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

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Abstract

Unprecedented economic growth has been experienced over the several decades worldwide, but such rapid economic growth wasn't accompanied by equally-substantial improvement in health, especially health inequalities between the rich and poor. This study examines the role of housing in income-related health inequalities (income-health gradient) in urban China. We here analyze 1991-2015 China Health and Nutrition Survey data to ask how housing affects income-related health inequalities in urban China. We find pro-poor inequalities in self-reported bad health but pro-rich inequalities in objective bad health (general overweight/obesity, central obesity and high blood pressure). Housing conditions serve to reduce the health gradient, especially for objective health. On the contrary, homeownership 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

1. Introduction

Five of the United Nations' 17 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 for 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).

As stated by the CSDH, the socio-economic and political context led to a set of socioeconomic positions, in which populations are stratified according to income, education, occupation, social class, gender, race/ethnicity and other factors (Solar and Irwin, 2010; WHO, 2008). In the CSDH's conceptual framework (see 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 appeared in a large number of existing contributions (Angel and Bittschi, 2019; Jacobs et al., 2009; Koh and Restuccia, 2018; Krieger and Higgins, 2002; Ludwig et al., 2013; Nie et al., 2021a; Webster, 2015), its intermediate effect on income-related health inequalities (which we will call the income-health gradient, or just the health gradient) remains largely unexplored (Urbanos-Garrido, 2012). This nexus was however important, as it provided insights for public policy such as housing interventions to effectively mitigate health inequalities.

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 10,475 *Yuan* (deflated to 1978) in 2020 (National Bureau of Statistics, 2021). This rapid economic growth was not however accompanied by equally-substantial improvements in health (Baeten et al., 2013). Despite the rise in Chinese life expectancy from 68 in 1981 to 77 in 2020 (National Bureau of Statistics, 2021), China's health reputation has been shrinking (Jiang and Zhang, 2020; Liu and Zhang, 2019), and rising health disparities between the rich and the poor produced dissatisfaction (Liu and Zhang, 2019).

At the same time as these developments in health and income, China's housing market also attracts concern (Funke et al., 2019; Tsai and Chiang, 2019). Housing reform, which is an important component of the Reform and Opening-Up Policy, transformed China from a country dominated by public-housing renters to one with an extremely high rate of homeownership, rising from 28 percent in 1993 to 84.6 percent in 2002 (Chen and Hu, 2019) and the strikingly high rate of 90.8 percent in 2013 (Cui et al., 2021): this is 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., 2021). More importantly, homeownership, coupled with *hukou* (the household registration system), constituted 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. Meanwhile although average housing conditions improved significantly, not every urban household benefited equally from housing reform, producing housing inequality (Tan et al., 2016). As the housing reform led to the introduction of a market-oriented housing system and the rapid growth of the real estate industry in urban China, households with greater economic purchase power (e.g., household income) have likely benefited more from housing consumption than other households (Tan et al., 2016). In addition, China's urban house prices rose at a rate almost double that of household income following the market-oriented housing reform (Chen et al., 2020). Soaring house prices and rising housing inequality reshape 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 income-health gradient in emerging and developed countries.

We will here consider housing (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 income-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., 2017a). 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 employ a new decomposition technique – the re-centered influence function (RIF) regression decomposition method for both the Erreygers Index (*EI*) and the Wagstaff Index (*WI*) – to look at the potential housing determinants of the income-health gradient. This method directly decomposes the socioeconomic-related health inequality and relaxes the rank and weighting-function ignorability assumptions (it is important in measuring and decomposing bivariate inequality), which require that the determinants of health do not determine the rank or the weighting function respectively (Heckley et al., 2016). Additionally, RIF regression decompositions require fewer restrictive assumptions than the Wagstaff decomposition approach (WDW in what follows) (Heckley et al., 2016), and the results are easier to estimate and simpler to interpret (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. Section 5 discusses the major findings and Section 6 concludes.

