many reasons such as: more resources devoted to health or better knowledge about what improves health), from health to income (poor health may restrict a family's capacity to earn income or to accumulate assets by limiting work or by raising medical expenses), or both may be determined by other common factors. To deal with the problem of endogeneity, the idea of instrumental variables is to find a variable x_{it}^k which is correlated to the endogenous variable $inc_{i,t-1}$, but which is not correlated with the error term ν_{it}. Indeed, when one of the coefficients (e.g. δ), which defines the relationship between a variable (e.g. the income $inc_{i,t-1}$) and the dependent variable (in our case the health h_{it}) cannot be interpreted in a causal way, this might be because of endogeneity issues of the income variable. As explained earlier, this issue implies:

$$E(\nu_{it}|inc_{i,t-1}) \neq 0$$

If health and income are simultaneously determined, the endogeneity problem implies that standard estimation procedures which assume that income is exogenous will produce biased estimates of the parameters and thus a biased interpretation. As a result, one has to find some solution like the instrumental variables method or the use of exogenous shocks on the endogenous variable, to solve this issue. In section 2.1 we reviewed the papers which attempt to establish the causality between income and health. These papers try to produce consistent estimates of the effect of income on health using these solutions. In the case where the relationship is not exogenous then the estimation will not be convergent (Dormont [2007]). Indeed, we need to estimate a model representing a causal relationship (Goldberger [1972]), contrary to a model which simply highlights a relationship capturing statistical associations. The instrumental variables approach allows us to eliminate all biases due to the correlation of income with the error term in the health equation such that we have the following estimate:

$$\tilde{h}_{it} = \kappa_0 + \lambda\tilde{h}_{i,t-1} + X_{it}\beta + \delta inc_{i,t-1} + \Theta x_{it}^k + Z_{it}\Omega + c_t + \nu_{it} \tag{4}$$

which consists of equation 3, together with x_{it}^k the instrument we introduce.
Instrumenting (Θx_{it}^k) eliminates measurement errors as well as any endogeneity bias. We find two instruments thanks to the data availability. From a macroeconomic point of view, we can use the unemployment rate of each country and each wave since this is correlated to the amount earned each month. Whether the individual has an income also depends on whether he is working. However, this will be a valid instrument only if the changes in health are due solely to differences in income. At the microeconomic level, we can use the location of the main residence of individuals as a valid instrument. Indeed income is correlated with where individuals live. We assume that the location of the main residence is correlated to the employment regions, and thus to the income of individuals. In order to see if these variables are good instruments, we perform a first stage estimation (see table 12 in the annex section). The results show that all these variables are statistically significant, or in other words, they constitute good predictors of income.

To go further and to be sure of correctly assessing the endogeneity issue, we also apply an exogenous income shock to the equation 4. Thanks to the data availability, we can follow the intuition of Meer et al. [2003] using information about the amount of financial or material gift received (worth 250€ or more) and the amount of gift or inheritance (worth 5 000€ or more). These two variables correspond to unexpected gifts or inheritances which are assumed not to be endogenous. This information will be included as dummy variables so that the final equation to estimate is:

$$\begin{aligned}\tilde{h}_{it} = \kappa_0 + \lambda\tilde{h}_{i,t-1} + X_{it}\beta + \delta inc_{i,t-1} + \Theta x_{it}^k + \Gamma_1 \mathbb{1}_{GIFT_{it}^1} \\ + \Gamma_2 \mathbb{1}_{GIFT_{it}^2} + Z_{it}\Omega + c_t + \nu_{it}\end{aligned} \quad (5)$$

which is an expansion of equation 4 where Γ_1 and Γ_2 correspond to the impact of the dummy variables associated to the exogenous income shocks.

4 Data

The dynamic interaction of changing humans in changing environments is not thought to be captured adequately by simple relationships among variables at a point in time and this is why we want to explore the panel dimension of the database.

4.1 SHARE Survey

The Survey of Health, Ageing and Retirement in Europe (SHARE) is a multidisciplinary and cross-national panel database of micro data on health, socio-economic status and social and family networks of more than 123 000 individuals aged 50 and over from many European countries and Israel. Since 2004, SHARE asks questions to a sample of households throughout Europe with at least one member who is 50 and older. These households are re-interviewed every two years in the panel. The first wave (2004-2005, 27 014 individuals) and the second one (2006-2007, 34 393 individuals) were used to collect data on health status, medical consumption, socio-economic status, and living conditions. The 2008-2009 survey (Wave 3) "SHARE-LIFE" was extended to life stories by collecting information on the history of the respondents. Since it does not contain the required information for our research, this wave is not taken into account in the pooled database used. The number of participants increased from 12 countries in wave 1 (Börsch-Supan [2016a]), to 15 (adding Ireland, Israel, Poland and Czech Republic) in wave 2 (Börsch-Supan [2016b]), while the third wave contains information about 13 countries. Wave 4 (2010-2011), is a return to the initial questionnaire of waves 1 and 2 (Börsch-Supan [2016c]). It collects data from 56 675 individuals in 16 European countries. Finally, the fieldwork of the fifth wave (Börsch-Supan [2016d]) was completed in November 2013. The following countries are included in the scientific release of 2015: Austria, Belgium, Switzerland, the Czech Republic, Germany, Denmark, Estonia, Spain, France, Israel, Italy, Luxembourg, Netherlands, Sweden, and Slovenia. This wave contains the responses of 63 626 individuals. As a result, the pooled database contains information on 180 606 observations and individuals are present for on average

1.7 years in the panel. However, researchers should also be aware of the potential disadvantage of this database. Indeed, Börsch-Supan et al. [2013] explain that in some waves there are relative low response rates and moderate levels of attrition (even though the overall response rate is high compared to other European and US surveys with an average retention rate over the year of 81 %) which are presumably due to the economic crises faced by some of the countries implying a decrease in the participation rates.

