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# Income-related health inequality in urban China (1991-2015): The role of homeownership and housing conditions

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**Abstract**

We analyze 1991-2015 data from the China Health and Nutrition Survey to ask how housing affects income-related health inequalities in urban China. We use the Erreygers Index (EI) to measure the health gradient, and apply a re-centered influence function (RIF) decomposition to estimate its determinants. We find pro-rich inequalities in self-reported health between 2000 and 2015 but pro-poor inequalities in objective health between 1991 and 2015. Housing conditions serve to reduce the health gradient, and especially that for objective health. Homeownership, however, exacerbates the health gradient. Improving housing conditions thus appears to be an effective way of reducing the income-health gradient in urban China.

**Keywords:** Income-related health inequality; housing conditions; homeownership; decomposition; urban China.

**JEL Classification:** D63; I10; I12; R21.

## 1. Introduction

Five of the Sustainable Development Goals (SDGs) – poverty reduction, health and wellbeing for all, equitable education, gender equality and the reduction of inequalities within and between countries – set explicit targets related to the reduction of health inequalities, both nationally and worldwide (Niessen *et al*., 2018). As highlighted by the World Health Organization (WHO) report of the Commission for Social Determinants of Health (CSDH), the understanding of the dynamics of health inequalities and their determinants is important for the establishment of informed policies to reduce them (WHO, 2008). This research question is attracting increased attention in economics, epidemiology and public health.

In addition, as stated by the CSDH (WHO, 2008; Solar and Irwin, 2010), the socio-economic and political context leads to a set of socioeconomic positions, in which populations are stratified according to income, education, occupation, social class, gender, race/ethnicity and other factors. In the CSDH's conceptual framework (see Appendix Figure A1), health inequalities come from these socioeconomic positions, which are "structural determinants", via the "intermediate determinants" that include material circumstances (such as housing and neighborhood quality), psychosocial circumstances, behavioral and/or biological factors, and the health system itself. Improved housing and neighborhood conditions may then reduce health inequalities (Gibson *et al*., 2011). Although the role of poor housing in health appears in a large number of existing contributions (Angel and Bittschi, 2019; Jacobs David *et al*., 2009; Koh and Restuccia, 2018; Krieger and Higgins, 2002; Ludwig *et al*., 2013; Webster, 2015; Xiao *et al*., 2018), its effect on socioeconomic-related health inequalities (which we will call the income-health gradient, or just the health gradient) remains largely unexplored (Urbanos-Garrido, 2012).

China is a particularly apt case for analysis in this context, with its very rapid and dramatic economic, social and demographic transitions. China experienced unprecedented economic growth over the four decades following the 1978 Reform and Opening-Up Policy: real per capita GDP increased over 20-fold from 385 Yuan in 1978 to 9,931 Yuan in 2018 (National Bureau of Statistics, 2019). This rapid economic growth has not however been accompanied by equally substantial improvements in health (Baeten *et al*., 2013). Despite Chinese life expectancy growing from 68 in 1981 to 77 in 2018 (National Bureau of Statistics, 2019), China's health reputation has been shrinking (Tang *et al*., 2008; Baeten *et al*., 2013), and rising health disparities between the rich and the poor have produced dissatisfaction (Tang *et al*., 2008).

At the same time as these developments in health and income, China's housing market has also attracted concern (Funke *et al*., 2019; Tsai and Chiang, 2019). Housing reforms, which were an important component of the Reform and Opening-Up Policy, have transformed China from a country dominated by public-housing renters to one with an extremely high rate of homeownership, rising from 28% in 1993 to 84.6% in 2002 (Chen and Hu, 2019) and the strikingly high rate of 90.8% in 2013 (Cui *et al*., 2019), one of the highest homeownership-rates in the world (Gan *et al*., 2013).

In addition to providing economic well-being, the accumulation of wealth, social assimilation and attachment to the community (Page-Adams and Sherraden, 1997; Spilerman, 2000), owning a house is considered to be a symbol of personal achievement in China (Cui *et al*., 2019). More importantly, homeownership, coupled with *hukou* (the household registration system), constitutes a form of citizenship that grants access to education and health-care facilities, as well as other welfare benefits (Fan, 2002). Housing is also an integral part of social stratification. Although average housing conditions have improved significantly, not every urban household has benefited equally from housing reform, producing housing inequality (Tan *et al*., 2016). China's urban house prices rose at a rate almost double that of household income following the market-oriented housing reform (Chen *et al*., 2018). Soaring house prices and rising housing inequality have reshaped the Chinese urban landscape and affected the well-being of urban residents (Cheng *et al*., 2016). The distinctive development of the Chinese housing market, as compared to that in Western countries, provides a unique opportunity for the analysis of the comparative relationship between housing and the health gradient in emerging and developed countries.

We will here consider housing (and particularly homeownership and housing conditions) and the health gradient for Chinese urban adults using both subjective and objective health measures from the 1991-2015 China Health and Nutrition Survey (CHNS). We contribute to the health-gradient literature in three ways.

First, given China's unprecedented economic growth and unique urban housing market, we provide the first attempt to explore the potential role of housing (including homeownership and housing conditions) in the health gradient for urban Chinese.

Second, in addition to self-reported health (SRH), we consider objective measures of health outcomes, including general overweight/obesity, central obesity and high blood pressure (HBP). The combination of subjective and objective health measures is important for the evaluation of the relationship between income and health, as SRH is subjective and may suffer from reporting bias (Cai *et al*., 2017*a*). This reporting bias has been shown to vary systematically with income and other socioeconomic status (SES) measures when assessing SES-health inequality, calling the reliability of SRH into question (Bago d'Uva *et al*., 2011; Bago d'Uva *et al*., 2008; Rossouw *et al*., 2018). The use of SRH also produces higher estimates of health inequality than those from more objective health indicators (Nesson and Robinson, 2019).

Last, we apply a recent decomposition technique – the re-centered influence function (RIF) regression decomposition method, as proposed by Heckley *et al*. (2016). The RIF regression decomposition approach has a number of advantages: (i) it directly decomposes the weighted covariance of health and socioeconomic rank to account for socioeconomic-related health inequality (Heckley *et al*., 2016); (ii) it can decompose all types of inequality measures, such as the Erreygers index (*EI*: Erreygers and Van Ourti, 2011) and the Wagstaff index (*WI*: Wagstaff *et al*., 2003); (iii) it relaxes the rank and weighting-function ignorability assumptions, [1] and requires fewer restrictive assumptions than the Wagstaff decomposition approach (Heckley *et al*., 2016); and (iv) RIF regression decompositions are easier to estimate and the results ease to interpret

[1] The rank-ignorability and weighting-function ignorability assumptions require that the determinants of health do not determine the rank or the weighting function respectively (Heckley *et al*., 2016).

(Firpo *et al*., 2009).

The remainder of the paper is organized as follows. Section 2 reviews some of the relevant literature. Section 3 describes the datasets used and the empirical strategy, and then Section 4 presents the results. Last, Section 5 discusses the major findings and concludes.

## 2. The income-health gradient in China

A number of contributions have used bivariate rank dependence indices to quantify and decompose income-related health inequalities and their potential causes in China. Most of this work considers subjective health measures like SRH. Regarding SRH in the CHNS (the same survey that we will analyze below), Yang and Kanavos (2012) find pro-rich inequalities in SRH and physical-activity limitation (i.e. the rich are more likely to report better SRH and are less likely to have physical-activity limitations) in the 2006 CHNS, with income, employment status and education being three key driving factors, and Baeten *et al*. (2013) also underline the role of rising income inequality in SRH inequality in 1991-2006 CHNS data. Wang and Yu (2016) consider 1997-2009 CHNS health inequality via an income-health matrix[2] that connects income rank to health status in the population to show that income-related SRH inequality has risen, with aging, income inequality, the urban-rural division and environmental deterioration being the key determinants.