2. Literature review

A number of previous analyses use 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 (Baeten et al., 2013; Nie et al., 2021b; Shao et al., 2016; Wang and Yu, 2016; Yang and Liu, 2018; Yang and Kanavos, 2012; Zhou et al., 2017) and find pro-rich inequalities in SRH (that is, the rich are more likely to report better SRH). Specifically, 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 limitations in the 2006 CHNS, with income, employment status and education being three 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 1997-2006 CHNS health inequality via an income-health matrix[1] 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. Recently, using the 2020 China COVID-19 Survey, Nie et al. (2021b) show pro-rich

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

inequality in SRH with income being the leading contributor, accounting for 62.7% of income-related SRH inequality.

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 in Shaanxi province, with household consumption expenditure and education being two of the 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.

Evidence for objective income-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. Su et al. (2018) document pro-poor inequality in HBP in 2011 CHNS data, with income, education attainment and age being the key factors. More recently, Zhou et al. (2020) using the 1997-2011 CHNS, find that inequalities in both general obesity and central obesity have declined over time, and that household income, marital status and education are the key contributors.

There have thus been a number of contributions using Chinese data to investigate the income-health gradient. These mostly reported rising pro-rich health inequality, and highlighted the major drivers of this inequality such as income and education. To our knowledge, only two studies have employed the RIF regression decomposition method to decompose income-related SRH inequality (Cai et al., 2017a; Wang and Zhu, 2018). Using 1991-2006 CHNS data and RIF regression decompositions, Cai et al. (2017a) found pro-rich SRH inequality; this was mainly caused by income and secondary education. This observed is confirmed by Wang and Zhu (2018), who employ the 2013 and 2015 China Health and Retirement Longitudinal Study data, showing that income not only improves SRH but also mitigates SRH inequality.

We complement this existing work in three ways. First, 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 Liu and Zhang (2019), the social determinants of health have become more unequal in China. We will below present a comprehensive picture of how housing conditions (both internal and external) and homeownership affect the income-health gradient in urban China. Second, we 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). Last, the previous literature primarily used the traditional bivariate rank dependent index – a concentration index – to quantify the health gradient and the WDW 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 housing determinants of the health gradient. Only Cai et al. (2017a) and Wang and Zhu (2018) have employed the RIF decomposition in this context (although they only look at SRH).

3. Methods and materials

3.1. Data and study sample

We use data from nine waves of the CHNS – 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011 and 2015. It covers nine Chinese provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi and Guizhou) that had notably different social, economic and health characteristics (Zhao et al., 2018a). 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 CHNS is designed to evaluate how the socioeconomic transformation of Chinese society is affecting the health and nutritional status of its population (Zhang et al., 2014).

Our analysis sample consists of adults aged 18+ in urban China for whom detailed demographic, socio-economic, living-condition and anthropometric information are available. We exclude pregnant women and respondents in the 1989 CHNS wave, which only covers adults aged 20-45. We have information on individual weight, height, systolic blood pressure (SBP) and diastolic blood pressure (DBP) in all years, SRH in all years apart from 2009 and 2011, and waist circumference (CW) from 1993 onwards. Our analysis sample covers 20,029 individuals for SRH, 24,829 for the Body Mass Index (BMI), and hence general overweight or obesity, 23,978 for HBP, and 21,998 for central obesity. We use pooled CHNS data to explore the potential role of housing in the income-health gradient in the main results.

3.2. Housing variables

The CHNS housing variables cover housing conditions and homeownership. The former includes 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 a binary variable. However, the homeownership questions are not the same over the various survey waves. In the 1991-2006 CHNS, respondents were 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). 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 were simply asked directly whether they owned 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).[2] We have in addition objective health information regarding the respondent's weight, height, CW, SBP and DBP. The use of these objective health measures help to address any bias inherent in SRH (Shields et al., 2011), which was important for the assessment of income-related health inequality (Nesson and Robinson, 2019).