We choose to focus on this survey since it has all the information needed to carry out this research. Indeed, the dependant variable in our study is the self-perceived health status where individuals are asked to classify their health from “poor” to “excellent” (see figure 2).

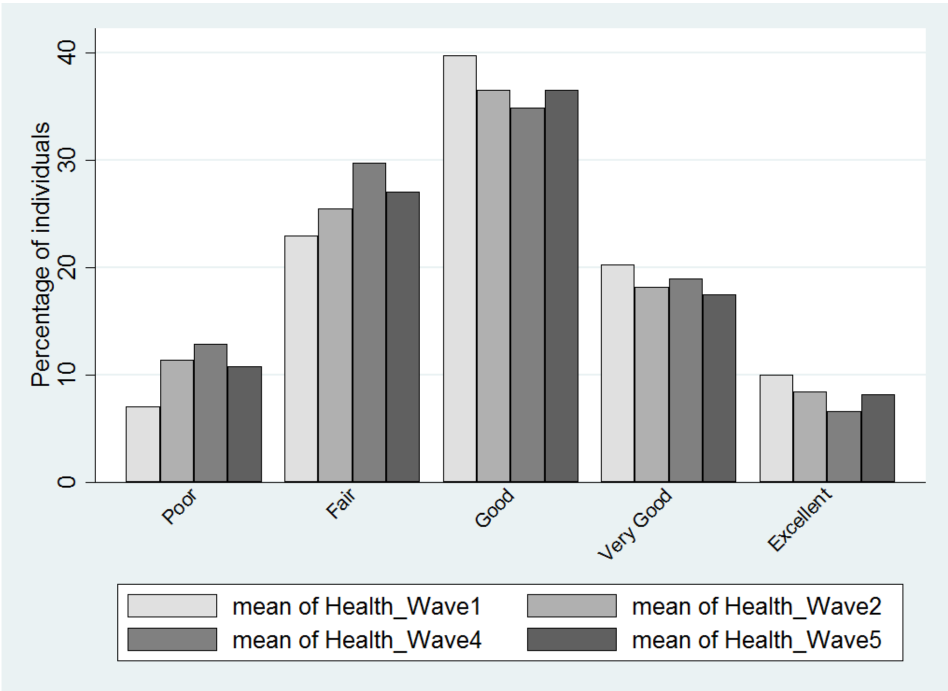

Figure 2: Distribution of the self-perceived health status - SHARE

4.2 The income variable

As explained earlier in this paper, we have to control for the income. In this database, income corresponds to the sum of individual imputed income for all household components. We intend to apply two methods to make sure of the robustness of the causal link. First, we chose to apply an instrumental variables method to get rid of the endogeneity issue. As mentioned earlier, a good instrument has to be correlated with the income but not with the health of individuals. Due to data availability, we decided to introduce into the econometric analysis, two variables which have been previously estimated and chosen from an auxiliary equation in a first stage (see tables 8 to 12 for detailed statistics). The first variable is a microeconomic instrument corresponding to the location of the main residence. This is a categorical variable in which individuals say whether they live in a big city, the suburbs or outskirts of a big city, a large town, a small town or a rural area. We thus create dummy variables and take as a reference category "living in a rural area". The second variable is the unemployment rate[5] and can be considered as a macroeconomic instrument, since it is computed for each country at each year of the survey (Meer et al. [2003]). Second, we would like to know what are the changes in the health status following positive income shocks. As a result, we have to find a variable implying a positive shock of income for individuals. The use of data on financial gifts creates a setting as close as possible to the idealized laboratory experiments. One piece of information given in the survey is whether an individual has received an amount of 250€ or more (material gift or not) or if the individual has ever received a gift or inheritance (worth 5 000€ or more). One can ask whether a financial gift is a good instrumental variable. We are mindful of the possible concerns with our instrumentation strategy. One can support that inheritance does not satisfy all the exclusion restrictions such that this is not a very strong income shock (a family member dying might signal something about the individual's health or other unobserved variables might drive both heath and inheritance using the idea of "privileged backgrounds"). However, the significant power of these variables have been tested and validated from a first stage regression (table 12 in the appendix part), thus it seems reasonable to think that these shocks and instruments are appropriate for income changes (Michaud and Van Soest [2008]).