Other work has considered subjective health measures in other Chinese data. Zhou *et al*. (2017) analyze 2008 and 2013 National Health Services Survey data to reveal pro-rich inequality in health-related quality of life (HRQoL) in Shaanxi province, with household consumption expenditure and education being two central determinants. Shao *et al*. (2016) equally uncover pro-rich SRH inequality in the 2012 China Labor-force Dynamic Survey for migrant workers, with income as the most important contributing factor. The same conclusion is reached by Yang and Liu (2018) in 2014 China Family Panel Studies data.

[2] A detailed discussion of the income-health matrix approach appears in Zheng (2011).

Evidence for an objective health gradient in China is more limited. Feng *et al*. (2010) find persistent, but stable, socioeconomic regional inequalities in maternal mortality in 1996-2006 National Maternal and Child Mortality Surveillance System data. Chen *et al*. (2014) show that income-related inequality in the height-for-age z-score (HAZ) among children under 18 has worsened over time in 1989-2009 CHNS data. However, According to Mújica *et al*. (2014) income-related inequalities in infant mortality have fallen substantially in China. More recently, Su *et al*. (2018) document pro-poor inequality in HBP in 2011 CHNS data, with income, education attainment and age being the key factors.

To our knowledge, Cai *et al*. (2017a) is the only contribution in China that assesses income-related SRH inequality using the RIF regression decomposition approach. In 1991-2006 CHNS data they find pro-rich SRH inequality; this is mainly caused by income and secondary education, with housing conditions (including tap water and indoor flush toilets) playing no role.

There have thus been a number of contributions using Chinese data to investigate the income-health gradient. These mostly report rising pro-rich health inequality, and have highlighted major drivers of this inequality such as income and education. In this context we complement this existing work in three ways. We first take both subjective and objective health measures into account (which we believe to be important in assessing the income-health gradient), and track changes in income-related health inequalities over more than two decades (from 1991 to 2015). Second, the previous literature primarily uses the traditional bivariate rank dependent index – a concentration index – to quantify the health gradient and the Wagstaff decomposition (Wagstaff *et al*., 2003) to consider its possible determinants. We instead employ a new decomposition technique – the RIF regression decomposition method for both *EI* and *WI* – to look at the potential determinants of the health gradient. Only Cai *et al*. (2017a) have employed the RIF decomposition in this context (although they only look at SRH). Last, existing research has paid only little attention to housing conditions and housing tenure as potential determinants of the health gradient. In a systematic review, Gibson *et al*. (2011)

emphasize that housing conditions and tenure, and neighborhood conditions, are widely thought of as important social determinants of health inequalities. And as stressed by Tang *et al*. (2008), the social determinants of health have become more unequal in China. We will present a comprehensive picture of how housing conditions (both internal and external) and homeownership affect the income-health gradient in urban China.

## 3. Data and methods

### 3.1 Data and analysis sample

We use data from nine waves of the CHNS – 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011 and 2015 – and cover nine Chinese provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi and Guizhou) that have notably different social, economic and health characteristics (Zhao *et al*., 2018). The survey is carried out using a multi-stage random cluster sampling method (based on different income levels and weighted sampling) with the following steps. First, after randomly selecting four counties and two cities within each province, the CHNS randomly identifies villages and towns in each county, and urban and suburban regions in each city. 20 households from each of these communities are then selected. The data thus provide broad coverage of the Chinese population's social, economic and health situation over both space and time (Zhang *et al*., 2014).

Our analysis sample consists of adults aged 18 or over in urban China for whom detailed demographic, socio-economic, living-condition and anthropometric information is available. We exclude pregnant women and respondents in the 1989 CHNS wave, which covers only adults aged 20–45. In addition, SRH is recorded only starting in 1997 (and not in 2009 or 2011), individual weight, height, systolic blood pressure (SBP) and diastolic blood pressure (DBP) from 1991 to 2015, and waist circumference (CW) from 1993 onwards. Our analysis sample then covers 14,867 individuals for SRH, 24,829 for the Body Mass Index (BMI), and hence general overweight or obesity, 23,978 for HBP, and last 21,998 for central obesity.

### 3.2 Housing variables

The CHNS housing variables cover housing conditions and homeownership. The former include binary variables for the presence of tap water, an indoor flush toilet, clean cooking fuel and there being no excreta around the dwellings. Homeownership is equally a binary variable. However, the homeownership questions are not the same over the various survey waves. In the 1991-2006 CHNS, respondents are asked how they obtained their apartment or house, with responses: 1=Rent from the State, 2=Rent from a work unit, 3=Rent from a private individual, 4=Own, 5=Stay for free and 6=Part ownership (this last category was added from 1997 to 2006, reflecting diversified housing property rights during the housing reforms: Davis, 2004). The CHNS views households reporting any of first three categories (Rent from the State, Rent from a work unit or Rent from a private individual) as tenants during this 1991 to 2006 period, while the other three categories are combined into homeownership (Fu, 2015). The construction of the homeownership dummy in the 2009-2015 CHNS is straightforward, as respondents there are simply asked directly whether they own or rent their house or apartment.

### 3.3 Health variables

We have a variety of health indicators: SRH, general overweight/obesity, central obesity and HBP. The SRH variable has four response categories (Poor, Fair, Good and Excellent) in almost all the CHNS surveys, which we convert into a bad-health dummy (1 = Fair/Poor; 0 = Excellent/Good).[3] We have in addition objective health information regarding the respondent's weight, height, CW, SBP and DBP. The use of these objective health measures helps to address any bias inherent in SRH (Shields *et al.*, 2011), which is important for the assessment of income-related health inequality (Nesson and Robinson, 2019).

Our objective bad health outcome measures are general overweight/obesity, central

[3] There were five self-reported health (SRH) categories in 2015: Very Bad, Bad, Fair, Good and Very Good. Our bad-health dummy here is 1 = Fair/Bad/Very Bad; 0 = Good/Very Good.

obesity and HBP. General overweight/obesity (represented by a BMI of 24 kg/m$^2$ or over) and central obesity (CW $\geqslant$ 85 cm for men and CW $\geqslant$ 80 cm for women) are assessed according to the criteria of the Working Group on Obesity in China (Zhou and the Cooperative Meta-analysis Group of Working Group on Obesity in China, 2002). These are clinically measured in the CHNS data. We here consider the overweight/obese as one group, given the relatively lower prevalence of general obesity (defined in the Chinese context as a BMI of 28 kg/m$^2$ or over) at 8.6% of the sample. We will later also consider the WHO's overweight criterion (BMI $\geqslant$ 25 kg/m$^2$) as a robustness check.

These weight criteria are different from those for Westerners, as the Chinese have a higher percentage of body fat than Westerners with the same BMI (e.g., Choo, 2002). Although BMI is the most common measure of overweight and obesity, it does not capture the distribution of body fat, which can lead to misleading results. CW, however, is a more accurate measure of the distribution of body fat and has been shown to be more strongly associated with morbidity and mortality (Dagan *et al*., 2013). Considering both BMI and CW is particularly important in China, as not considering CW would omit approximately two-thirds of the obese (Du *et al*. 2013). Our use of clinical measures of individual weight, height and CW is an advantage, as these eliminate any reporting biases that are inherent in self-reported weight and height (Shields *et al*., 2011); these biases tend to produce underestimated BMI (Burkhauser and Cawley, 2008). In the CHNS, blood pressure measurements are taken three times by a health professional using a mercury sphygmomanometer, with a time interval between successive pairs of measures of at least one minute (Lei *et al.*, 2012). We calculate the mean values of SBP and DBP based on three blood-pressure measurements (Hou, 2008). HBP is a dummy for the respondent's mean SBP being $\geqslant$ 140mmHg or their mean DBP being $\geqslant$ 90mmHg (Whiteworth, 2003; Hou, 2008).

