Health in Cities: Neighborhood Effects and Socioeconomic Determinants in the Spanish Case

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Abstract

The impact of place on individual outcomes, like health, presents many causal challenges that have disputed treatments in the literature. A 2011 study by Bilger Carrieri addresses them via instrumentation, to surprising results that equate neighborhood impact with that of economic deprivation and even education. The aim of this paper is to use this strategy as a guide to address the questions for Spain with more recent data: What links exist between income, neighborhood problems, and health? Can we proceed in a way to certainly avoid bias and endogeneity? How much does neighborhood impact health outcomes?

These are answered by assessing the microdata from the 2018 Spanish Survey on Living Conditions, for three different health outcomes given the use of a neighborhood problems aggregate (tested for the independence of these indicators). Testing neighborhood effects on health with the assumption of no endogeneity and performing endogeneity tests, correcting for the identification problem by testing instruments for neighborhood effect and income. Finally, an ordered probit model is fitted to evaluate the incremental effects of neighborhood problems, income and education on health outcomes.

Keywords: urban studies, endogeneity, instrumental variables, self-assessed health, neighborhood effect

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1 Introduction

In the context of epidemiology, sociology and economics, practitioners have sought to understand and quantify the impact of place effects on health outcomes of residents. It is a narrowly studied impact in economics because of the issues of identification, self-selection, and endogeneity. New sources of data add a compelling avenue to study these impacts.

The United Nations' Sustainable Development Goals name lifelong health and resilient cities as key to a thriving society, and recent scholarship has studied this impact at the neighborhood level to understand the influence of green space and individual characteristics on health, showing that place characteristics may have an outsize impact, even compared to traditional measures like education and income.

Tackling social inequalities in health is a persisting priority for international health authorities and for many national governments in Europe. The level and nature of inequalities vary between countries according to the distribution of determinants of health inequalities. While various subfields in economics and social science have posited different approaches to examining the effect of geographic placement on individual health outcomes (this area of study has grown over the last 25 years in particular), causal inference challenges abound, yet the study grows especially for the newly compelling for the ability to work in programmatically addressing geodata tied to individual responses, as well as standardized (European) indices for resource deprivation in cities. Observational cross-sections, census-based boundaries, and two-level designs are common structures for the data studied. In any case, however, the challenges of self-selection, endogeneity and other biases prevent more generalized conclusions; nonetheless specific cases such as those in European studies have used nationally representative data to explore local effects on health outcomes – it is the one after which this work is modeled, to study Spanish national micro-data in an advantageous non-experimental, cross-sectional structure.

The question of individual socioeconomic traits is paired with neighborhood characteristics to understand neighborhood effects, though theoretical, historic, and social factors should be considered to bolster any insights given by the statistical analysis alone. Simply targeting behavioural risk factors hardly works if structural or distal factors remain unaffected (Nason 2020). Understanding types of determinants empirically is important in order to target appropriate interventions at the policy level; for this reason, determining econometrically sound modeling strategies is of great concern to economic practitioners.

1.1 Challenges in Empirical Study of Neighborhood Effects

In the context of sustainable development, economists have sought to understand and quantify the impact of place effects on life satisfaction and particularly health outcomes of residents. Neighborhood effects are a narrowly studied impact in economics because of the issues of identification, self-selection, and endogeneity; these are the primary concerns addressed in this paper.

As economists approach the study of the relationship between neighborhood factors that influence outcomes, the typical barriers are self-selection (the outcome of interest is correlated with neighborhood choice), the potential inherent endogeneity of the neighborhood and income effects, and the identification problem. Sari (2012) deals with the aspect of non-random sorting into neighborhoods, finding significant linkage to employment as a mechanism. Ioannides and Zabel (2008) developed a two-step model of housing structure demand which controlled for the non-random sorting into neighbourhoods.

While this paper does not explicitly deal with selection bias, as in Bilger & Carrieri, by assuming that the effects of sorting are not correlated with health outcomes or at least that they are equal in scale, other practitioners have dealt with modeling specifically selection and sorting models, and found the pursuit of neighborhood effect to nonetheless be valid. For example, even when correcting for the differential sorting (unequal probability that an individual chooses to live in a particular area) into specific neighborhoods, the neighborhood effect found by Van Ham (2017) remains significant.

Using a given approach does not guarantee that the estimates obtained will be valid estimates of causal parameters, so intuition and theoretical framework are critical. Although using the most appropriate model for the research question is important, inferring causality is a more complicated process and requires more than statistical models. Many approaches to model building are worth examining to determine whether "neighborhood effects" (i.e. the effects of specific neighborhood attributes on individual-level outcomes) are valid. Van Ham (2017) proposes a two-step framework to help disentangle selection processes in the relationship between neighbourhood deprivation and earnings, confirming non-random neighborhood selection.

It is further motivated to find the specific neighborhood impact in order to increase allotment of financing could be distributed to neighborhood-level projects that seek to target economic development and disparities linked to poverty in service of public health; in 2017, for example, the Consejo Economico y Social de Espana, or the Spanish Economic and Social Council, allotted only 8 out of 284 projects at the neighborhood level, compared to 231 at the general city level and 45 at the regional level.

1.2 Salient Environmental Measures: SILC & UN SDG

It is taken as a given fact that equality of access to a healthy and productive life should be sustained especially in cities, constructed as they are by policies that govern infrastructure and design. The United Nations' Sustainable Development Goals name lifelong health and resilient cities as key to a thriving society, and recent scholarship has studied this impact at the neighborhood level to understand the influence of green space and individual characteristics on health, showing that place characteristics may have an outsize impact, even compared to traditional measures like education and income. The SDGs that are the motivation for this area of study are no.3: Ensuring healthy lives and promote well-being for all at all ages and no.11: Make cities and human settlements inclusive, safe, resilient and sustainable. The first goal identified specifically cites reducing the mortality rate attributed to cardiovascular disease, cancer, diabetes or chronic respiratory disease - the latter is striking in a time of Covid-19. The SDGs aim to strengthen capacity of all countries for early warning, risk reduction and management of national and global health risks, it is considering this that the identification of the role of neighborhood effects at a national level is considered.

Meanwhile, SDG no.11 very specifically addresses quality of life considering urban residency. Better management of urban growth will be crucial in order to guarantee sustainable urbanization. Globally, urban areas are expanding at a faster rate than their populations, which makes urban design and neighborhood measures more urgent. Between 2000 and 2014, areas occupied by cities grew 1.28 times faster than their populations. 9 in 10 people in urban areas breathe air that exceeds WHO particulate matter guidelines; more than 50% of the world population experienced increases in large particulate air pollution. It goes to reason that air quality is one of the key factors that can indicate good living conditions as well as outcomes.

The rest of the paper is organized as follows. *Section 2* covers an overview of the literature on neighborhood effect on health. *Section 3* describes the data set used and the key measures for the analysis. In *Section 4* the econometric model is described and the methodology adopted. *Section 5* displays the results. Finally, *Section 6* presents the conclusions of the paper.