4.3 Measurement of the morbidity

It is important to measure health status in terms of non-fatal health outcomes since these are important for the burden of a disease. Morbidity indicators can be broadly defined by the prevalence or incidence of diseases, but also by the degree of disability and the risky behaviors of individuals, which can cause diseases. Morbidity is strongly correlated with the self-perceived health status (Manor et al. [2001]; Latham and P. [2012]; Chan et al. [2015]). As a result, it has to be taken into account when one studies self-perceived health status.

Dormont et al. [2006] use a French microeconomic dataset (Santé Protection Sociale, conducted by IRDES) in order to construct morbidity indicators. We will base our construction of indicators on their method, since they produce these indicators with the help of general practitioners who assure their validity. As regards morbidity, we consider the last two indicators of the Mini European Health Module

[5] Source: OECD website.

(MEHM), which consists of indicators representing three concepts of health.[6] The first one concerns the self-perceived health status which assesses general perceived health rather than the present state of health. This indicator, first recommended by the World Health Organization in 1988, seeks to incorporate different dimensions of health (i.e. physical, social, and emotional, as well as functional signs and symptoms). Despite its subjective nature, indicators of perceived general health have been found to be a good predictor of people's future health care use and mortality (DeSalvo et al. [2006]; Cox et al. [2009]). The second indicator is the morbidity and it assesses the incidence or prevalence of a disease or of all diseases. This indicator gives information about people having long-standing illness or health problems. The last indicator is about activity limitation and disability, which assess self-perceived long-standing limitations in usual activities due to health problems. Thus we will use a vector of chronic illnesses and disability indicators for morbidity. Indeed, a variety of lifestyle factors and health-related behaviors, such as alcohol consumption, physical activity and dietary habits, can affect a person's health. An unhealthy lifestyle often results in a higher risk of chronic diseases.

The SHARE database presents the advantage of providing information about many morbidity indicators which can be divided into three main parts.[7] The first part concerns the degree of invalidity of individuals and is represented using the following indicators: Activities of Daily Living (ADLs), Instrumental Activities of Daily Living (IADLs), the Global Activity Limitation Indicator (GALI) and an indicator about mobility limitation. The second indicator is about chronic diseases and gives the number of chronic diseases of an individual. Finally, the third category of morbidity indicators concerns the risky behaviors of individuals.[8] We choose the alcohol consumption variable which informs us on the drinking habits.

4.4 Measurement of the technical progress

Technical progress, which allows an improvement in medicine, will have an ameliorating on the self-perceived health status in the future. On one hand, it can be modelled using a proxy for "the lengthening of the lifetime", but this information is not easily obtainable in the dataset. However, similar information is provided by life expectancy. The OECD gives information for Europeans countries about the life expectancy at 65 years of age. We distinguish the women's life expectancy

[6] The MEHM is included in several European survey programs (EU-SILC, SHARE, EHIS and Eurobarometer).

[7] See the appendix part in order to have detailed statistics and definitions on the indicators.

[8] We do not include information about smoking since this variable contains a lot of missing information such that it would considerably reduce the number of observations. However, we did the entire microsimulation method with the inclusion of this variable and find similar results. The results are not reported here but available upon request.

from that of men in each country, in order to have the most accurate information. Technological progress can also be viewed as a variable which is homogeneous for all individuals for a given year. As a result, we also add time dummy variables to the specification. Since, life expectancy is not completely collinear to the time dummy variables, both variables are added into the specification, in order to capture the real trend implied by the technical progress. As a result, we can say that technological trend represents the unobserved heterogeneity. because in the specification it is represented as a fixed-effect.

5 Results

In order to illustrate the usefulness of the microsimulation approach, we first present the results of the ordered probit model of equation 1. Since we want to highlight the Granger causality of income on health, we include lagged variables for the income and the health (the phenomenon of persistence). We lose observations due to these delayed variables, because all individuals are not always present during the four waves of the panel. This is why this analysis gives us access to 77 479 observations corresponding to 52 569 individuals. Indeed, at the beginning we have 181 620 observations, including 50 972 individuals who are present only once in the panel, 71 674 present twice, 26 154 present during three waves, and 32 820 individuals present during all four waves. By adding the lagged values in the microsimulation method we lose 103 732 observations (see table 1). Moreover, equation 3 (the last step of the microsimulation method) includes the phenomenon of persistence, derived from the continuous health variable computed using the microsimulation. As a result, we also lose information since we add another lag into the specification. Once we

Table 1: The loss of observations due to lagged variables

Presence of ind. in the panel	Number of obs.	Obs. lost
1 wave	50 972	50 972
2 waves	71 674	$\div$ 2 = 35 837
3 waves	26 154	$\div$ 3 = 8 718
4 waves	32 820	$\div$ 4 = 8 205
Total obs.	181 620	103 732
Nb. obs. after the lagged var.	181 620 - 103 732 = 77 888	
Nb. obs. with the missing values	77 479 (corresponding to 52 569 ind.)	
Nb obs. after the lagged of the phenomenon of persistence	52 569 - 35 837 = 16 732	

have this information in mind, we can start the econometric analysis. The first step is to estimate the health equation 1 with an ordered probit model, since the key variable represents the self-perceived health status of individuals, which is recorded in five modalities, in order to get the contributions of each factor to the health status (estimated coefficient). Results in Table 2 display a strong phenomenon of persistence in the health status. Past income has a positive impact on the sentiments of individuals concerning their present health. This result is significant and has the intuitive sign, according to the literature where it is said that a higher income improves health status. Thus, income has a permanent effect on health. Concerning the morbidity indicators, which represent the prevalence or incidence of a disease, the results imply that being affected by a disease, or by limitations, decreases the self-rated health status. One exception is for the drinking variable. In fact, a received idea among individuals is that drinking two glasses of wine per day decreases cardiovascular risk. This explains the positive coefficient associated to this variable, meaning that drinking improves their subjective health.[9] Finally for technical progress, we include both life expectancy and cohort fixed effects (wave 1 is not included since the analysis has been performed using lagged variables). When life expectancy increases, this helps individuals to feel better.