**3.4 Control variables**

We introduce a number of variables into our health equations, following the existing literature. These include demographic characteristics (Apouey and Clark, 2015, Maas *et al*., 2006) and SES and lifestyle factors (Molarius *et al*., 2006). Our demographic and socio-economic variables are gender, age (18-34, 35-59 and 60+, with 18-34 as the reference group), marital status (never married, married and widowed/separated/divorced, with never married being the omitted category), household size, education (Low - illiterate or primary school, Medium - middle school, high school or a vocational degree, and High - university or higher education, with Low as the reference group), a dummy for employment (as opposed to unemployment or not being in the labor force) and per capita household income. This latter income variable is expressed in real 2015 terms and will be log-transformed in the empirical analysis to capture any non-linearity in the relationship between income and health (Ettner, 1996). Individual lifestyle choices are measured by the consumption of alcohol, smoking and whether the respondent has medical insurance. Last, our regressions will include Province and wave dummies.

### 3.5 Methods

#### *3.5.1. Measuring income-related health inequality*

Socioeconomic inequality in health can be measured using various concentration indices (*CI*), which are a family of bivariate rank-dependent indices (Heckley *et al*., 2016). A *CI* calculates the socioeconomic inequality in a certain health variable as the cumulative percentage of the health variable that is concentrated in a cumulative percentage of the population ranked by some socioeconomic variable (Kakwani *et al*., 1997; Wagstaff *et al*., 1991; Kjellsson and Gerdtham, 2013). In detail, the *CI* is calculated as twice the area between the concentration curve and the diagonal line, ranging from -1 to 1. Higher absolute values of *CI* correspond to greater socioeconomic inequality in health, with a positive *CI* value indicating that good health is more concentrated among those with higher socioeconomic rank, so that there is pro-rich health inequality.

As the *CI* is derived from the Gini coefficient of the income distribution, it requires that the health variables be measured on the same scale as income, i.e. a ratio-scale without an upper bound (Erreygers, 2009; Kjellsson and Gerdtham, 2013). However, health variables are likely bounded and either ordinal or cardinal. Erreygers (2009) and Wagstaff (2005) respectively deal with this issue by proposing the *EI* and *WI* indices. These two indices measure socioeconomic-related health inequalities differently, as they do not weight the absolute concentration (*AC*) index in the same way (Kjellsson and Gerdtham, 2013). Following Heckley *et al*. (2016), we can express *AC*, *EI*, and *WI* for a binary health variable as:

$$AC = 2cov(h, F_Y) \tag{1}$$

$$EI = f^{EI}(\mu_h, n)AC = 4AC \tag{2}$$

$$WI = f^{WI}(\mu_h, n)AC = \frac{1}{(1-\mu_h)\mu_h}AC \tag{3}$$

where $h$ is the binary health variable, $\mu_h$ its mean, $n$ the sample size and $f(\mu_h, n)$ the weighting function for the index. We rank individuals by per capita household income, $Y$, and the CDF of $Y$, $F_Y$, produces the fractional rank for each individual (Heckley *et al*., 2016). A higher absolute value of either *EI* or *WI* means an increase in health inequality. However, if it becomes more positive (negative) then health is more concentrated amongst those of higher (lower) rank.

With respect to the bounded binary health-outcome variable, the *EI* and *WI* do not weight the *AC* in the same way, as they differ regarding the definition of the most unequal state[4] (Kjellsson and Gerdtham, 2013). Kjellsson and Gerdtham (2013) argue that the choice between the two indices is a value judgement, with there being no consensus as to which index is preferred (Heckley *et al*., 2016). We will here use *EI* in the main analysis and then carry out robustness checks using *WI*.

### *3.5.2 The RIF-EI-OLS regression decomposition*

Wagstaff *et al*. (2003) propose a regression-based decomposition approach for health:

[4] As Kjellsson and Gerdtham (2013) highlight: "*WI answers the questions of how far the society is, given its overall level of health, from a state where only the individuals at the top of the income distribution are healthy, while EI answers the question of how far the society is from a state where only the upper 50% of the income distribution are healthy, independent of prevalence*" (p. 667).

however, this method explains the degree of variation in health rather than the covariance between health and socioeconomic rank (Erreygers and Kessels, 2013; Heckley *et al*., 2016; Kessels and Erreygers, 2019). Erreygers and Kessels (2013) and Kessels and Erreygers (2016) have thus proposed a set of two-dimensional decompositions, considering both socioeconomic rank and health. They nonetheless only decompose *AC* (Heckley *et al*., 2016), although, in most cases, it is unclear which index is preferred.

We thus appeal to a recent decomposition method – the RIF regression decomposition, as proposed by Heckley *et al*. (2016). This decomposition method is carried out in two steps: i) calculate the RIF value of the rank-dependent inequality index for each individual and ii) regress the RIF value on a set of covariates, generating the marginal effects of the covariates on the health-inequality index. The mean of all individuals' RIF values is the *EI* or *WI*. A RIF value that denotes each individual's influence on the statistic (here *EI* or *WI*) can be calculated using the formulae in Heckley *et al*. (2016). These show how the statistic would change were the individual to be removed from the sample (Heckley *et al*., 2016; Kessels and Erreygers, 2019). This technique assumes a linear relationship between the RIF and the covariates, so that ordinary least squares (OLS) regressions can be used and the estimated coefficients are the marginal effects of the covariates on the health-inequality index. One advantage of this method is that it can be used to decompose all forms of bivariate rank-dependent indices such as the *AC*, *EI* and *WI* indices, the Attainment relative concentration index and the Shortfall relative concentration index (Heckley *et al*., 2016). It also allows us to explore how the results differ according to the particular value judgement that is made (e.g. the choice of the *EI* or *WI* index). We will use the RIF-EI-OLS decomposition for our binary health variables.[5] Following Heckley *et al*. (2016) and Kessels and Erreygers (2019), the influence function (IF) and the RIF of the rank-dependent inequality index $R$ for individual $i$ are as follows:

$$IF_i^R = \mu_h - h_i - 2R + 2h_iF_Y(y_i) - acc_i \tag{4}$$

where $acc_i$ stands for the absolute concentration curve co-ordinate of individual $i, i = 1, \ldots, n$. To empirically estimate the RIF, the $n$ observations in the data are first

[5] We carry out these RIF-EI-OLS decompositions using the Stata module *rifhdreg*, which is available in Rios-Avila (2019).

ordered by a rank variable $Y$, so that $y_1 \leq y_2 \leq \cdots \leq y_n$. $\hat{F}_Y(y)$ and $\widehat{acc}_i$ can then be calculated as follows:

$$\hat{F}_Y(y_i) = \frac{\sum_{j=1}^{i} 1}{n} \tag{5}$$

$$\widehat{acc}_i = \frac{\sum_{j=1}^{i} h_j}{n} \tag{6}$$

The RIF for index R is then the sum of IF and the value of R:

$$RIF_i^R = IF_i^R + R \tag{7}$$

where $R$ is the *EI* or *WI* in our case.