Our objective bad health outcome measures are general overweight/obesity, central obesity and HBP. General overweight/obesity (represented by a BMI of 24 kg/m^2 or over) and central obesity (CW ⩾ 85 cm for men and CW ⩾ 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 percent of the sample.

These weight criteria is different from those for Westerners, as the Chinese had a higher percentage of body fat than Westerners with the same BMI (Choo, 2002). Although BMI is the most common measure of overweight and obesity, it does not capture the distribution of body fat, which could 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

[2] 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.

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 ⩾ 140mmHg or their mean DBP being ⩾ 90mmHg (Hou, 2008; Whiteworth, 2003).[3]

3.4. Control variables

We introduce a number of variables into our decomposition regression equations, following the existing literature. These include demographic characteristics (Apouey and Clark, 2015; Maas et al., 2006), 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 reference 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 annual 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-linearities in the relationship between income and health (Ettner, 1996). Individual lifestyle choices are reflected in alcohol consumption, smoking and whether the respondent has medical insurance. Last, our regressions include Province and wave dummies to control for unobserved province-specific factors (e.g. different policies regarding housing and health) and any time-specific variables that are associated with both heath status and housing conditions.

[3] Some objective health measures may affect subjective health, although the evidence on the relationship between objective and subjective health is mixed. Given this, we did not introduce objective health into the estimation for the income-SRH gradient.

3.5. Statistical analyses

3.5.1. Measuring income-related health inequality.

Socioeconomic inequality in health could be measured using concentration indices (CI), which are a family of bivariate rank-dependent indices (Heckley et al., 2016).[4] 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 variables (Kakwani et al., 1997; Wagstaff et al., 1991). In detail, the CI is calculated as twice the area between the concentration curve and the diagonal line, ranging from -1 to 1. We here analyze dummies for bad health. Higher absolute values of CI then correspond to greater socioeconomic inequality in bad health, with positive (negative) values indicating that bad health is more concentrated among those with higher (lower) socioeconomic rank, so that there is pro-poor (pro-rich) health inequality.

As the *CI* was derive from the Gini coefficient of the income distribution, it requires that the health variables be measured on the same scale as income, that was, a ratio-scale without an upper bound (Erreygers, 2009; Kjellsson and Gerdtham, 2013). However, health variables are likely bounded and either ordinal or cardinal. Thus EI (Erreygers, 2009) and WI (Wagstaff, 2005) indices deal with this. These 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 Kjellsson and Gerdtham (2013) we express *AC*, *EI*, and *WI* for a binary health variable as:

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

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

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

where h is the binary bad-health variable, μ_h its mean, n the sample size and

[4] Regarding bivariate rank-dependent indices for regression-based decomposition, there are no essential differences between the rank-dependent and level-dependent indexes (see, e.g. Erreygers et al., 2016; Kessels and Erreygers, 2019). As such, we use rank-dependent indices to measure income-related health inequality.

$f(\mu_h, n)$ the weighting function for the index. We rank individuals by per capita household income Y, and the cumulative distribution function (CDF) of Y (F_Y) produces the fractional rank for each individual. The larger the absolute value of either EI or WI, the greater is health inequality.

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 (Kjellsson and Gerdtham, 2013).[5] 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; Kjellsson and Gerdtham, 2013). We here use EI in the main analysis and then carry out robustness checks using WI.

3.5.2. The RIF-EI-OLS regression decomposition.

Bivariate rank-dependent indices should be thought of as two-dimensional indices that consider the covariance between health and rank. However, the Wagstaff approach is one-dimensional decomposition because it focuses on health variation but ignores socioeconomic rank (Erreygers and Kessels, 2013). This decomposition thus explains the degree of variations in health rather than the covariance between health and socioeconomic rank, i.e. income-heath gradient (Erreygers and Kessels, 2013; Heckley et al., 2016; Kessels and Erreygers, 2019). Thus a set of two-dimensional decompositions is proposed, considering both socioeconomic rank and health (Erreygers and Kessels, 2013; Kessels and Erreygers, 2016). They nonetheless only decompose AC (Heckley et al., 2016), although in most cases it is unclear which index is preferred. Moreover, it is difficult to interpret the estimated coefficients from this method.