Table 2: First step - ordered probit model (equation 1)

Variables	**Coefficients**
Dependant variable: Health_t	
Granger Causality	
Health_{t-1}	0.547 ***
	(0.005)
Log of income_{t-1}	0.086 ***
	(0.003)
Morbidity Indicators	
ADL	-0.055 ***
	(0.008)
IADL	-0.055 ***
	(0.006)
GALI	-0.146 ***
	(0.007)
Mobility indicator	-0.162 ***
	(0.003)
Chronic diseases	-0.195 ***
	(0.003)
Drinking	0.063 ***
	(0.011)
Technical progress	

[9] However, according to the World Health Organization, this does not decrease risks of cardiovascular diseases and quite the reverse since it is dangerous for health.

Table 2: First step - ordered probit model (continued)

Variables	**Coefficients**
Wave 2	0.300 ***
	(0.019)
Wave 4	-0.009
	(0.009)
Wave 5	*Reference*
Life Expectancy	0.025 ***
	(0.003)
Co-variables	
Age	-0.032 ***
	(0.006)
Age squared	0.0002 ***
	(0.0001)
Women	0.025 *
	(0.015)
Married	*Reference*
Living with partner	0.015
	(0.029)
Living as a single	0.033 *
	(0.017)
Never married	-0.030
	(0.020)
Divorced	0.018
	(0.016)
Widowed	0.063 ***
	(0.014)
Education	0.006 ***
	(0.001)
Numb. of obs.	77 479
Numb. of groups	52 569

***: 1% significant; **: 5% significant; *: 10% significant.

To have an accurate causal relationship between health and income, researchers need also to account for factors such as morbidity which can influence the health-income relationship. Thus, the microsimulation method allows us to control for the endogeneity associated to these indicators. With this approach, a continuous self-perceived health status is computed, based on the previous estimated coefficients, and the lagged values of the factors which could influence the relationship. In Table 3, wee see that the signs of the coefficients do not change from the estimation of equation 1, being a bit smaller in magnitude but qualitatively similar. Thus, the previous conclusion saying that income has a permanent and positive impact on self-perceived health continues to hold true. We rid ourselves of the endogeneity issues of the morbidity indicators on the self-perceived health status by fixing all the morbidity indicators to their lagged values. In this estimation, the morbidity indicators all have a negative and significant impact on the continuous health status, except for drinking habits, which has the same interpretation as before. Morbidity has an overall negative impact on self-perceived health status because it corresponds to health issues or diseases. As a result, we can ensure that our microsimulation approach allows us to get rid of the morbidity endogeneity issue which influences the health-income relationship. Indeed, as explained earlier we assume that the morbidity indicators only have an instantaneous correlation with the error term such that accounting for their lagged values eliminates this correlation. Concerning life expectancy, the effect is qualitatively the same as before, implying that technological trend improves life expectancy and thus the self-perceived health status of individuals.

Table 3: Results of the last step of the microsimulation (equation 3)

Variables	**Coefficients**
Dependant variable: $\text{Health}_{\text{microsim},t}$	
<u>Granger causality</u>	
$\text{Health}_{\text{microsim},t-1}$	0.303 ***
	(0.005)
Log of income_{t-1}	0.109 ***
	(0.004)
<u>Morbidity Indicators</u>	
ADL	-0.037 ***
	(0.008)
IADL	-0.027 ***
	(0.007)
GALI	-0.247 ***
	(0.012)
Mobility	-0.101 ***
	(0.003)
Chronic Diseases	-0.129 ***
	(0.004)

Table 3: Results of the last step of the microsimulation (continued)

Variables	**Coefficients**
Drinking	0.035 **
	(0.014)
Technical progress	
Life expectancy	0.146 ***
	(0.006)
Wave 4	-1.742 ***
	(0.006)
Wave 5	*Reference*
Co-variates	
Age	-0.036 ***
	(0.009)
Age squared	0.0002 ***
	(0.0001)
Gender (=1 if women)	0.063 ***
	(0.021)
Education	0.036 ***
	(0.004)
Married, living with spouse	*Reference*
Registered Partnership	-0.089 *
	(0.042)
Married, not living with spouse	0.083
	(0.051)
Never married	-0.039
	(0.024)
Divorced	0.001
	(0.021)
Widowed	-0.00001 **
	(0.016)
Numb. of obs.	24 752
Numb. of groups	16 662