Specifically, following Heckley *et al.* (2016), we express the RIF for *EI* and *WI* as:

$$RIF_i^{EI} = EI + 4IF_i^{AC} \tag{8}$$

$$RIF_i^{WI} = WI + \frac{(2\mu_h - 1)(h_i - \mu_h)}{((1-\mu_h)\mu_h)^2} AC + \frac{1}{(1-\mu_h)\mu_h} IF_i^{AC} \tag{9}$$

The regression equation for the $RIF_i{}^R$ of the health-inequality index is:

$$RIF_i^R = \alpha_0 + \alpha_1 X_i + \varepsilon_i \tag{10}$$

where $RIF_i^R$ denotes the RIF value of individual $i$'s health-inequality index R, $X_i$ a vector of explanatory variables, $\alpha_1$ the marginal effects of the explanatory variables on $RIF_i^R$, and $\varepsilon_i$ the error term with $E(\varepsilon_i|X_i) = 0$.

## 4. Results

### 4.1 Descriptive statistics

The descriptive statistics of our sample appear in Table 1. Regarding the dependent variables, 41% of respondents report bad health, and the mean BMI and CW values are 23.2 and 81.8, respectively. The respective prevalence of general overweight/obesity, central obesity and HBP is 38%, 48% and 23%. With respect to housing conditions, 93%, 64%, 68% and 84% of households have tap water, an indoor flushing toilet, clean cooking fuel and no excreta around dwellings respectively. The average rate of homeownership is 82%, which is consistent with other estimates of urban homeownership in China (Cui *et al*., 2019; Fu, 2015; Tang *et al*., 2011). For example, the average homeownership rate in the 2013 China Household Finance Survey in Cui *et al*. (2019) is 81.2%.

Table 1. Descriptive statistics for adults aged 18+ in urban China, CHNS 1991-2015

| Variable | Definition | Obs. | Mean | SD |
|---|---|---|---|---|
| Bad self-reported health (SRH) | 1997-2006: 1 = Fair/Poor; 0 = Excellent/Good. 2015: 1 = Fair/Bad/Very Bad; 0 = Good/Very Good | 14867 | 0.41 | |
| Body Mass Index (BMI) | Weight/height squared (kg/m$^2$) | 24829 | 23.16 | 3.38 |
| General overweight/obesity | 1 if BMI ⩾ 24 kg/m$^2$; 0 otherwise | 24829 | 0.38 | |
| Circumference of waist (CW) | Cm | 21998 | 81.78 | 10.63 |
| Central obesity | 1 if CW ⩾ 85 cm for men and CW ⩾ 80 cm for women; 0 otherwise | 21998 | 0.48 | |
| High blood pressure (HBP) | 1 = Yes; 0 = No | 23978 | 0.23 | |
| Tap water | 1 = Yes; 0 = No | 24829 | 0.93 | |
| Indoor flush toilet | 1 = Yes; 0 = No | 24829 | 0.64 | |
| Clean cooking fuel | 1 = Electricity/natural gas; 0 = Others | 24829 | 0.68 | |
| No excreta around dwellings | 1 = Yes; 0 = No | 24829 | 0.84 | |
| Homeownership | 1 = Yes; 0 = No | 24829 | 0.82 | |
| Gender | 1 = Female; 0 = Male | 24829 | 0.53 | |
| Age group | Aged 18-34 [a] | 24829 | 0.23 | |
| | Aged 35-59 | 24829 | 0.51 | |
| | Aged 60+ | 24829 | 0.26 | |
| Marital status | Never married [a] | 24829 | 0.11 | |
| | Married | 24829 | 0.81 | |
| | Widowed/separated/divorced | 24829 | 0.08 | |
| Education | Low [a] | 24829 | 0.36 | |
| | Medium | 24829 | 0.55 | |
| | High | 24829 | 0.10 | |
| Employment status | 1 = Employed; 0 = Unemployed or not in the labor force | 24829 | 0.55 | |
| Per capita household income | In logs in 2015 values | 24829 | 9.00 | 1.06 |
| Smoking | 1 = Yes; 0 = No | 24829 | 0.31 | |
| Heavy drinking | 1 = Yes; 0 = No | 24829 | 0.16 | |
| Medical insurance | 1 = Yes; 0 = No | 24829 | 0.64 | |
| Household size | | 24829 | 3.60 | 1.45 |

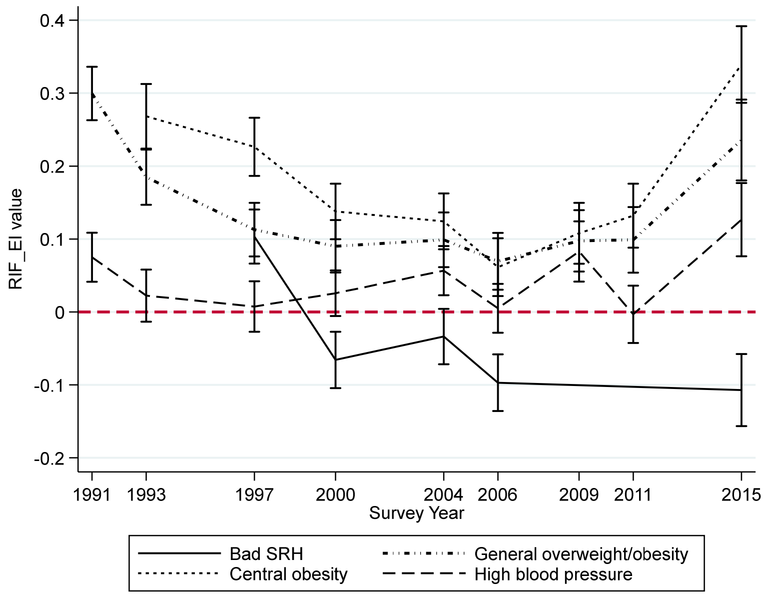
*Notes*: Education is defined on a 3-point scale: Low (illiterate or primary school), Medium (middle school, high school or a technical or vocational degree) and High (university or higher education). Heavy drinking is defined as 1 if the respondent consumes alcohol three or more times per week, and 0 if fewer than three times per week.

[a] Denotes the reference group.

### 4.2 Income-related health inequality in urban China from 1991 to 2015

Figure 1 depicts the time profile of the income-health gradient. From 1997 to 2015, the mean RIF value of *EI* for bad self-reported health fell from approximately 0.10 to -0.11, while that for general overweight/obesity fell from 0.30 in 1991 to 0.07 in 2006 but then rose to 0.24 in 2015. Similarly, the RIF-EI index of central obesity fell from 0.27 to 0.06 from 1993 to 2006 but then rose to 0.34 in 2015. Last, the RIF-EI index of HBP rose slightly over the 1991-2015 period, from 0.08 to 0.13. As such, subjective bad health is now concentrated among the poor, whereas objective bad health is concentrated among the rich. Figure 1 then suggests that SRH on its own may not capture the full picture of income-related health inequality, so that a combination of subjective and objective health measures is preferable.