2 Literature Review

Research in the area of neighborhood effects has grown significantly since the mid-2000s, illustrating the dominance of observational cross-sectional study designs, and usually depend on single-level, census-based neighborhood definitions. Studies of neighborhood effects on health that are based on cohort data are subject to bias induced by neighborhood-related selective study participation (Chaix et al 2011). Widely accepted as correlated with health (Chaix 2011, Smith 1999), or even a determinant of its outcomes, is income.

Considered a landmark study, the Moving to Opportunity project in the United States (Ludwig 2013) was a randomized controlled trial that linked health outcomes for individuals to neighborhood residence and studied the effects following mobility, finding moderate evidence that high-poverty individuals (and otherwise experiencing deprivation) were linked to subjective, but not real, outcome improvement after the voucher transfer to better-evaluated neighborhoods. The study did not see significant positive shifts in health and education outcomes (no significant overall effects of this intervention on adult economic self-sufficiency or physical health), but there were substantial effects but differences by age and gender (Kling et al 2007, Ludwig et al 2013). A noted finding nonetheless is that even considering variation in treatment intensity across voucher types and cities, the relationship between neighborhood poverty rate and outcomes was found to be approximately linear, making the examination of income in our model more relevant. Nonetheless, its conclusions are widely noted, such as by Aliprantis (2017) as limited due to the restricted nature of the group studied: individuals experiencing poverty. For this reason basing analysis on a national survey such as the SILC avoids this aspect of selection bias. Others such as Aliprantis (2017) find some resolution to the identification strategy by relaxing assumptions around SUTVA causal baseline, which allow attribution to neighborhood separate from program effect.

One Australian 10-year longitudinal study observed neighborhood disadvantage was associated with poorer self-rated health, mental health, and physical functioning, higher probability of smoking, and less frequent physical activity (Jokela 2014). Within-person differences to be nominal but between-person differences in health outcomes to be more pronounced, also noting poor health predicted selective residential mobility to less advantaged neighborhoods - evidence of social selection. These findings provide little support for social causation in neighborhood health associations and suggest that correlations between neighborhoods and health may develop via selective residential mobility; this work also found that individuals self-sort into communities which share individual characteristics like indicators of poor health. The causal challenge was further taken on by many (Kawachi and Subramanian 2007, Sampson 2002) and *instrumentation* found as a valid tool to approach more precise inference.

More recent neighborhood effects literature has the benefit of using more sophisticated databases with geodata coordinates enabling location in specific distances to resources common to civic life, as schools, parks, or water sources. In such work, inequalities in health can nowadays be traced to very small unit areas with deprivation indices, such as in the case of Ribeiro, Mayer, Miranda and de Pina (2017) in Porto, Portugal. Health could be measured as the dependent variable of BMI (Body Mass Index), self-assessed well-being (more holistic), but we proceed to use 3 different measures: overall self-assessed health, chronic health issues, and limitations on daily tasks. The results seen for these tend to be consistent, with some minor differences*. Deprivation indices sometimes used to measure neighborhood effects are constructed with this and national-level figures (Hoffiman, Barros and Ribero 2017).

Measuring and comparing individuals' health outcomes can vary based on differences in healthcare accessibility and other systems, hopefully helping develop more efficient policies and increase understanding of the underlying mechanisms and causes of social health inequalities. Evidence-based health policies require reliable and accurate measures of a population's socioeconomic environment. From a European perspective, it is important that these measurements can be comparable or at least transferable between different European countries, despite their sociocultural differences, in order to improve the comparability and reproducibility of health inequality studies across countries, based on standardized indices like the European Deprivation Index (EDI) and the like (Guillame et al. 2015).

Focusing specifically on the work done by economists Marcel Bilger and Vincenzo Carrieri in 2011: their Italian case presents sound findings for neighborhood effects in Southern European countries, to which Spain is a perfect complement. Bilger finds a clear correlation between neighborhood problems, identifies instruments (non-labor income for income, urbanization degree for neighborhood problems) and fitting the model for health outcomes. Income was found to be endogenous for SAH and ADLs but not for chronic conditions. Tests showed urbanization as uncorrelated with health when the neighborhood problems aggregate was included into the SAH and chronic conditions model, but urbanization was directly correlated with ADLs to some extent; therefore, the exogeneity of the instrument is questionable.

Interaction terms between the neighborhood problems aggregate and urbanization were statistically significant for all three health models, and their negative coefficients indicating the neighborhood effect is greater (in absolute terms) in thinly populated areas. Finally, the tests of over-identifying restrictions did not detect any sign of endogeneity of urbanization for any of the three health variables. Instrumented income was found to be endogenous only in the ADL model, and thus was not included. In the end, their findings were that the most problematic neighborhoods are strongly health damaging, even more than the traditionally identified variables of economic deprivation and about as much as having minimal education. This paper works off some of the same assumptions and similar instrumentation strategy, but done for the case of Spain with more current data.

3 The Data

The data used comes from the *Living Conditions Survey (LCS)* or Encuesta de Condiciones de Vida (ECV), carried out and disseminated annually since 2004 by the National Institute of Statistics. Based on harmonised criteria for all European Union countries, it serves as a reference source on statistics comparing income distribution, poverty and social exclusion within Europe. The questionnaire is collected and linked in 4-year rounds or rotations, therefore it is available as time series (panel) data as well as cross-sectional. More specifically, the cross-section of 2018 is used.

Specifically, the LCS is designed to obtain information on: income of private households and, in general, their economic situation; poverty, deprivation, social protection and equal treatment; employment and activity; retirements, pensions and socioeconomic situation of the elderly; housing and associated costs; regional development; level of education, health and effects of both on the socioeconomic condition. As it is a longitudinal database, it is possible to know the gross change or the temporal evolution of the variables of interest in each individual, and the study of transitions, durations and intervals between events.

The sample size for the 2018 cross-section used is of 13,368 households and 28,370 people. The weighted sample is therefore representative of *all the adult Spanish population* of 13,799,595 households and 28,748,811 individuals. The data represent the adult population between 14 and 65 years of age. Four separate files of individual and household level data were matched according to their respective identifiers. The type of sampling is two-stage stratified sampling in the first stage units (census sections, then households). The questionnaire is conducted mainly by personal interview and is representative *NUT2* level (Nomenclature of Territorial Units for Statistics). As of 2013, LCS data are calculated using the 2011 Census population (carried out by INE every 10 years). This offers, among other data, updated information on population figures, as well as age structure and household composition, which are fundamental in household surveys to elevate the data obtained to the population as a whole.

It is important to note that net income is gathered at the household level (gross income with the deduction of social security and other deductions), which should limit its endogeneity as health indicators are taken at the individual level. The data related to household income have been prepared using a mixed methodology combining the information provided by the informant with the administrative records of the State Tax Administration Agency, Social Security, the Navarra Tax Department, the Provincial Council of Bizkaia and the Provincial Council of Gipuzkoa.