***: 1% significant; **: 5% significant;
*: 10% significant.

Finally, the main goal of our study was to establish the causality of income on health. As a result, once we get rid of the effects of morbidity, technical progress and other individual socioeconomic characteristics, we need to consider income endogeneity issues. We decide to both implement an instrumental variables method, as well as adding positive income shocks to the estimation. The estimation of equation 5 is reported in Table 4. In this estimation, we instrument the income with the unemployment rate by country and year and the location of the main residence of individuals. The results highlighting the Granger causality are the same as before implying the robustness of our results. In other words, past income always has a positive and significant impact on health. Moreover, we also add two income shocks to the estimation (financial gift of 250€ or more and financial gift of 5 000€ or more). None of these shocks is significant, meaning that an expected amount of money does not have a perceptible effect on health. An explanation would be that these shocks are not large enough to have a significant and permanent impact on the self-perceived health status. Concerning the impact of the morbidity indicators as well as the impacts of the technical progress the results are qualitatively identical. Thus, overall, we find strong and permanent evidence of causal effects from income to self-perceived health status.

Table 4: Results with the use of IV and exogenous shocks (equation 5)

Variables	**Coefficients**
Dependant variable: $\text{Health}_{\text{microsim},t}$	
Granger Causality	
$\text{Health}_{\text{microsim},t-1}$	0.305 ***
	(0.009)
Log of income_{t-1}	0.159 ***
	(0.035)
Exogenous income shocks	
Financial gift (250€ or more)	0.017
	(0.026)
Financial gift (5000€ or more)	-0.024
	(0.024)
Morbidity Indicators	
ADL	-0.051 ***
	(0.011)
IADL	-0.029 ***
	(0.009)
GALI	-0.271 ***
	(0.014)
Mobility	-0.098 ***
	(0.004)
Chronic Diseases	-0.132 ***

Table 4: Results with the use of IV and exogenous shocks (continued)

Variables	**Coefficients**
	(0.005)
Drinking	0.016
	(0.018)
<u>Technical progress</u>	
Life expectancy	0.143 ***
	(0.008)
Wave 4	-1.739 ***
	(0.019)
Wave 5	*Reference*
<u>Co-variates</u>	
Age	-0.048 ***
	(0.011)
Age squared	0.0003 ***
	(0.0001)
Gender (=1 if women)	0.067 **
	(0.027)
Education	0.026 ***
	(0.008)
Married, living with spouse	*Reference*
Registered Partnership	-0.108 **
	(0.055)
Married, not living with spouse	0.087
	(0.057)
Never married	-0.035
	(0.028)
Divorced	0.009
	(0.023)
Widowed	0.015
	(0.019)
Numb. of obs.	16 215
Numb. of groups	11 729

Instruments: Location of the main residence (dummies) and unemployment rate.

***: 1% significant; **: 5% significant; *: 10% significant.

6 Conclusion

A heavily researched topic in health economics is the relationship between income and health and more specifically the direction of causality between the two. This paper sheds light on the question of whether income implies health in a causal way. While it seems well-known that people with higher incomes enjoy better health, it is far more difficult to establish the direction of the causality of this relationship. The definition of causality which is chosen here is that of Granger including a persistence phenomenon in the relationship, as well as a permanent causal link due to lagged variables. Factors such as morbidity or technical progress are controlled for in this paper, since they could influence the health-income relationship. We use a rich longitudinal database (SHARE survey) which covers a statistically representative sample of Europeans individuals aged 50 and over and reports detailed information on their income and health, as well as health behaviors.

We implement an original microsimulation method to highlight the Granger causality of income on health. This enables us to identify the components of the health-income relationship and to control for the endogeneity issues which can arise. With this approach, we get rid of the endogeneity of the morbidity indicators since we fix their values to the previous date and look at their impacts on the current health status of individuals. Instantaneous endogeneity of morbidity on health is then no longer an issue. Moreover, in order to get rid of the income endogeneity issue which can bias our estimates, we implement an instrumental variables method, as well as adding exogenous income shocks to the estimation.

Since researchers need a clear understanding of the direction of the causality in this relationship, the results presented here contribute to a central point in the analysis of health and income. Our dynamic method and results ensure the Granger causality of income on health. In other words, we show that income has a permanent effect on subjective health status. Since our results appear to be robust, we have apparently rid ourselves of the possible reverse causation in this relationship. The results vary quantitatively but they all tell essentially the same story in qualitative terms (the coefficients always have the same signs among each step). This paper contributes to the health-income relationship and allows a better understanding of the direction of the causality in this literature. This is important for policy makers who want to reduce health inequalities in which income is shown to be an important lever. Finally, this is the first study analysing the health-income relationship using the SHARE database and establishing a strong and permanent causal impact of income on self-perceived health status using the concept of Granger causality.

References

J. Adda, H.-M. Gaudecker, and J. Banks. The impact of income shocks on health: evidence from cohort data. *Journal of the European Economic Association*, 2009.

B. Apouey and A. E. Clark. Winning big but feeling no better? the effect of lottery prizes on physical and mental health. *Health economics*, 2015.

M. Arellano and S. Bond. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The review of economic studies*, 58(2):277–297, 1991.