Subsequent decomposition methods such as RIF regression decomposition (Heckley et al., 2016) address these issues. The RIF regression decomposition considers both health and socioeconomic ranking when decomposing bivariate rank dependent indices. Unlike conventional decomposition methods, this approach decomposes all types of

[5] 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 percent of the income distribution are healthy, independent of prevalence*' (p. 667).

bivariate rank-dependent indices such as the *AC*, *EI* and *WI* indices. In addition, it required fewer rank and weighting-function ignorability assumptions. More importantly, RIF decomposition results are easy to interpret.

We use this decomposition method here, and apply it in two steps: i) calculate the RIF value of the rank-dependent inequality index (*EI* or *WI*) for each individual; and ii) regress the RIF vector on a set of covariates, generating the marginal effects of the covariates on the income-related health-inequality index. A RIF value that denotes each individual's influence on the statistic (here *EI* or *WI*) could be calculated following existing formulae (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). The RIF is a vector where each element corresponds to a particular individual's influence on the statistic of an inequality index. This is useful for decomposition as it allowed any statistic to be expressed as a mean of the RIF vector. The mean of each element of the RIF vector is the overall inequality index *EI* or *WI* of the sample. This technique assumes a linear relationship between the RIF vector and the covariates, so that ordinary least squares (OLS) regressions could be used and the estimated coefficients are the marginal effects of the covariates on the health-inequality index. It also allows us to explore how the results differed according to the particular value judgement that is made (for example the choice of the *EI* or *WI* index).

We use the RIF-EI-OLS decomposition for our binary health variables. The influence function (IF) and the RIF of the rank-dependent inequality index *R* for individual i are as follows (Heckley et al., 2016; Kessels and Erreygers, 2019):

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

where acc_i is the absolute concentration curve co-ordinate of individual $i, i = 1, \dots, n$. To empirically estimate the RIF, the n observations in the data are first ordered by a rank variable Y, so that $y_1 \leq y_2 \leq \cdots \leq y_n$. The estimated $\hat{F}_Y(y)$ and $\widehat{acc}_i$ could then be calculated as follows:

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

$$\widehat{acc}_i = (\sum_{j=1}^{i} h_j)/n \quad (6)$$

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

$$RIF_i^R = IF_i^R + R \quad (7)$$

where R is the EI or WI in our case.

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

$$RIF_i^{EI} = EI + 4IF_i^{AC} \quad (8)$$

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

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

$$RIF_i^R = \alpha_0 + \alpha_1 X_i + \varepsilon_i \quad (10)$$

where RIF_i^R denotes the RIF value of individual i's health-inequality index R, X_i a vector of explanatory variables, α_1 the marginal effects of the explanatory variables on RIF_i^R, and ε_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, 37 percent 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 percent, 48 percent and 23 percent. For housing conditions, 93 percent, 64 percent, 68 percent and 84 percent 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 percent, which is consistent with other estimates of urban homeownership in China (Cui et al., 2021; Fu, 2015). For example, the average homeownership rate in the 2013 China Household Finance Survey was 81.2 percent (Cui et al., 2021).

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

Variables	Definition	Obs.	Mean	SD
Bad self-reported health (SRH)	1991-2006: 1 = Fair/Poor; 0 = Excellent/Good. 2015: 1 = Fair/Bad/Very Bad; 0 = Good/Very Good	20029	0.37	
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 annual 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 a dummy for the respondent consuming alcohol three or more 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 1991 to 2015, the *EI* for bad SRH fell from approximately -0.03 to -0.25, while that for general overweight/obesity rose from 0.06 in 1991 to 0.09 in 2004 but then fell to 0.04 in 2015.