3.1 Variable Selection and Units

The main variables of interest, that will then serve as covariates for the model, are as follows:

Table 1: Variables of interest

Personal characteristics	**Neighborhood problems**
Age	Crime
Education	Noise
Housing	Pollution
Income	**Home living conditions**
Region of residence	Cold
Sex	Dark
	Humid
Health	**Additional**
Self-assessed health (SAH)	Degree of urbanization
Presence of chronic condition	Equivalized household size
Daily living tasks limitations (ADLs)	Labor/ retirement status
	Tenure of house status

The variables are considered typical individual-level characteristics and environmental factors. Some notes on the units to measure these variables have to be mentioned. First, *education* is converted into a categorical variable as the International Standard Classification of Education (ISCED), which is four categories: Less than primary, Secondary I, Secondary II and Tertiary. The *degree of urbanization* is a three category variable that indicates the population density as thin, intermediate or highly populated areas.

Housing refers to: 1. the type of household, i.e. if it is one adult, a couple with no kids, etc., and 2. if the house is owned or rented by the individual. The home living conditions are binary variables that capture the reported presence of *cold, darkness, or humid* dwelling. Including home living conditions variables prevents from biasing the neighborhood effect by the effect that these housing characteristics have on health, as per Macintyre et al. (2000).

Lastly, *income* is captured at the household level, and then it is measured as total household disposable income divided by the *equivalized household size (EHS)* according to the OECD-modified scale rule to accommodate disproportionate household growth due to economies of scale in consumption, which is given by $EHS = 1 + 0.5(HM14_{+} - 1) + 0.3HM13_{-}$, where $HM14_{+}$ and $HM13_{-}$ are the number of household members aged 14 or more and 13 and less, respectively.

3.2 Neighborhood Problems Indicators

The key measure for the model is the neighborhood effect, this is assessed by using variables for self-reported problems existing in the neighborhood of the surveyed individual, and then combining them into an neighborhood index to include in the model.

The index concerning neighborhood problems is as follows, where the presence/absence of the following is reported:

1. Pollution, filth, other environmental problems
2. Noise caused by neighbors, traffic, and industry among other sources
3. Crime, violence, and vandalism in the area

These indicators are among the most common used in European public data collection. In this case, place of residence (neighborhood) is defined as the area where individual usually shops and walks back home, which is consistent with the definition of neighborhood used in the economic literature (Manski, 1993).

3.3 Health Status Indicators

There are three separate indicators used concerning health outcomes, wherein individuals report their personal estimated level of health as well as two other metrics, all non-exclusive, which are:

1. Self-assessed health (SAH)
2. Presence of chronic conditions
3. Limitations in average daily living tasks (ADLs)

For *SAH*, the responses are a traditional five-point scale: very good, good, fair, bad and very bad health[1]. In the following case we proceed to take the extreme two values (bad health and very bad health) as indicators of bad health in general. *Chronic* conditions are simply measured by a binary variable of the respondent's answer 'yes or no' to the presence of a chronic illness. Lastly, the presence of limitations in *ADLs* are measured by a three category variable: severe limitations, moderate limitations or no limitations. In this case, severe and moderate limitations are taken as bad health.

[1] It can be considered as interval censoring – a data point is somewhere on an interval between two values.

Let us note that self-assessment, rather than objective evaluation, of health can be considered valid per Elo et al (2009), who found a 70% correlation between the two in the case of the United States. In other words, people do tend to make fair judgment about the general level of their health standing (SAH), which cannot be said for estimating other relative traits, like social positionality in the case of class sorting, where individuals are wildly off-base in placing their own individual category (Ríos, 2020).

Figure 1 shows the relation of bad health, in all three measures, compared to age. It is logical to see an exponential-like behavior. Across all the age distribution the most persistent health problem in the population is chronic conditions, followed by limitations in ADLs. The amount of people reporting being in bad general health is the least common, with those under 25 reporting bad health in almost zero percent of the cases.

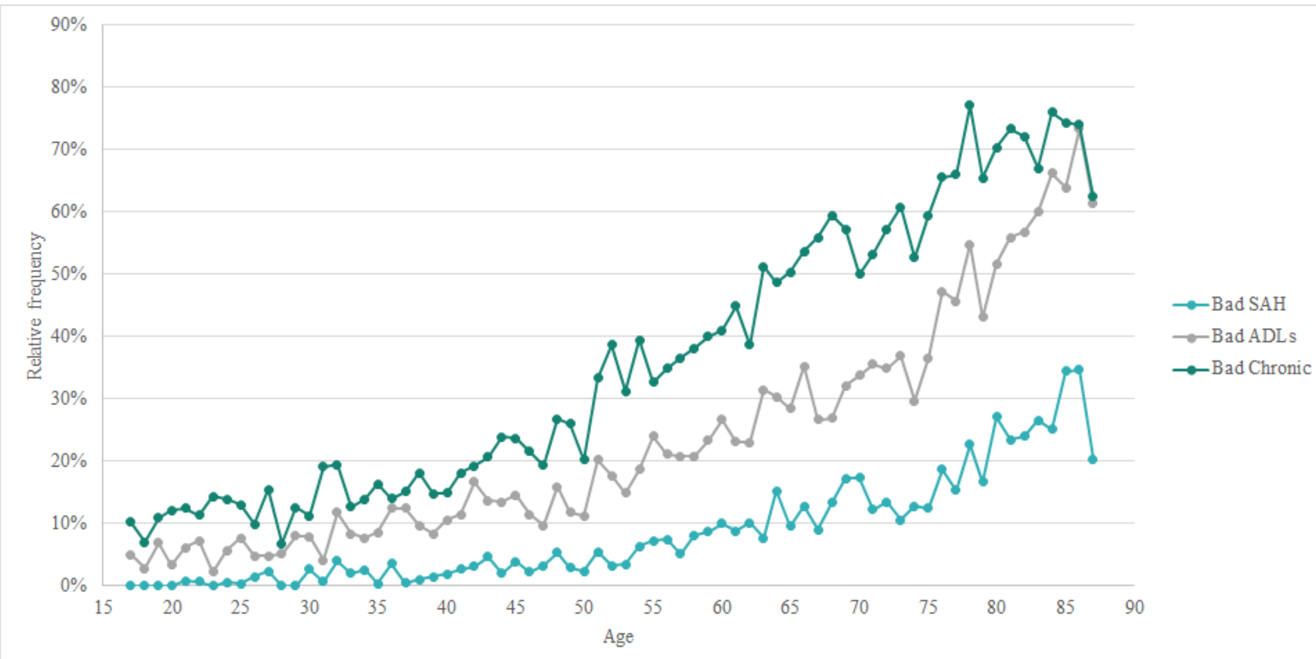

Figure 1: Health indicators by age

4 Identification Strategy

4.1 The Model

The empirical model estimated is the following:

$$H^* = \alpha \cdot NP + \beta \cdot INC + \gamma \cdot EDU + \delta \cdot X + \epsilon$$

where H^* is latent health (one of the three measures), NP is neighborhood problems, INC is a measure of income, EDU is the education categories and X is a vector covariates. Then, $\alpha, \beta, \gamma, \delta$ are the parameters to be estimated and ϵ is an error term. The covariates included were discussed in *Table 1* and, before fitting the model, the neighborhood problems aggregate is constructed, as well as the measure for income is tested to get the best results or the estimation.