H. Benitez-Silva, M. Buchinsky, H. Man Chan, S. Cheidvasser, and J. Rust. How large is the bias in self-reported disability? *Journal of Applied Econometrics*, 19 (6):649–670, 2004.

J. Bond, H. O. Dickinson, F. Matthews, C. Jagger, C. Brayne, and MRC CFAS. Self-rated health status as a predictor of death, functional and cognitive impairment: a longitudinal cohort study. *European Journal of Ageing*, 3(4):193–206, 2006.

A. Börsch-Supan. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 1. Release version: 5.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w1.500. 2016a.

A. Börsch-Supan. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 2. Release version: 5.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w2.500. 2016b.

A. Börsch-Supan. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 4. Release version: 5.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w4.500. 2016c.

A. Börsch-Supan. Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 5. Release version: 5.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w5.500. 2016d.

A. Börsch-Supan, M. Brandt, C. Hunkler, T. Kneip, J. Korbmacher, F. Malter, B. Schaan, S. Stuck, and S. Zuber. Data Resource Profile: the Survey of Health, Ageing and Retirement in Europe (SHARE). *International Journal of Epidemiology DOI: 10.1093/ije/dyt088*, 2013.

J. Cabrero-García and R. Juliá-Sanchis. The global activity limitation index mainly measured functional disability, whereas self-rated health measured physical morbidity. *Journal of clinical epidemiology*, 67(4):468–476, 2014.

V. Carrieri and A. M. Jones. The income–health relationship 'beyond the mean': New evidence from biomarkers. *Health Economics*, 2016.

A. Case, D. Lubotsky, and C. Paxson. Economic status and health in childhood: The origins of the gradient. *The American Economic Review*, 2002.

Y. Y. Chan, C. H. Teh, K. K. Lim, K. H. Lim, P. S. Yeo, C. C. Kee, M. A. Omar, and N. A. Ahmad. Lifestyle, chronic diseases and self-rated health among Malaysian adults: results from the 2011 National Health and Morbidity Survey (NHMS). *BMC public health*, 2015.

B. Cox, H. Van Oyen, E. Cambois, C. Jagger, S. Le Roy, J.-M. Robine, and I. Romieu. The reliability of the minimum European health module. *International Journal of Public Health*, 2009.

A. Deaton and N. Cartwright. Understanding and misunderstanding randomized controlled trials. Technical report, National Bureau of Economic Research, 2016.

K. B. DeSalvo, V. S. Fan, M. B. McDonell, and S. D. Fihn. Predicting mortality and healthcare utilization with a single question. *Health services research*, 40(4): 1234–1246, 2005.

K. B. DeSalvo, N. Bloser, K. Reynolds, J. He, and P. Muntner. Mortality prediction with a single general self-rated health question. *Journal of General Internal Medicine*, 2006.

B. Dormont. *Introduction à l'économétrie*. 2nd edition, 2007.

B. Dormont, M. Grignon, and H. Huber. Health expenditure growth: reassessing the threat of ageing. *Health economics*, 2006.

A. Economou and I. Theodossiou. Poor and sick: estimating the relationship between household income and health. *Review of Income and Wealth*, 57(3):395–411, 2011.

S. L. Ettner. New evidence on the relationship between income and health. *Journal of health economics*, 1996.

P. Frijters, J. P. Haisken-DeNew, and M. A. Shields. The causal effect of income on health: Evidence from German reunification. *Journal of health economics*, 2005.

J. Gardner and A. J. Oswald. Money and mental wellbeing: A longitudinal study of medium-sized lottery wins. *Journal of health economics*, 2007.

A. S. Goldberger. Structural equation methods in the social sciences. *Econometrica: Journal of the Econometric Society*, 1972.

C. WJ Granger. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 1969.

M. Grossman. On the concept of health capital and the demand for health. *Journal of Political economy*, 1972.

T. J. Halliday. Earnings growth and movements in self-reported health. *Review of Income and Wealth*, 2016.

N. Hoeymans, A.J.M. van Loon, M. van den Berg, M.M. Harbers, H.B.M Hilderink, J.A.M. van Oers, and C.G. Schoemaker. A healthier Netherlands: Key findings from the dutch 2014 public health status and foresight report. *RIVM, Bilthoven*, 2014.

D. Kuehnle. The causal effect of family income on child health in the UK. *Journal of health economics*, 2014.

K. Latham and C. W. P. Self-rated health and morbidity onset among late midlife US adults. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, page gbs104, 2012.

M. Lindahl. Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income. *Journal of Human resources*, 2005.

O. Manor, S. Matthews, and C. Power. Self-rated health and limiting longstanding illness: inter-relationships with morbidity in early adulthood. *International Journal of Epidemiology*, 2001.

J. Meer, D. L. Miller, and H. S. Rosen. Exploring the health–wealth nexus. *Journal of health economics*, 2003.

P.-C. Michaud and A. Van Soest. Health and wealth of elderly couples: Causality tests using dynamic panel data models. *Journal of health economics*, 27(5):1312–1325, 2008.

S. H. Preston. The changing relation between mortality and level of economic development. *Population studies*, 1975.

J. P. Smith. Healthy bodies and thick wallets: the dual relation between health and economic status. *The journal of economic perspectives: a journal of the American Economic Association*, 1999.