Similarly, the *EI* index of central obesity rose from -0.01 to 0.12 from 1993 to 2004 but then fell to 0.05 in 2015. Last, the *EI* index of HBP rose over the 1991-2004 period, from -0.001 to 0.05, with a subsequent modest decrease from 2004 to 2015. The values of *EI* with 95% confidence intervals show that for bad SRH, general overweight/obesity and central obesity EI is far below or above 0, while the HBP *EI* index fluctuates around 0, suggesting that for the first three bad-health measures, the absolute values of *EI* are significantly different from 0 but are close to 0 for HBP. Given that the absolute value of *EI* reflects the degree of inequality, there seems to be income-related bad-health inequalities for the first three health measures, but not so for HBP. The time profiles in Figure 1 show that subjective bad health is now concentrated among the poor, whereas objective bad health is concentrated among the rich.[6] SRH on its own then does not capture the full picture of income-related health inequality, and a combination of subjective and objective health measures is likely preferable.

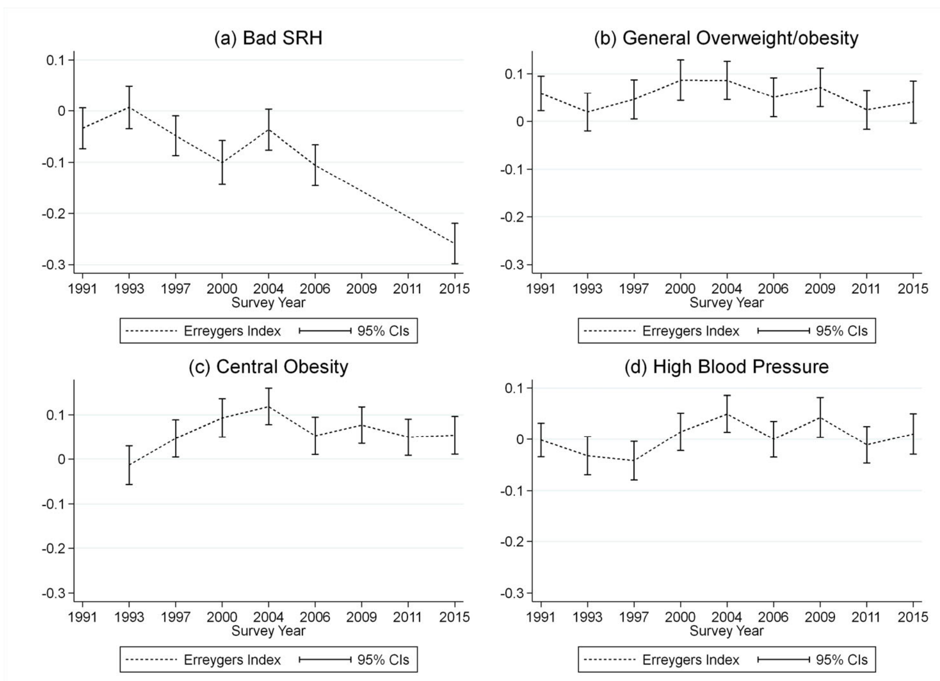

Figure 1 EI for the different health measures by wave, CHNS 1991-2015.

[6] According to the definition of the bivariate rank-dependent inequality index, the positive (negative) sign of *EI* reflects that the bad health is more concentrated amongst those of higher (lower) socioeconomic rank.