4.1.1 Wald Test for Neighborhood Problems

The three measures of neighborhood problems - crime, noise and pollution - were aggregated into a single variable indicating the magnitude of neighborhood problems. Taking advantage of the fact that there are only eight different possible combinations between the three binary variables, all are first introduced into the health models by means of seven neighborhood binary variables[2]: 3 binary variables indicating the presence of pollution, noise, and crime alone, 3 binary variables for all pairs of neighborhood problems, and 1 binary variable indicating that all neighborhood problems are present. Then, using a Wald test for the grouping of these variables, there is not sufficient evidence to reject the hypothesis that each neighborhood problem has the same effect on health. In other words, the neighborhood problems aggregate can simply be defined as the number of problems that are present in the neighborhood.

4.1.2 Akaike Test for Income

After the neighborhood problems aggregate, the most important covariate is individual income, which is measured as the equivalent household income. Typically, for health models, linear relation is assumed (Ettner, 1996), although there is some debate on if income should be linearly introduced into health models, as some authors find this assumption to be overly restrictive (Bilger & Carrieri, 2013). In the field of labor economics, it is common to include income squared, which would imply that the relation wears off at a certain point. To get the best estimation possible, various specifications of income were compared using the Akaike goodness-of-fit criterion and results indicate that including the basic, linear form of income rather than INC^2 or another, higher-level polynomial would be the best specification.

4.2 Suspected Sources of Bias

4.2.1 Income Effect

It is commonly accepted that income is directly related to better health outcomes by virtue of access to healthcare, usually throughout a lifetime, and certainly contemporaneously. It can also be the case of reverse causality, as good health increases earnings opportunities[3]. In fact, there is not a case of bad health (SAH) in the sample after the benchmark of a 5,000 Euro monthly equivalized income. This leads us to suspect that income is indeed endogenous in our sample and should then be instrumented.

The idea of income as endogenous to the outcomes of health is not a new one, much literature has linked overall wealth in absolute and relative terms to better living standards, besides the obvious intuition behind this fact. We nonetheless want to understand the relation of wealth in the model, and find that a potential instrument may be a variable combining two sources of non-labor income, which is defined as the sum of income by interest-generating assets, i.e. dividends and investments, and income coming from renting a second property (*Figure 3*).

[2] Neighborhoods without problems acted as a reference category.

[3] It is possible for the income effect to also result in second-order bias to the estimate of the neighborhood effect.

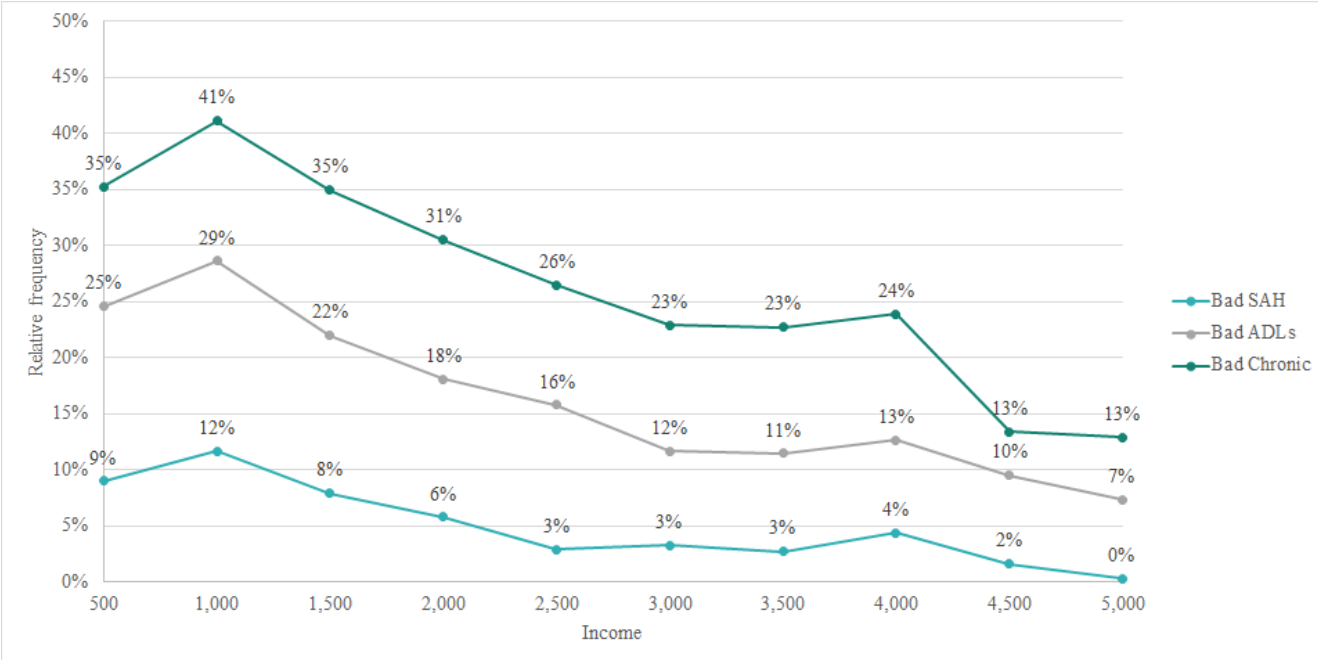

Figure 2: Health indicators by monthly household income

Here in *Figure 2*, each health indicator is plotted by income. The relative frequencies follow as expected, bad health decreasing with growing income. Interestingly, not a single person in the sample was found to be in bad health who had an income greater than 5,000 Euro; for this, the visualization is truncated. Chronic conditions may indicate disability, so for practically every measure, they are the most prevalent. One can imagine that pre-existing conditions like asthma, for example, would be marked regardless of other factors, but *bad health* would be noted only if pollution, humid dwelling, or low income (for example) played a role in exacerbating such conditions. Regardless, the key observation is the generally consistent decrease of all measures as income increases, sharply after 1,000 and nominally after 2,500 monthly household income. The steadiness of this pattern leads to reasonable suspicion of its endogeneity in determining health.

4.2.2 Neighborhood Effect

Similar to income, intuition leads us to suspect the possible endogeneity of the neighborhood effect because individuals may group together in certain neighborhoods due to their health. In order to move forward with modeling the neighborhood effect in a sound way, we must test for the potential endogeneity, the results of which an instrumentation (IV) approach may be used (as for the income case). To be a valid instrument to be excluded from the health models (exclusion restriction). Additionally, it has to be sufficiently partially correlated with neighborhood problems, which is easy to assume that more densely populated areas, although not harmful per se, more often have various problems present, such as crime, noise and pollution. This variable is also expected to be greatly correlated with neighborhood choice. The main issue with the instrumentation of the neighborhood effect is to find an adequate variable to act as the instrument, due to the lack of theory on the precise mechanisms linking neighborhood and health.