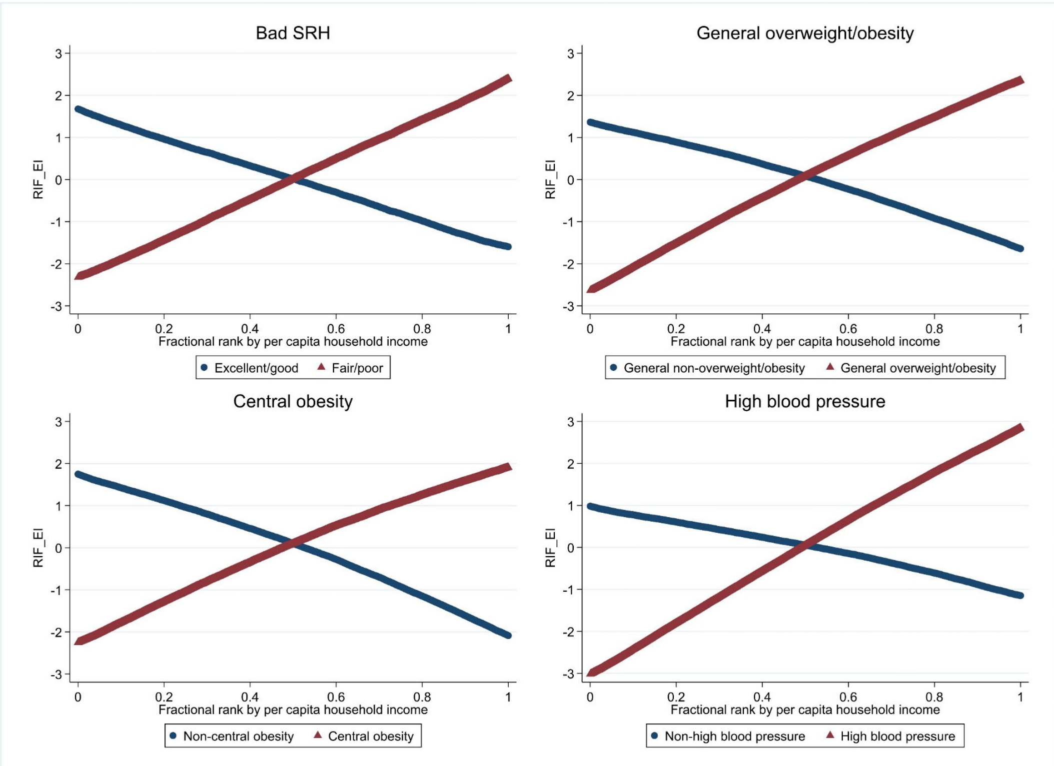
Figure 1. Mean RIF values of *EI* for the different health measures, CHNS 1991-2015.




The *EI* is a bivariate rank-dependent index, showing the joint distribution of health and socioeconomic rank. Figure 2 then plots the RIF-EI values for the bad health measures against per-capita household income. Here, the Y-axis shows an individual's influence on the RIF-EI statistic were they to be removed from the sample, which is minus that individual's RIF value weighted by the inverse of the sample size (Heckley *et al.*, 2016).

Figure 2 reveals that those at the extremes of the income distribution have the largest influence on the *EI*, consistent with existing work (Heckley *et al*., 2016; Monti, 1991). Moreover, the unhealthy (with bad SRH, general overweight/obesity or HBP) affect the *EI* more than do the healthy, as the slope of ill-health is larger than that for health (except for central obesity).[6] The gap between the influence of the healthy and the unhealthy on the *EI* is the most obvious for HBP. Overall, incomes at either end of the distribution have the greatest influence on *EI*. And the good or bad health outcomes are unequally distributed among the rich and the poor because of the non-zero RIF values for both healthy and unhealthy groups except for those at the median income rank (the bivariate rank dependent index such as *EI* gives zero weight to these at the median income rank and increasing weight to those further away from the median: Heckley *et al*., 2016).

Figure 2. Individual RIF of *EI* values against individual fractional income rank




[6] A back-of-the-envelope calculation using the height of the slopes in Figure 2 produces absolute values of the slopes (between the income ranks of zero and one) for bad SRH, general overweight/obesity and HBP of around 4.5, 5 and 6 respectively. These are to be compared to the absolute values of slopes for good SRH, general non-overweight/ obesity and non-HBP of 3.2, 3 and 2 respectively.

### 4.3 Income-related health inequality decomposition: The role of homeownership and housing conditions

Table 2 lists the RIF-EI-OLS decomposition results, which show the effects of the covariates on the health gradient. Housing conditions have no effect on the bad SRH gradient, with the exception of the positive effect (at the ten per cent level) of clean cooking fuel. On the contrary, the correlations for the objective bad health measures are far more significant. Tap water is negatively associated with the RIF-EI values of general overweight/obesity and central obesity, as is clean cooking fuel and no excreta around dwellings. Similarly, an indoor flush toilet and no excreta around dwellings are negatively correlated with the RIF-EI score for blood pressure. Overall then, better housing conditions reduce the income-related inequalities in objective health. Our results concur with those in Urbanos-Garrido (2012) for Spain, showing that housing deprivation[7] is positively associated with income-related poor-SRH inequality.

Homeownership attracts a positive and significant estimated coefficient for both general overweight/obesity and central obesity: owning a house is associated with a higher RIF value and worsens income-related inequalities for these two health outcomes. One possible explanation here is that wealth and its distribution are generally associated with health and health inequality (Deaton, 2002; Semyonov *et al*., 2013). As Fang *et al*. (2010) highlight, China's rising health inequality has been accompanied by rapid economic growth and a widening wealth distribution. In particular, homeownership has become an important indicator of household wealth in urban China. Unlike Western countries where investors have an array of options in which to invest, there are only limited choices in China for wealth investment. This role of housing, plus China's phenomenal growth in the past four decades, is such that property now accounts for 70% of China's household wealth (Tan, 2015; Gao, 2017). The rate of homeownership is higher among the rich than the poor (88.5% vs. 76.7%) in urban

[7] Housing deprivation in Urbanos-Garrido (2012) is a dummy variable for the individual's home suffering from at least one deprivation problem among the following: no toilet, no bath/shower, inability to maintain a warm temperature during the winter, leaks, moisture or rot in floors, ceilings, foundations, windows or doors, and overcrowding.

China (Gan, 2013). The homeownership gap between the rich and the poor may thus account for the positive effect of homeownership on income-related health inequalities.

With respect to the demographic and socioeconomic characteristics, the medium educated and those in larger households help to reduce the income-bad SRH gradient. However, respondents aged 35 or over, the high educated and the employed increase the income-bad SRH gradient. Regarding objective bad health measures, women, respondents aged 35 or over, the highly-educated, the employed and those in larger households mostly have lower RIF values and help to reduce the income-related inequalities in our three objective bad health measures. Health insurance is also negatively correlated with income-related objective health inequalities, suggesting that this helps urban residents access health care and reduces the overall mean RIF value and so income-related health inequality.[8] On the contrary, being married, having medium education and higher household income positively contribute to income-related objective bad health inequalities, as in the Chinese results in Cai *et al*. (2017*a*).

Conditional on the other control variables, we find relatively little effect of health-related behaviors in Table 2, with the exception of a positive coefficient for the link between heavy drinking and central obesity. Last, the wave dummies reveal the (conditional) trends in income-related health inequalities, which turn out to be similar to those in Figure 1.

Income, as a central determinant of health, reduces income-related bad SRH inequality. The first row of Table 2 shows that the mean RIF of bad SRH is -0.04, consistent with Cai *et al*. (2017*b*) in China, so that higher income reduces the absolute overall mean of the RIF and as such produces health equality. On the contrary, income increases income-related obesity inequalities, as individuals with higher incomes have higher RIF values. This may reflect the positive relationship between income and obesity in developing countries (Zhou, 2019). In China, those with higher incomes are more likely

[8] In urban China, the Urban Employee Basic Medical Insurance (UEBMI) scheme for urban employees and the Urban Residents Medical Insurance (URMI) scheme for non-working residents and children are the main forms of health insurance (Cai *et al*., 2017a)

to have unhealthy diets (with higher levels of fat and sugar), unhealthy behaviors (e.g. more sedentary activities, as suggested by Du *et al*., 2002, and Kim, 2004), and be able to buy sufficient or even an excessive amount of food (Zhou, 2019). China's public-transport infrastructure has also substantially improved, with additional buses and subways, while increased wealth has increased vehicle ownership (by a factor of over 15 between 1991 and 2011: National Bureau of Statistics, 2017) with far more Chinese (and particularly the rich) using private cars as their dominant transportation mode (Zhao *et al*., 2013). The poor, on the contrary, are more likely to engage in labor-intensive work that reduces their probability of gaining weight (Zhou, 2019).[9] Our results also show higher income being associated with greater likelihood of HBP for urban residents. Those with higher SES may have higher-salt diets, with a consequent greater probability of HBP (Fang *et al*., 2015).