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

Table 2 lists the RIF-*EI*-OLS decomposition results for the effects of the covariates on the health gradient, and in particular for our variables of our interest – housing conditions and housing ownership. The first row shows the mean RIF value of *EI* which is the income-related bad health inequality in the full sample. Housing conditions have no effect on the bad SRH gradient[7], with the exception of the positive effect of clean cooking fuel. On the contrary, the correlations for the objective bad health measures are far more significant. Tap water has a negative effect on *EI* values of general overweight/obesity and central obesity, as do clean cooking fuel and no excreta around dwellings. Similarly, an indoor flush toilet and no excreta around dwellings have negative effect on *EI* for blood pressure. We could also interpret these coefficients as deviations from the observed unconditional averages (Rios-Avila, 2020). For example, a 10 percent rise in the population proportion of no excreta around dwellings (from 84 percent to 94 percent, say) is associated with a fall in the *EI* inequality index for general overweight/obesity of 4.6 percent (0.064/0.14×0.1). Overall, better housing conditions reduce the income-related inequalities in objective health. Our results concur with results for Spain, showing that housing deprivation[8] is positively associated with income-related poor-SRH inequality (Urbanos-Garrido, 2012). Homeownership attracts a positive and significant estimated coefficient for bad SRH, general overweight/obesity and central obesity: owning a house is associated with a higher RIF value and so worsens income-related health inequalities.

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[7] Given that the survey questions for SRH are inconsistent between 2015 and other waves, we also drop the 2015 wave and re-run the estimates: the results for bad SRH (available upon request) are quantitively similar to those in Table 2.

[8] 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.

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

	Bad SRH	General overweight/obesity	Central obesity	High blood pressure
Mean RIF	0.010	0.140	0.168	0.044
Tap water	-0.048	-0.063**	-0.094***	-0.020
	(0.033)	(0.029)	(0.035)	(0.027)
Indoor flush toilet	-0.002	0.024	-0.040**	-0.029*
	(0.020)	(0.018)	(0.020)	(0.017)
Clean cooking fuel	0.042**	-0.052***	-0.045**	-0.024
	(0.020)	(0.018)	(0.020)	(0.016)
No excreta around dwellings	0.021	-0.064***	-0.076***	-0.038*
	(0.025)	(0.022)	(0.025)	(0.020)
Homeownership	0.037*	0.062***	0.059***	0.021
	(0.021)	(0.019)	(0.022)	(0.018)
Female	-0.023	-0.112***	-0.100***	-0.021
	(0.021)	(0.019)	(0.020)	(0.017)
35-59	-0.073***	-0.036*	-0.103***	-0.107***
	(0.021)	(0.019)	(0.023)	(0.015)
60+	-0.088***	0.008	-0.067**	-0.076***
	(0.032)	(0.028)	(0.031)	(0.026)
Married	0.035	0.010	0.063**	0.055***
	(0.026)	(0.023)	(0.029)	(0.018)
Widowed/separated/divorced	-0.041	0.059	0.080*	-0.027
	(0.043)	(0.036)	(0.041)	(0.034)
Education: Medium	0.075***	0.045**	0.102***	0.071***
	(0.020)	(0.018)	(0.019)	(0.016)
Education: High	-0.165***	-0.091***	-0.057*	-0.112***
	(0.036)	(0.031)	(0.033)	(0.028)
Employed	-0.054***	0.003	-0.050***	-0.031**
	(0.021)	(0.018)	(0.019)	(0.016)
Per capita household income	0.086***	0.047***	0.071***	0.056***
	(0.014)	(0.012)	(0.013)	(0.011)
Smoking	-0.029	0.025	-0.007	-0.005
	(0.022)	(0.020)	(0.021)	(0.019)
Heavy drinking	-0.013	0.015	0.064***	-0.007
	(0.024)	(0.021)	(0.023)	(0.021)
Medical insurance	0.008	-0.043***	-0.040**	-0.017
	(0.018)	(0.017)	(0.018)	(0.015)
Household size	0.014**	-0.014**	-0.017***	-0.007
	(0.006)	(0.006)	(0.006)	(0.005)
1993	-0.031	-0.125***		-0.060**
	(0.027)	(0.027)		(0.025)
1997	-0.125***	-0.184***	-0.030	-0.053**
	(0.029)	(0.028)	(0.031)	(0.026)
2000	-0.252***	-0.225***	-0.145***	-0.056**
	(0.030)	(0.029)	(0.031)	(0.026)
2004	-0.197***	-0.239***	-0.183***	-0.041
	(0.032)	(0.030)	(0.033)	(0.028)
2006	-0.259***	-0.262***	-0.241***	-0.086***
	(0.033)	(0.031)	(0.033)	(0.028)
2009		-0.227***	-0.190***	-0.024
		(0.032)	(0.034)	(0.030)
2011		-0.226***	-0.168***	-0.103***
		(0.034)	(0.035)	(0.031)
2015	-0.260***	-0.093**	0.023	0.020
	(0.040)	(0.039)	(0.039)	(0.035)
Constant	-0.675***	0.020	-0.119	-0.232**
	(0.134)	(0.116)	(0.127)	(0.109)
N	20029	24829	21998	23978