However, following the methodology of Bilger & Carrieri (2013), the instrument tested is urbanization degree. Another note is that the instrument has to be exogenous with respect to health, which isn't a given, as living in the city or the country results from a choice and thus could be endogenous in the health models. If this were the case, urbanization would not be an adequate instrument to correct the endogeneity bias. Testing for endogeneity justifies use of instrumentation, which is then itself tested.

5 Results

5.1 Descriptives

In *Table 2* the detailed descriptive statistics on the key variables are presented.

Table 2: Descriptive statistics of the main variables

	Urbanization			**Bad health**			**Neighborhood**			**Income**
	Thin	Intermediate	Dense	SAH	ADLs	Chronic	Crime	Pollution	Noise	Mean
Urbanization										
Thin	100.0	0.0	0.0	9.1	22.6	34.9	5.7	4.6	9.3	16,010
Intermediate	0.0	100.0	0.0	6.8	18.1	30.8	7.6	7.2	16.4	18,683
Dense	0.0	0.0	100.0	6.6	21.3	33.0	14.6	13.2	20.7	20,717
Bad health										
SAH	31.8	20.6	47.6	100.0	93.3	95.4	17.4	14.1	20.2	14,750
ADLs	27.5	18.9	53.6	32.3	100.0	88.1	14.4	12.4	20.8	16,242
Chronic	26.9	20.4	52.7	21.0	56.0	100.0	13.6	11.8	19.6	17,155
Neighborhood										
Crime	13.4	15.4	71.2	11.7	27.9	41.3	100.0	32.8	42.8	17,066
Pollution	12.1	16.2	71.7	10.5	26.9	40.2	36.5	100.0	54.4	19,107
Noise	14.0	21.3	64.7	8.7	25.8	38.4	27.5	31.3	100.0	18,197
Unconditional means	*25.5*	*21.9*	*52.7*	*7.3*	*21.0*	*33.0*	*10.8*	*9.7*	*16.9*	*18,885*

Table 2 clearly shows that neighborhood problems are highly correlated. For instance, in 54.4% of the neighborhoods where pollution is reported, noise is also deemed to be a problem. This has to be compared with the unconditional mean, which indicates that only 16.9% of the neighborhoods are deemed noisy in the whole population. *Table 2* also shows that health problems are more prevalent when neighborhood problems are also reported. For instance, 40.2% of the individuals living in polluted neighborhoods have a chronic condition, in contrast to 33.0% in the general population. Bad health is more conditioned on crime than it is on pollution or noise. Interestingly, health is better in densely populated areas. This is likely to result from an income effect, as income is significantly higher in cities, as shown in the last column of the table. However, health remains an important urban problem: crime, pollution, and noise are dramatically more concentrated in densely populated areas. For instance, pollution is a problem for 71.7% of those living in the cities as compared with only 12.1% in the country. The income effect is also revealed by the fact that for all three bad health indicators, the conditional means are less than the unconditional mean of 18,882.

5.2 Endogeneity Tests

In what follows, the estimations of the empirical model described in Section 4.1 are presented.

The estimated models are ordered probit for SAH and ADLs, and probit for chronic conditions. All models estimated by maximum likelihood. First, to account for the suspected endogeneity of income and neighborhood effect, the endogeneity tests described in section 4.2 are summarized in *Table 3*.

Table 3: Endogeneity tests

Statistical Test	**Instrumented Variable**	**Health Model** SAH	Chronic	ADLs
Weak Instruments Test	neighborhood	271	271	271
(partial F-test statistic)	income	1361	1361	1361
	both	6439	6439	6439
Endogeneity test	neighborhood	0.224	0.538	0.149
(H0: exogenous variable, p-value)	income	0.027	0.317	0.599
Non-labor income, Wald test (p-value)	none	0.029	0.208	0.024

From the tests presented in *Table 3*, several conclusions are made. First, the partial F-test statistic from the weak instruments test yields quite large values, for all models[4]. This suggests that all the instruments are very powerful. Then, the tests displayed in the second part do not reveal any endogeneity for the neighborhood problems aggregate for any of the health variables, i.e. we cannot reject that the neighborhood effect is exogenous therefore it is not instrumented in any of the models.

As for income, the p-value of 0.027 for the SAH model confirms the potential endogeneity. However, that is not the case for ADLs and chronic conditions. This results in income being instrumented only in the SAH model. The last part of *Table 3* shows the effect of non-labor income as an instrument for income, with the p-value being less than 0.05 for the SAH model indicating that it is not an adequate variable to act as an instrument for income, as it may also be endogenous. Even so, it is important that non-labor income is present across the entire income distribution of the population as in *Figure 3*, and this does not inherently depend on health, as investments or rent income do not rely on an able-bodied individual sustaining employment which is correlated with their health status (Ettner, 1996; Smith, 1999; Lindhal, 2005). It is finally worth noting that the results for the SAH model should be taken very carefully as a valid instrument was not found.

[4]Stock & Watson (2003) suggest that an F-statistic smaller than 10 indicates the presence of a weak instrument.