S. Tubeuf, F. Jusot, M. Devaux, C. Sermet, et al. Social heterogeneity in self-reported health status and measurement of inequalities in health. *Paris: Irdes (12)*, 2008.

E. Van Doorslaer, A. Wagstaff, H. Bleichrodt, S. Calonge, Ulf-G Gerdtham, M. Gerfin, J. Geurts, L. Gross, U. Häkkinen, R. E. Leu, et al. Income-related inequalities in health: some international comparisons. *Journal of health economics*, 1997.

J. Wooldridge. Econometric analysis of cross section and panel data. *The MIT Press*, 2002.

E. Zucchelli, A. M. Jones, N. Rice, et al. The evaluation of health policies through dynamic microsimulation methods. *International Journal of Microsimulation*, 2012.

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A Descriptive Statistics

A.1 Variables of interest and covariates

Table 5: Descriptive statistics of the variables of interests and some covariates

Variables	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Nb. of obs.**
Self perceived health	2.846	1.087	1	5	181 620
Micro-simulated health	-0.195	1.068	-6.625	2.616	77 485
Log of income	9.922	1.304	0.014	16.122	181 620
Exogenous Shock:	%				
Financial gift 250€ or more	7.19				125 483
Financial gift 5000€ or more	16.44				125 170
Instrumental variables:					
Unemployment rate	8.571	4.478	3.2	26.1	181 620
Big city (%)	11.49				
Suburbs of a big city (%)	10.57				
Large Town (%)	13.72				
Small town (%)	18.80				
Rural area (%)	22.48	*Reference*			
Age	66.141	10.086	50	111	181 620
Education:	%				
Without diploma	4.14				
Primary	21.05				
Lower secondary	18.49				
Upper secondary	35.56	*Reference*			
First Stage of tertiary	19.91				
Second stage of tertiary	0.71				
Still in school	0.004				
Missing	0.13				
Marital Status:	%				
Married living with spouse	68.15	*Reference*			
Married living single	9.18				
Registered partnership	2.28				
Never married	3.65				
Divorced	5.79				
Widowed	9.59				
Missing	1.35				

A.2 Morbidity indicators

As explained earlier, the morbidity indicators have been chosen following the selection of Dormont et al. [2006]. Our morbidity indicators are divided into three main parts corresponding to the indicators of the Minimum European Health Module (MEHM). The first category concerns the degree of invalidity of individuals and contains information on four health aspects. ADLs consist of "basic activities that are necessary to independent living (e.g. walking, bathing, dressing, toileting, brushing teeth and eating)", according to the World Health Organization (WHO). This concept determines an individual's ability to perform the activity with or without assistance. IADLs, according to the World Health Organization, are "activities with aspects of cognitive and social functioning, including shopping, cooking, doing housework, managing money and medication, and using the telephone or the computer". These tasks support an independent lifestyle. GALI belongs to the family of disability indicators, targeting situations in which health disorders and conditions have impacted people's usual activities (number of limitations with mobility, arm function and fine motor skills). It is a single-item survey instrument where individuals are asked: " For at least the last 6 months, have you been limited because of a health problem in activities people usually do?" and they have to answer: "1) Yes, strongly limited, 2) Yes, limited, or 3) No, not limited". Moreover, in the SHARE survey, individuals are asked to give the number of their limitations concerning mobility (from 0 to 10).

The second category of indicators, corresponding to the chronic disease, gives the number of chronic diseases an individual suffer from (heart problem, high blood pressure/high blood cholesterol, stroke or cerebral vascular disease, diabetes, cancer...).

Finally, we also take into account the risky behavior with a drinking variable. The World Health Organization recommendations for a reasonable consumption is a maximum of two glasses of alcohol per day.[10]

Table 6: Morbidity Indicators

Variables	Mean	Std. dev.	Min.	Max.	Nb. of obs.
ADLs	0.248	0.857	0	6	181 620
IADLs	0.344	1.06	0	7	181 620
GALI	1.133	1.093	0	3	181 620
Mobility	1.633	2.349	0	10	181 333
Chronic diseases	1.718	1.55	0	14	181 307
Drinking	0.17	0.376	0	1	180 689

[10]However, the WHO also states to abstain from alcohol at least one day in the week, and not to consume more than four drinks on an one-time opportunity.

A.3 Technical progress

Table 7: Life expectancy at 65 years old for all waves and individuals (females and males)

Country	Mean	Std. dev.	Min.	Max.	Nb. of obs.
Austria	20.015	1.719	17.3	21.7	11 976
Germany	18.242	2.899	11.9	21.2	12 600
Sweden	19.728	1.48	17.4	21.3	12 149
Netherlands	19.289	1.776	16.3	21.2	12 306
Spain	20.841	2.211	17.2	23.4	14 297
Italy	20.333	1.956	17.3	22.6	13 140
France	21.286	2.301	17.7	23.8	15 869
Denmark	18.531	1.529	15.9	20.4	10 423
Greece	18.673	1.428	16.9	20.1	5 618
Switzerland	20.652	1.551	18.2	22.6	8 989
Belgium	19.469	1.884	16.5	21.6	17 449
Israel	20.256	1.111	18.7	21.3	4 671
Czech Republic	17.566	1.819	14.3	19.3	13 649
Poland	17.358	2.199	14.5	19.9	4 111
Luxembourg	20.581	1.398	19.8	21.9	1 590
Hungary	16.547	1.985	14.3	18.3	2 974
Portugal	19.918	1.888	17.8	21.6	1 920
Slovenia	19.422	2.089	16.9	21.4	5 525
Estonia	18.023	2.564	14.3	20.3	12 364
Total	19.431	2.335	11.9	23.8	180 620