The effect of education is non-monotonic: Medium-level education increases income-related objective bad health inequalities while high-level education reduces them: high education produces lower RIF values while medium education increases them. Generally one of the likely benefits of higher education is general knowledge (and in particular medical knowledge) that helps individuals become more health-conscious and take preventive actions (Costa-Font and Gil, 2008; Mirowsky and Ross, 2003; Martin *et al*., 2012). In addition, high-education is related to higher income. Therefore, high-level education, which is linked with both being healthier and richer, yields lower RIF values and therefore decreases pro-rich objective health inequalities. On the contrary, medium-level education is related with lower odds of obesity and hypertension but does not raise income much, thereby leading to higher RIF values and greater pro-rich objective bad health inequalities.

Employment increases bad SRH inequality but reduces inequalities in central obesity and HBP. This may reflect that China does not have a universal health-insurance system, and even those who are insured have different degrees of coverage, depending on the

[9] Since the BMI cutoffs in the Chinese criteria are slightly lower than the WHO's, we have re-run the RIF-EI-OLS estimation using the WHO criteria (defining general overweight/obesity as BMI ≥ 25 kg/m$^2$). The results, available on request, are quantitatively similar to our results in Table 2.

exact employment status and job characteristics (Kim and Chung, 2019). Thus, the employed are those who are rich and healthy (e.g. better SRH and a lower obesity rate), producing pro-poor bad SRH inequality and a higher absolute RIF value, but on the contrary pro-rich obesity inequality and a lower central obesity inequality RIF value. As such, the employed positively contribute to the income-bad SRH gradient but reduce the income-obesity gradient.

Table 2. RIF-EI-OLS decomposition estimates of income-related health inequality for urban adults in China: CHNS 1991-2015

| | (1)<br>Bad SRH | (2)<br>General overweight/obesity | (3)<br>Central obesity | (4)<br>High blood pressure |
|---|---|---|---|---|
| Mean RIF | -0.040 | 0.140 | 0.168 | 0.044 |
| Tap water | -0.001 | -0.063** | -0.094*** | -0.020 |
| | (0.042) | (0.029) | (0.035) | (0.027) |
| Indoor flush toilet | -0.010 | 0.024 | -0.040** | -0.029* |
| | (0.024) | (0.018) | (0.020) | (0.017) |
| Clean cooking fuel | 0.046* | -0.052*** | -0.045** | -0.024 |
| | (0.024) | (0.018) | (0.020) | (0.016) |
| No excreta around dwellings | 0.042 | -0.064*** | -0.076*** | -0.038* |
| | (0.032) | (0.022) | (0.025) | (0.020) |
| Homeownership | 0.043 | 0.062*** | 0.059*** | 0.021 |
| | (0.028) | (0.019) | (0.022) | (0.018) |
| Female | -0.018 | -0.112*** | -0.100*** | -0.021 |
| | (0.024) | (0.019) | (0.020) | (0.017) |
| 35-59 | -0.090*** | -0.036* | -0.103*** | -0.107*** |
| | (0.027) | (0.019) | (0.023) | (0.015) |
| 60+ | -0.107*** | 0.008 | -0.067** | -0.076*** |
| | (0.038) | (0.028) | (0.031) | (0.026) |
| Married | 0.027 | 0.010 | 0.063** | 0.055*** |
| | (0.033) | (0.023) | (0.029) | (0.018) |
| Widowed/separated/divorced | -0.068 | 0.059 | 0.080* | -0.027 |
| | (0.050) | (0.036) | (0.041) | (0.034) |
| Education: Medium | 0.081*** | 0.045** | 0.102*** | 0.071*** |
| | (0.024) | (0.018) | (0.019) | (0.016) |
| Education: High | -0.146*** | -0.091*** | -0.057* | -0.112*** |
| | (0.039) | (0.031) | (0.033) | (0.028) |
| Employed | -0.087*** | 0.003 | -0.050*** | -0.031** |
| | (0.023) | (0.018) | (0.019) | (0.016) |
| Per capita household income | 0.057*** | 0.047*** | 0.071*** | 0.056*** |
| | (0.016) | (0.012) | (0.013) | (0.011) |
| Smoking | -0.014 | 0.025 | -0.007 | -0.005 |
| | (0.026) | (0.020) | (0.021) | (0.019) |
| Heavy drinking | 0.034 | 0.015 | 0.064*** | -0.007 |
| | (0.028) | (0.021) | (0.023) | (0.021) |
| Medical insurance | -0.018 | -0.043*** | -0.040** | -0.017 |
| | (0.021) | (0.017) | (0.018) | (0.015) |
| Household size | 0.017** | -0.014** | -0.017*** | -0.007 |
| | (0.008) | (0.006) | (0.006) | (0.005) |
| 1993 | | -0.125*** | | -0.060** |
| | | (0.027) | | (0.025) |
| 1997 | | -0.184*** | -0.030 | -0.053** |

| | | | | |
|---|---|---|---|---|
| | | (0.028) | (0.031) | (0.026) |
| 2000 | -0.183*** | -0.225*** | -0.145*** | -0.056** |
| | (0.028) | (0.029) | (0.031) | (0.026) |
| 2004 | -0.170*** | -0.239*** | -0.183*** | -0.041 |
| | (0.029) | (0.030) | (0.033) | (0.028) |
| 2006 | -0.235*** | -0.262*** | -0.241*** | -0.086*** |
| | (0.029) | (0.031) | (0.033) | (0.028) |
| 2009 | | -0.227*** | -0.190*** | -0.024 |
| | | (0.032) | (0.034) | (0.030) |
| 2011 | | -0.226*** | -0.168*** | -0.102*** |
| | | (0.034) | (0.035) | (0.031) |
| 2015 | -0.272*** | -0.093** | 0.023 | 0.020 |
| | (0.036) | (0.039) | (0.039) | (0.035) |
| Constant | -0.491*** | 0.020 | -0.119 | -0.232** |
| | (0.156) | (0.116) | (0.127) | (0.109) |
| *N* | 14867 | 24829 | 21998 | 23978 |
| Adj. $R^2$ | 0.013 | 0.014 | 0.021 | 0.013 |

*Notes*: The regressions also include Province dummies. Robust standard errors appear in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

### 4.4 Robustness checks

#### *4.4.1 RIF-WI-OLS regression decomposition*

As a robustness check, Table 3 reports the results from a RIF-WI-OLS decomposition. We here only show the estimated coefficients on the housing variables (the results for the control variables here are similar to those in Table 2). As in Table 2, our four better housing conditions reduce the health gradient, especially for objective health. On the contrary, homeownership reinforces this gradient, in particular for obesity.