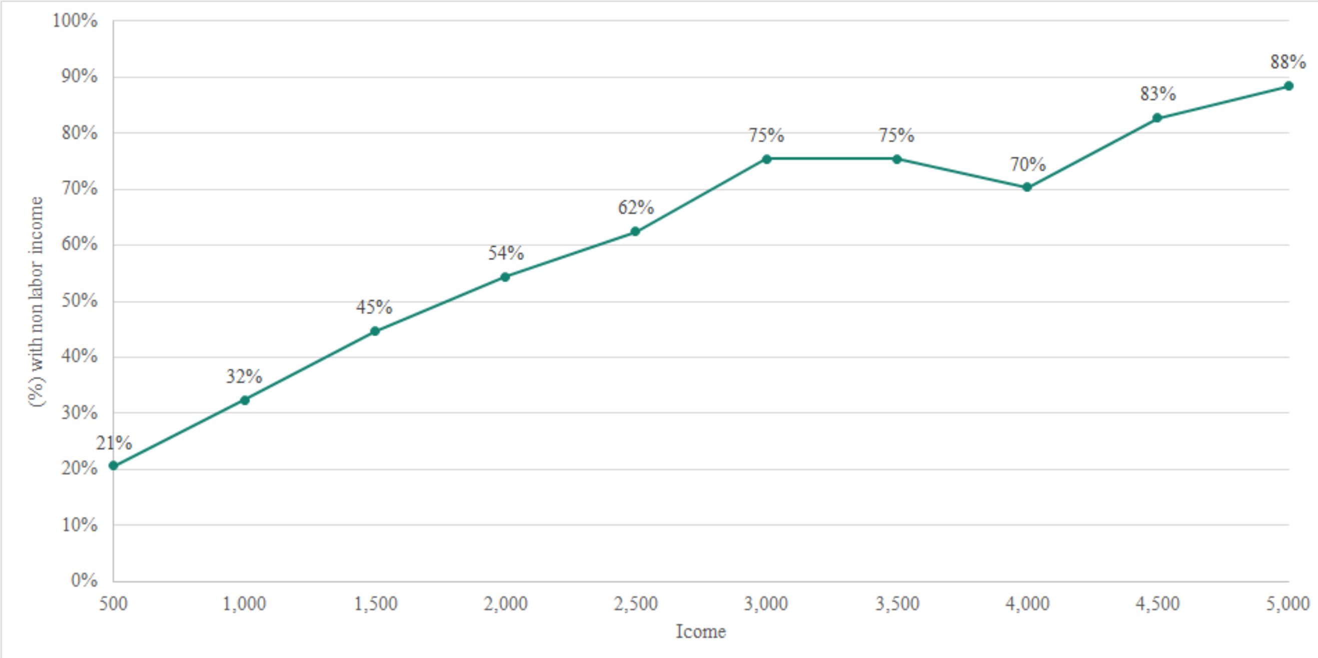

Figure 3: Presence of non-labor income across the income distribution

5.3 Marginal Effects

Now we are estimating the most efficient unbiased models. Here is indicated the exogenous models for chronic conditions and ADLs, as well as the income instrumented model for SAH, and the full model coefficients in *Table A1*.

The marginal effects are calculated using these coefficients to predict the probability of each individual to be in a given health state (e.g. SAH = very bad) while setting a given covariate at two different values for all individuals (e.g. neighborhood problems, NP, at 1 and 0). The difference between these two probabilities, averaged over all surveyed individuals, provides an estimate of the incremental effect of the covariate.

Thus, marginal effects are defined as:

$$\frac{\partial Pr(y = m|x)}{\partial x_k} = Pr(y = m|x) \left[\beta_{k,m|J} - \sum_{j=1}^{J} \beta_{k,j|J} Pr(y = j)|x \right]$$

as the value of x_k changes, the sign of the marginal effect can change; for example, at one point the marginal effect of a certain level of education on having a bad health outcome could be positive (like the consistent result in *Table 6* for those indicating the lowest education), while at another point the marginal effect could be negative (at higher education levels, individuals are some percentage points [ppoints] less likely to indicate bad health). The incremental, or marginal, effects corresponding to the *neighborhood problems aggregate, income, and education* are displayed in Tables 4–6, respectively.

For neighborhood problems, the marginal effects show that, on average, the presence of an additional neighborhood problem gives the difference in likelihood to experience the indicated health outcome, using the baseline or reference indicated.

Table 4: Neighborhood effect on health

	Probability	Incremental effect		
	(no problems)	1 problem	2 problems	3 problems
SAH (ref: very good)				
Very bad	0.017	0.006	0.003	0.009
	(0.001)	(0.001)	(0.002)	(0.004)
Bad	0.055	0.013	0.005	0.015
	(0.002)	(0.003)	(0.004)	(0.006)
Chronic (ref: no)				
Yes	0.344	0.065	0.010	0.003
	(0.004)	(0.008)	(0.014)	(0.023)
ADLs (ref: no limitations)				
Severe	0.044	0.015	0.001	0.001
	(0.002)	(0.003)	(0.005)	(0.008)
Moderate	0.169	0.028	0.002	0.001
	(0.003)	(0.005)	(0.008)	(0.013)

Standard errors displayed in parenthesis

We observe the results for the neighborhood effect on health in *Table 4*. The interpretation for the tables is as follows: the first results column, probability (no problems), is tied to the outcome for each health indicator. For instance, the probability that an individual has *very bad health* SAH when then have *no problems* in the neighborhood aggregate is 1.7%, using the *very good* health indicator as a reference. The incremental effects can be seen to follow: 1 neighborhood problem has a 0.6% probability that *very bad health* is encountered. Negative results here would mean that an increase in the number of neighborhood problems reduces the chances of being in the *very bad* or *bad* health, having chronic conditions, or limitations (ADLs).

With low standard errors for all estimates, we can see that the effect of having bad health grows cumulatively by neighborhood problems, although the inclusion of just one problem has the higher impact and the consequent added problems have a lower -but positive- effects each. However, this is not the case for the SAH model, as general bad health is affected the most by the inclusion of the third problem: 3 problems has three times the effect than 2 problems.

Though chronic conditions are the most likely (34.4% probability), it is also the health outcome most affected by the presence of just one neighborhood problem, with an incremental effect of 6.5%; interestingly, although chronic conditions increment by 7.9% with three problems, being in very bad health has the highest relative impact as it doubles its probability from none to the maximum neighborhood problems indicated by the aggregate.

Table 5: Income effect on health

	Probability	Incremental effect		
	(1st quartile)	Median	3rd quartile	4th quartile
SAH (ref: very good)				
Very bad	0.020	-0.001	0.000	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)
Bad	0.062	-0.002	-0.001	-0.007
	(0.002)	(0.002)	(0.002)	(0.003)
Chronic (ref: no)				
Yes	0.382	-0.013	-0.009	-0.031
	(0.007)	(0.007)	(0.007)	(0.007)
ADLs (ref: no limitations)				
Severe	0.054	-0.006	-0.001	-0.006
	(0.002)	(0.002)	(0.002)	(0.002)
Moderate	0.189	-0.012	-0.003	-0.012
	(0.005)	(0.004)	(0.004)	(0.005)

Standard errors displayed in parenthesis

Predictably, the impact of income on health grows as income does. *Table 5* shows how as income changes from a quartile to the next, the probability of being in bad health, in all the models, decreases, i.e. the lowest income quartile faces highest probability to face any health issues.

Chronic problems most likely across all income quartiles, starting at 38.3% likelihood at the first quartile and lowering to 33% in the fourth. After chronic problems, moderate limitations in ADLs have the highest probability of occurrence in the first quartile with 18.0%, and is reduced by 2.7% when moving up to the fourth quartile.

Bad health decreases with higher income but it is interesting to note that the effect of jumping from the third quartile to the fourth is larger than that of going from the first quartile to the median, showing that the effect of becoming rich is higher than the one of overcoming poverty. In Spain, this may be interpreted to track with access to a private health care system in addition to the public option that is more widely distributed and acts as a baseline of healthcare attainment for citizens.

Table 6: Education effect on health

	Probability	Incremental effect		
	(primary or less)	Secondary I	Secondary II	Tertiary
SAH (ref: very good)				
Very bad	0.023	-0.006	-0.005	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)
Bad	0.073	-0.013	-0.012	-0.008
	(0.003)	(0.002)	(0.002)	(0.002)
Chronic (ref: no)				
Yes	0.417	-0.039	-0.037	-0.032
	(0.008)	(0.007)	(0.007)	(0.007)
ADLs (ref: no limitations)				
Severe	0.064	-0.018	-0.012	-0.007
	(0.003)	(0.002)	(0.002)	(0.002)
Moderate	0.221	-0.034	-0.028	-0.019
	(0.006)	(0.005)	(0.005)	(0.005)

Standard errors displayed in parenthesis

Results in *Table 6* show that higher education does reduce the probability of being in bad health, but each subsequent step has a diminishing return: payoff from education are highest when advancing just one category (from *less than primary* to Secondary I), and tertiary educational attainment generally has smallest incremental effect.