A.4 Exogenous Shock

Table 8: Exogenous shock of income per country

Country	**Gift 250€ or more**			**Gift 5000€ or more**		
	Yes (%)	No (%)	Nb. of obs.	Yes (%)	No (%)	Nb. of obs.
Austria	10.12	89.88	8 726	13.55	86.45	8 699
Germany	7.69	92.31	8 510	21.98	78.02	8 485
Sweden	7.40	92.60	8 646	27.11	72.89	8 622
Netherlands	4.23	95.77	8 561	17.50	82.50	8 533
Spain	3.28	96.72	9 463	9.95	90.05	9 438
Italy	6.48	93.52	8 820	10.06	89.94	8 803
France	3.92	96.08	11 047	13.07	86.93	11 034
Denmark	8.45	81.55	7 282	25.59	74.41	7 262
Greece	11.03	88.97	3 990	19.98	82.02	3 960
Switzerland	5.77	94.23	6 487	23.23	76.77	6 475
Belgium	4.84	95.16	12 296	23.77	76.23	12 237
Israel	11.61	88.39	2 692	6.19	93.81	2 697
Czech Republic	0.01	99.99	9 310	11.78	88.22	9 295
Poland	7.42	92.58	2 805	9.81	90.19	2 802
Luxembourg	10.52	89.48	1 188	25.97	74.03	1 182
Hungary	5.35	94.65	1 963	15.32	84.68	1 952
Portugal	4.32	95.69	1 252	13.40	86.60	1 246
Slovenia	4.14	95.86	4 054	13.74	86.26	4 053
Estonia	9.40	90.60	8 391	7.08	92.92	8 395
Total	9 019	116 464	125 483	20 583	104 587	125 170

Table 9: Exogenous shock of income per wave

Waves	**Gift 250€ or more**			**Gift 5000€ or more**		
	Yes (%)	No (%)	Nb. of obs.	Yes (%)	No (%)	Nb. of obs.
Wave 1	5.43	94.57	20 016	28.53	71.47	19 905
Wave 2	7.10	92.90	23 400	14.89	85.11	23 378
Wave 4	7.20	92.80	38 745	16.30	83.70	38 651
Wave 5	8.04	91.96	43 322	11.85	88.15	43 236
Total	9 019	116 464	125 483	20 583	104 587	125 170

A.5 Instrumental variables for the income

Table 10: Unemployment rate

Waves	Wave 1		Wave 2				Wave 4			Wave 5
Country	2004	2005	2006	2007	2009	2010	2010	2011	2012	2013
Austria	5.49		5.25	4.86				4.6		5.3
Belgium	8.39	8.44	8.25	7.46				7.1		8.4
Czech Republic			7.15	5.32				6.7		7
Denmark	5.51		3.9	3.8				7.6		7
Estonia							16.7	12.3		8.6
France	8.47	8.49	8.45	7.66				8.8		9.9
Germany	9.79		10.25	8.66				5.8	5.38	5.2
Greece	10.59	9.99	9.01	8.4						
Hungary								11		
Israel					7.54	6.64				6.2
Italy	8		6.78	6.08				8.4		12.1
Luxembourg			4.73	4.07						5.8
Netherlands	4.56		3.91	3.18				5		7.2
Poland			13.85	9.61				9.6	10.09	
Portugal								12.7		
Slovenia								8.2		10.1
Spain	10.97		8.45	8.23				21.4		26.1
Sweden	6.53	7.48	7.07	6.16				7.8		8.1
Switzerland	4.3		4	3.6				4		4.4
Nb. of country	11		14					16		15

Table 11: Location of the main residence (%)

	Big City	**Suburbs**	**Large town**	**Small town**	**Rural area**
Wave 1	13.97	18.34	18.65	25.47	23.58
Wave 2	16.25	15.71	19.65	22.41	25.98
Wave 4	14.99	10.47	16.47	23.94	34.13
Wave 5	14.37	11.92	16.91	25.74	31.05

A.6 Instrumental variables - first step estimation

Table 12: First step estimation of the IV method

Variables	**Coefficients**
Dependant variable: Log of income$_{t-1}$	
Big city	0.072 ***
	(0.019)
Suburbs	0.241 ***
	(0.019)
Large town	0.132 ***
	(0.017)
Small town	0.018
	(0.015)
Rural area	*Reference*
Unemployment rate	-0.052 ***
	(0.001)
Nb.of obs.	57 847
Nb. of groups	41 407
Wald Chi2(5) - stat	1716.22
Prob > Chi2	0.000 ***

Taking jointly, all the coefficients are significant.