Table 3. RIF-WI-OLS decomposition estimates of income-related health inequality for urban adults in China: CHNS 1991-2015

| | (1) Bad SRH | (2) General overweight/obesity | (3) Central obesity | (4) High blood pressure |
|---|---|---|---|---|
| Mean RIF | -0.041 | 0.149 | 0.169 | 0.062 |
| Tap water | -0.001 | -0.073** | -0.095*** | -0.034 |
| | (0.043) | (0.032) | (0.035) | (0.038) |
| Indoor flush toilet | -0.010 | 0.021 | -0.042** | -0.043* |
| | (0.025) | (0.020) | (0.020) | (0.023) |
| Clean cooking fuel | 0.048** | -0.059*** | -0.046** | -0.033 |
| | (0.025) | (0.019) | (0.020) | (0.023) |
| No excreta around dwellings | 0.042 | -0.071*** | -0.078*** | -0.055* |
| | (0.033) | (0.023) | (0.025) | (0.028) |
| Homeownership | 0.044 | 0.071*** | 0.060*** | 0.033 |
| | (0.029) | (0.021) | (0.022) | (0.026) |
| *N* | 14867 | 24829 | 21998 | 23978 |
| Adj. $R^2$ | 0.013 | 0.016 | 0.021 | 0.014 |

*Notes*: Robust standard errors appear in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

#### *4.4.2 A composite housing-conditions index*

Instead of looking at each of the four housing conditions (tap water, indoor flush toilets, clean cooking fuel and no excreta around dwellings) separately, we can create a composite index of housing-quality deprivation. This is the sum of deprivation in these four domains, with higher numbers referring to worse housing conditions. The results from the RIF-EI-OLS decomposition using this index appear in Table 4. Consistent with Tables 2 and 3, housing-quality deprivation steepens the health gradient, especially for objective health, so that better housing conditions are associated with lower income-related health inequalities. Homeownership continues to steepen the income-health gradient, in particular for obesity.

Table 4. RIF-EI-OLS decomposition estimates of income-related health inequality for urban adults in China: CHNS 1991-2015

| | (1) Bad SRH | (2) General overweight/obesity | (3) Central obesity | (4) High blood pressure |
|---|---|---|---|---|
| Mean RIF | -0.040 | 0.140 | 0.168 | 0.044 |
| Housing-quality deprivation | -0.013 | 0.030*** | 0.057*** | 0.028*** |
| | (0.011) | (0.008) | (0.009) | (0.007) |
| Homeownership | 0.032 | 0.067*** | 0.062*** | 0.017 |
| | (0.029) | (0.019) | (0.022) | (0.018) |
| *N* | 13663 | 24829 | 21780 | 23723 |
| Adj. $R^2$ | 0.013 | 0.014 | 0.021 | 0.012 |

*Notes*: Housing-quality deprivation is the sum of the binary variables for no tap water, no indoor flushing toilet, no electricity/natural gas for cooking, and excreta around dwellings. The regressions include the same non-housing control variables as in Table 2. Robust adjusted standard errors appear in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

#### *4.4.3 Do cohort effects really matter?*

All of the income-related health inequalities we measure are worse for the young. This can either reflect ageing or cohort effects. We can control for cohort effects via the estimation of a Hierarchical Age-Period-Cohort Cross-Classified Random Effects Model (HAPC-CCREM: Yang and Land, 2016). This has recently been applied in the fields of well-being (Yang, 2008) and health (Beck *et al*., 2014; Jiang and Wang, 2018). We define our cohorts here by 10-year birth-year intervals. The results in Appendix Table A1 show that cohort effects play an important role in explaining the changes in income-related health inequality. However, controlling for them does not meaningfully change our results for housing conditions and homeownership, which remain similar to those in Table 2. The estimated age effects controlling for cohorts are only smaller than in Table 2 for age 35-59 and objective bad health.

## 5. Discussion and conclusion

We have here used 1991-2015 CHNS data to consider how housing affects the income-health relationship in urban China. By doing so we extend the existing literature to China, which has experienced unprecedented economic growth and a distinctive development of its housing market compared to Western economies. We in addition are able to analyze both subjective and objective measures of health and consider changes in the income-health gradient over more than two decades. Last, we use the RIF regression decomposition approach to look at the determinants (including homeownership and housing conditions) of the income-health relationship. To our knowledge, this is the first comprehensive attempt to establish the role of housing characteristics on income-related health inequalities using both subjective and objective health measures, and the RIF regression method that is flexible for forms of inequality measures, is simple to estimate and produces results that are easy to interpret.

Our negative Erreygers index for subjective health reveals that the poor are more likely to report bad health. This is in line with existing work on China (Yang and Kanavos, 2012; Zhou *et al*., 2017) and may well show that the rich can afford healthcare (Zhou *et al*., 2011). However, the Erreygers indices for our objective bad-health measures are positive: the rich are more likely to suffer from obesity and HBP (as in Liu *et al*., 2018, Zhao *et al*., 2018 and Yang *et al*., 2017).

The income-related inequality in bad subjective health turned from positive to negative between 1997 to 2015, so that bad subjective health switched from being concentrated amongst the rich to amongst the poor. The same figure for obesity fell up to 2006 but then increased to 2015, while that for blood pressure rose slightly over the study period. We consider the role of housing, and show that better housing conditions reduce the income-related inequalities in objective bad health, which is consistent with the Spanish results in Urbanos-Garrido (2012). Because poor housing conditions may well then produce ill-heath (Angel and Bittschi, 2019). On the contrary, homeownership increases these inequalities for obesity and HBP (although not significantly so for the latter). Our findings here of a role for both housing conditions and homeownership in the income-health relationship adds an additional dimension to the health-inequality literature and, more importantly, confirms the emphasis in Gibson *et al*. (2011) on housing as an important determinant of health inequalities. We also find that the income-health gradient is related to gender, age, marital status, education, per capita household income, medical insurance and household size.

Regarding effect sizes, that of no excreta around the dwellings is the most important housing condition for income-related inequalities in general overweight/obesity and HBP, while for income-related central obesity inequality it is tap water. The marginal effect of homeownership is smaller than that of housing conditions. The marginal effects of all our housing variables are smaller than those on the wave dummies, showing that there remains a considerable amount of unexplained variation in the way in which the health-income relationship has changed over time.

These results have potentially important policy implications. Better housing conditions will reduce income-related health inequality, and as such may well be an effective way of mitigating health inequality in urban China. In addition, the worsening income-related health inequality associated with homeownership may suggest that the government should promote safety-net programs targeting those households without a house, such as better coverage of pension plans, public-health insurance, in order to reduce the role of homeownership and income in determining health outcomes.

**Conflict of interest**

None.

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## Appendix:

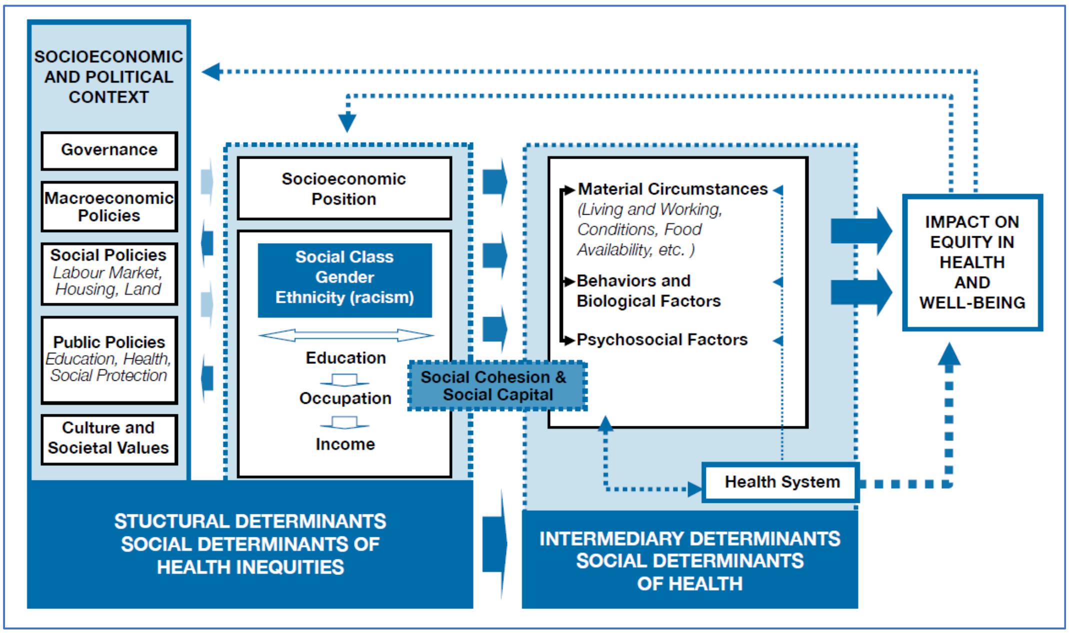
Table A1. HAPC-CCREM estimation based on RIF-EI-OLS decomposition estimates of income-related health inequality for urban adults 18+: CHNS 1991-2015