An interesting result is that ADLs is more largely impacted, in general, by education than income or neighborhood problems. And although education also has the highest effect on chronic conditions when compared to income and neighborhood problems (a 10.8% reduction), it is the least diminished in relative terms at 0.742 of the base probability.

Education mostly impacts, in relative terms, the probability of being in very bad health and that of being severely limited in ADLs, as moving from no education to tertiary education cuts both probabilities in less than half.

6 Discussion

In all, the modeling of neighborhood effects with recent Spanish national microdata was successful in determining a certain scale of impact on the health of individuals linked to their environmental factors. Income and age were found to be highly correlated with presence of health problems, and neighborhood problems tended to precipitate one another.

Chronic conditions were the most prevalent health contraindication (9.5 million in total) in any disagreggation or regardless of the other individual covariates considered in the model measuring the chronic issues health indicator. This could be tied to the widely acknowledged trend of an aging Spanish population, in that chronic conditions are twice as present as in the Italian findings for 2004, this likelihood in fact is found across all indicators of poor health when modeling the neighborhood, education, or income marginal effects. For the Spanish case considered here, the marginal effects were less notable and showed most in the addition of just one or all the neighborhood problems in the aggregate. The worst neighborhoods had a demonstrated negative effect on self-assessed health, although the most noted jump was with the presence of simply 1 neighborhood problem: individuals were 6.5 points more likely to have bad health in the chronic conditions model.

The income effect is as expected, with those in the first quartile seeing positive effects (higher likelihood) to face bad health, particularly chronic conditions or moderate daily activity limitations. Even despite the persistence of chronic problems seen across the income distribution, being in the fourth quartile reduces the probability of having a chronic condition by about 3%. The effect of education was interesting, where having *primary or less* education carried a probability between a 6 and 42 point probability difference that a bad health indicator was present compared to those in good health or no limitations. However, the critical part to understand is the diminishing returns on education: for each of the health indicators, the incremental effects reduced with each additional step in education.

Additional variables found to be significant in the models include age, humid or cold dwelling, and some geographies for all models and income for SAH (indicating evidence for further dealing with endogeneity).

Directions for further research include testing other instruments for income - as non-labor income was proved to be not a valid one - or neighborhood problems in the case that they are found to be endogenous in a particular health outcome model, as well as sensitivity analysis of indicator indices: adjusting the neighborhood status aggregate to observe differences in multiple health outcome models. Microdata with geographic coordinates (valid at NUT3 level, for example) can allow researchers to map location distribution: linking to granular neighborhood data (some data now have rich reporting on more neighborhood characteristics tied to household records).

7 Conclusion

By scaling the found effects to the entire 2018 Spanish population of 46.7 million, it can be said that addressing a neighborhood problem like pollution can have notable effects. Computing the proportions to those living in neighborhoods with 1 (0.175), 2 (0.064), and 3 (0.023) issues, a reduction of neighborhood problems could have the impact corresponding to the incremental effects in Table 3: the resulting calculation yields an estimated impact on health outcomes attributed to neighborhood problems. Such a shift would mean 140,000 fewer in bad health and 70,000 in very bad health, 570,000 fewer cases of chronic conditions, and a reduction of the cases with daily limitations by 240,000 (moderate) and 130,000 (severe).

In a general sense, a more sound modeling of the neighborhood effect relationship can increase attention to policies focused on improving the environmental factors of an area such as those identified in the UN Sustainable Development Goals. As mentioned before, funding for local development projects tends to address cities or regions more often than neighborhoods, and a stronger link between neighborhood level indicators and health outcomes can encourage a correction of disproportionate funding allotment.

8 References

1. Alberto Maydeu-Olivares, Dexin Shi & Yves Rosseel (2019) Instrumental Variables Two-Stage Least Squares (2SLS) vs. Maximum Likelihood Structural Equation Modeling of Causal Effects in Linear Regression Models, Structural Equation Modeling: A Multidisciplinary Journal, 26:6, 876-892.

2. Aliprantis, D. (2017). Assessing the evidence on neighborhood effects from Moving to Opportunity. Empir Econ 52, 925–954 .

3. Arias, A., et al. (1993). Desigualdades en salud en Barcelona y Valencia. Medicina Clínica, 100, 281–287.

4. Basile Chaix, Nathalie Billaudeau, Frédérique Thomas, Sabrina Havard, David Evans, Yan Kestens and Kathy Bean. (2011). Neighborhood effects on health: correcting bias from neighborhood effects on participation. Epidemiology. Vol 22, No 1.

5. Bilger & Carrieri, (2013). Health in the cities: When the neighborhood matters more than income. Journal of Health Economics 32, 1-11.

6. Clarke, P., Morenoff, J., Debbink, M., Golberstein, E., Elliott, M. R., & Lantz, P. M., (2014). Cumulative Exposure to Neighborhood Context: Consequences for Health Transitions Over the Adult Life Course. Research on Aging, 36 (1), 115-142.

7. Diez Roux, A. V. (2004). "Estimating neighborhood health effects: the challenges of causal inference in a complex world." Social Science & Medicine 58.

8. Dobek, A., Moliński, K., Skotarczak, E. (2015). Power comparison of Rao's score test, the Wald test and the likelihood ratio test in (2xc) contingency tables. Biometrical Letters. 52.

9. Elo, I., Mikyta, L., Margolis, R., Culhane, J. (2009). Perceptions of neighborhood disorder: the role of individual and neighborhood characteristics. Social Science Quarterly 90 (5), 1298–1320.

10. Ettner, S.L., (1996). New evidence on the relationship between income and health. Journal of Health Economics 15, 67–85.

11. Fox, J., 1997. Applied regression analysis, linear models, and related methods. Thousand Oaks, CA: Sage Publications.

12. Goldstein, H., & Rasbash, J., (1996). Improved approximations for multilevel models with binary responses. Journal of the Royal Statistical Society A, 159, 505–513.

13. Guillaume E., Pornet C., Dejardin O., & Launay, L. (2016). Development of a cross-cultural deprivation index in five European countries. J Epidemiol Community Health ; 70:493-499.

14. Jokela, Markus, (2014). Are neighborhood health associations causal? A 10-year prospective cohort study with repeated measurements. American Journal of Epidemiology. 180(8): 776-84.

15. Introduction to SAS. UCLA: Statistical Consulting Group, (2020). "FAQ: How are the Likelihood Ratio, Wald, and LaGrange Multplier (Score) Tests Different and/or Similar?" Institute for Digital Research & Statistical Consulting.

16. Kling, Jeffrey R., Jeffrey B. Liebman, and Lawrence F. Katz, (2007). Experimental Analysis of Neighborhood Effects. Econometrica, Vol. 75, No. 1, 83–119.

17. Kuhn, Moritz, Schularick, Moritz and Steins, Ulrike, (2018). Income and Wealth Inequality in America, 1949-2016. CESifo Working Paper Series No. 6608.