| | (1) Bad SRH | (2) General overweight/obesity | (3) Central obesity | (4) High blood pressure |
|---|---|---|---|---|
| Mean RIF | -0.040 | 0.140 | 0.168 | 0.044 |
| Fixed effects | | | | |
| Tap water | -0.008 | -0.021 | -0.072** | -0.009 |
| | (0.040) | (0.030) | (0.035) | (0.028) |
| Indoor flush toilet | -0.008 | 0.016 | -0.039* | -0.026 |
| | (0.026) | (0.019) | (0.021) | (0.018) |
| Clean cooking fuel | 0.041* | -0.077*** | -0.071*** | -0.034** |
| | (0.025) | (0.018) | (0.020) | (0.017) |
| No excreta around dwellings | 0.041 | -0.048** | -0.055** | -0.019 |
| | (0.030) | (0.022) | (0.025) | (0.020) |
| Homeownership | 0.036 | 0.057*** | 0.049** | 0.018 |
| | (0.029) | (0.021) | (0.023) | (0.018) |
| Female | -0.021 | -0.131*** | -0.113*** | -0.033* |
| | (0.025) | (0.022) | (0.023) | (0.019) |
| 35-59 | -0.107*** | -0.102*** | -0.205*** | -0.258*** |
| | (0.036) | (0.027) | (0.031) | (0.024) |
| 60+ | -0.059 | 0.027 | -0.085* | -0.135*** |
| | (0.050) | (0.041) | (0.046) | (0.038) |
| Married | -0.008 | -0.063** | -0.027 | -0.058** |
| | (0.038) | (0.030) | (0.034) | (0.027) |
| Widowed/separated/divorced | -0.081 | -0.032 | 0.036 | -0.033 |
| | (0.052) | (0.042) | (0.046) | (0.038) |
| Education: Medium | 0.072*** | 0.024 | 0.090*** | 0.062*** |
| | (0.025) | (0.021) | (0.022) | (0.019) |
| Education: High | -0.143*** | -0.055 | -0.033 | -0.073** |
| | (0.039) | (0.033) | (0.035) | (0.029) |
| Employed | -0.091*** | -0.027 | -0.062*** | -0.042** |
| | (0.024) | (0.018) | (0.020) | (0.016) |
| Per capita household income | 0.058*** | 0.045*** | 0.071*** | 0.052*** |
| | (0.010) | (0.008) | (0.009) | (0.007) |
| Smoking | -0.016 | 0.014 | -0.019 | -0.019 |
| | (0.026) | (0.021) | (0.023) | (0.019) |
| Heavy drinking | 0.034 | 0.002 | 0.059** | -0.010 |
| | (0.029) | (0.022) | (0.024) | (0.020) |
| Medical insurance | -0.018 | -0.043** | -0.043** | -0.034** |
| | (0.023) | (0.018) | (0.019) | (0.016) |
| Household size | 0.016** | -0.009 | -0.011* | 0.001 |
| | (0.008) | (0.006) | (0.007) | (0.005) |

| | | | | |
|---|---|---|---|---|
| Constant | -0.656*** | -0.108 | -0.206* | -0.297** |
| | (0.132) | (0.110) | (0.120) | (0.123) |
| Random effects | | | | |
| Period | | | | |
| 1991 | | 0.150*** | | 0.034* |
| | | (0.029) | | (0.020) |
| 1993 | | 0.032 | 0.097*** | -0.017 |
| | | (0.029) | (0.034) | (0.021) |
| 1997 | 0.165*** | -0.025 | 0.064** | -0.024 |
| | (0.030) | (0.029) | (0.033) | (0.020) |
| 2000 | -0.007 | -0.044 | -0.028 | -0.015 |
| | (0.031) | (0.028) | (0.033) | (0.020) |
| 2004 | 0.004 | -0.052* | -0.054* | 0.003 |
| | (0.030) | (0.028) | (0.032) | (0.020) |
| 2006 | -0.058* | -0.072** | -0.114*** | -0.033* |
| | (0.030) | (0.028) | (0.032) | (0.020) |
| 2009 | | -0.037 | -0.062* | 0.024 |
| | | (0.028) | (0.032) | (0.020) |
| 2011 | | -0.035 | -0.042 | -0.037* |
| | | (0.028) | (0.032) | (0.020) |
| 2015 | -0.104*** | 0.083*** | 0.138*** | 0.065*** |
| | (0.030) | (0.029) | (0.033) | (0.020) |
| Cohorts | | | | |
| 1895-1909 | -0.005 | 0.093 | 0.044 | -0.157 |
| | (0.075) | (0.120) | (0.131) | (0.156) |
| 1910-1919 | -0.011 | 0.096 | -0.057 | -0.470*** |
| | (0.062) | (0.070) | (0.080) | (0.064) |
| 1920-1929 | -0.119** | -0.059 | -0.084* | -0.140*** |
| | (0.043) | (0.043) | (0.048) | (0.035) |
| 1930-1939 | -0.032 | -0.077** | 0.013 | 0.174*** |
| | (0.034) | (0.034) | (0.037) | (0.025) |
| 1940-1949 | 0.065** | 0.056* | 0.100*** | 0.343*** |
| | (0.032) | (0.032) | (0.035) | (0.023) |
| 1950-1959 | 0.043 | 0.149*** | 0.178*** | 0.345*** |
| | (0.030) | (0.029) | (0.032) | (0.020) |
| 1960-1969 | 0.086*** | 0.116*** | 0.156*** | 0.241*** |
| | (0.030) | (0.029) | (0.033) | (0.020) |
| 1970-1979 | 0.058* | 0.059* | 0.053 | 0.095*** |
| | (0.032) | (0.031) | (0.035) | (0.023) |
| 1980-1989 | -0.049 | -0.164*** | -0.144*** | -0.142*** |
| | (0.040) | (0.040) | (0.042) | (0.033) |
| 1990-1997 | -0.104 | -0.270*** | -0.260*** | -0.290*** |
| | (0.061) | (0.076) | (0.078) | (0.076) |
| Variance component | | | | |
| Period | 0.009 | 0.006** | 0.008** | 0.001 |
| | (0.006) | (0.003) | (0.004) | (0.001) |
| Cohort | 0.006 | 0.020* | 0.021* | 0.074** |
| | (0.004) | (0.012) | (0.012) | (0.035) |
| Individual | 0.067*** | 0.287*** | 0.222*** | 0.139*** |
| | (0.012) | (0.010) | (0.011) | (0.007) |
| *N* | 14867 | 24829 | 21998 | 23978 |

*Notes*: The regressions include Province dummies. Standard errors appear in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1. The CSDH's conceptual framework




*Source*: Figure A in WHO (2008, p.6)