18. Lindahl, M., (2005). Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income. Journal of Human Resources 40, 144–168.

19. Long, J. Scott (1997). Regression Models for Categorical and Limited Dependent Variables. Thousand Oaks, CA: Sage Publications.

20. Ludwig, Jens, Greg J. Duncan, Lisa A. Gennetian, Lawrence F. Katz, Ronald C. Kessler, Jeffrey R. Kling, and Lisa Sanbonmatsu. (2013). "Long-Term Neighborhood Effects on Low-Income Families: Evidence from Moving to Opportunity." American Economic Review, 103 (3): 226-31

21. Macintyre, S., Hiscock, R., Kearns, A., Ellaway, A., (2000). Housing tenure and health inequalities: a three-dimensional perspective on people, homes and neighborhoods. In: Graham, H. (Ed.), Understanding Health Inequalities. Open University Press, Buckingham, PA, 129–142.

22. Manski, C.F., (1993). Identification of endogenous social effects: the reflection problem. The Review of Economic Studies 60 (3), 531–542.

23. Nason Maani, Jeff Collin, Sharon Friel, Anna B Gilmore, Jim McCambridge, Lindsay Robertson, Mark P Petticrew, (2020). Bringing the commercial determinants of health out of the shadows: a review of how the commercial determinants are represented in conceptual frameworks, European Journal of Public Health, Volume 30, Issue 4, 660–664.

24. Plan Nacional de Acción para la Inclusión Social del Reino de España. (2013-2016). Ministerio de Sanidad, Servicios Sociales e Igualdad.

25. Ríos, V., (2020). No, no eres clase media. The New York Times. Retrieved from http://www.nytimes.com

26. Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley, (2002). Assessing "Neighborhood Effects": Social Processes and New Directions in Research. Annual Review of Sociology. 28:1, 443-478.

27. Smith, J.P., (1999). Healthy bodies and thick wallets: the dual relation between health and economic status. The Journal of Economic Perspectives 13 (2), 145–166.

9 Appendix

Table A1: Estimated coefficients of the health models

	SAH (IV income)	Chronic (exogeneous)	ADLs (exogeneous)
Neighborhood problems	-0.1265***	-0.1271***	-0.0954***
	(0.0133)	(0.0163)	(0.0166)
Equiv. income	4.7e-06**	5.0e-06***	4.9e-06***
	(1.6e-06)	(1.1e-06)	(1.2e-06)
Education (ref: primary or less)			
Secondary 1	0.1442***	0.1224***	0.1850***
	(0.0269)	(0.0326)	(0.032)
Secondary 2	0.2970***	0.2399***	0.3400***
	(0.0294)	(0.0359)	(0.037)
Tertiary	0.4160***	0.3445***	0.4473***
	(0.0297)	(0.0363)	(0.038)
Male	0.0933***	0.0809***	0.1306***
	(0.0174)	(0.0217)	(0.0226)
Age	-0.0324***	-0.0295***	-0.0261***
	(0.0006)	(0.0007)	(0.0008)
Foreigner	-0.0466	0.1280**	0.0662
	(0.0332)	(0.0424)	(0.0453)
Houshold type (ref: 1 adult)			
2	0.0168	-0.0067	0.0066
	(0.0303)	(0.038)	(0.0392)
3	-0.0016	-0.0406	-0.0928*
	(0.0313)	(0.0391)	(0.0401)
4	0.0257	-0.0753*	-0.0489
	(0.0277)	(0.0345)	(0.0357)
Home owner	0.0768**	0.0079	0.0976**
	(0.0249)	(0.0315)	(0.0327)
Humid dwelling	-0.1651***	-0.2354***	-0.1828***
	(0.0257)	(0.0318)	(0.032)
Cold dwelling	-0.2175***	-0.2149***	-0.2657***
	(0.0311)	(0.0386)	(0.0372)
Dark dwelling	-0.0743	-0.025	-0.1372**
	(0.0414)	(0.0514)	(0.0505)
Region (ref: Andalucia)			
Aragon	0.041	-0.0729	0.0542
	(0.0499)	(0.0612)	(0.0639)

Table A1 continued from previous page

	SAH (IV income)	Chronic (exogeneous)	ADLs (exogeneous)
Canarias	0.2053***	-0.0442	-0.0717
	(0.0486)	(0.0597)	(0.0609)
Cantabria	0.1335**	0.2334***	0.1145
	(0.0514)	(0.0651)	(0.0683)
Castilla y Leon	-0.0473	-0.0531	-0.0148
	(0.0429)	(0.0529)	(0.0541)
Castilla-La Mancha	0.0255	0.1641*	0.1480*
	(0.0509)	(0.064)	(0.0671)
Cataluna	0.2982***	0.3316***	0.2418***
	(0.0402)	(0.0509)	(0.0536)
Ciudad Autonoma de Ceuta	-0.2406**	-0.4012***	0.0146
	(0.0799)	(0.097)	(0.1051)
Ciudad Autonoma de Melilla	-0.2406**	-0.4012***	0.0146
	(0.0791)	(0.1014)	(0.1171)
Comunidad Foral de Navarra	0.2461***	-0.0069	0.017
	(0.0545)	(0.0669)	(0.0697)
Comunidad Valenciana	0.2461***	-0.0069	0.017
	(0.0432)	(0.0538)	(0.0582)
Comunidad de Madrid	0.2461***	-0.0069	0.017
	(0.0374)	(0.0468)	(0.0481)
Extremadura	0.4033***	0.5429***	0.4433***
	(0.0587)	(0.0769)	(0.0818)
Galicia	-0.1289**	-0.1979***	-0.0913
	(0.0435)	(0.0536)	(0.0545)
Illes Balears	0.1306*	-0.0151	0.2785**
	(0.0664)	(0.0821)	(0.0951)
La Rioja	-0.0154	0.0257	-0.0703
	(0.0537)	(0.0661)	(0.0679)
Pais Vasco	-0.1055*	-0.2546***	-0.0611
	(0.0466)	(0.0574)	(0.0593)
Principado de Asturias	-0.1453**	0.0277	-0.0805
	(0.0472)	(0.0584)	(0.0589)
Region de Murcia	-0.1135*	-0.4440***	-0.1446*
	(0.0463)	(0.0573)	(0.0578)
Residuals, income equation	7.3e-06***		
	(8.8e-07)		

Table A1 continued from previous page

	SAH (IV income)	Chronic (exogeneous)	ADLs (exogeneous)
Estimated cut-off values			
Cut-off 1	-3.8649***	1.7354***	-2.9184***
	(0.0711)	(0.0745)	(0.0806)
Cut-off 2	-3.0551***		-1.8393***
	(0.0676)		(0.0785)
Cut-off 3	-1.9916***		
	(0.066)		
Cut-off 4	-0.2487***		
	(0.0643)		

Standard errors displayed in parentheses.

* Significance level = 10%.

** Significance level = 5%.

*** Significance level = 1%.