Notes: Pooled OLS estimates are applied. The regressions also include Province dummies. Robust standard errors appear in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

With respect to the demographic and socioeconomic characteristics, income, the medium-educated and those in larger households help to increase the income-bad SRH gradient. However, respondents aged 35 or over, the highly-educated and the employed reduce the income-bad SRH gradient. For the 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 so 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 help urban residents access health care and reduced the overall mean RIF value and so income-related health inequality. On the contrary, being married, having medium education and higher household income positively contribute to income-related objective bad-health inequalities, as in the some existing results (Cai et al., 2017a).

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.

4.4. Robustness checks

4.4.1. Panel data analysis.

When considering housing effects on income-related health inequality, one major concern was individual unobserved heterogeneity that is correlated with both housing characteristics and the weighted covariance of health and income rank (Heckley et al., 2016). As an example, individuals with a better family background are more likely to be healthy and live in a decent house. Equally, individual ability is likely important for both income and health. Not addressing these endogeneity issues from unobserved variables might produce biased estimates of the impact of housing on income-related health inequality. To mitigate some endogeneity issues due to omitted variables or/and measurement errors at the individual level, we controlled for individual fixed effects in an unbalanced panel (see Table 3, detailed results appeared in Table A1). The results show that housing conditions, in particular, clean cooking fuels, reduced the objective health gradient. Nonetheless, homeownership steepened this gradient, in particular for bad SRH and obesity. These results confirmed the cross-section findings in Table 2.[9] Considering that we cannot estimate the effects of time-invariant variables in individual fixed effects model we also do the random effects model based on such unbalanced panel data. The results are comparable.

Table 3 RIF-EI-OLS decomposition estimates of income-related health inequality for adults 18+: CHNS 1991-2015 (unbalanced panel)

	Bad SRH		General overweight/obesity		Central obesity		High blood pressure	
	FE	RE	FE	RE	FE	RE	FE	RE
Mean RIF	0.010		0.140		0.168		0.044	
Tap water	-0.066	-0.053	0.020	-0.016	-0.004	-0.067*	0.009	-0.004
	(0.049)	(0.035)	(0.041)	(0.032)	(0.046)	(0.035)	(0.037)	(0.029)
Indoor flush toilet	0.021	0.000	0.005	0.013	-0.013	-0.042**	-0.030	-0.029*
	(0.033)	(0.021)	(0.027)	(0.020)	(0.030)	(0.021)	(0.025)	(0.017)
Clean cooking fuels	0.009	0.032	-0.100***	-0.075***	-0.107***	-0.071***	-0.056***	-0.035**
	(0.026)	(0.020)	(0.022)	(0.018)	(0.025)	(0.020)	(0.021)	(0.017)
No excreta around dwellings	0.066**	0.031	-0.026	-0.046**	-0.017	-0.055**	0.012	-0.025
	(0.033)	(0.026)	(0.027)	(0.023)	(0.032)	(0.026)	(0.026)	(0.020)
Homeownership	0.089**	0.037*	0.075**	0.068***	0.066*	0.058**	0.032	0.023
	(0.035)	(0.022)	(0.033)	(0.022)	(0.035)	(0.024)	(0.030)	(0.019)
N	20029	20029	24829	24829	21998	21998	23978	23978

Notes: Unbalanced panel data are used. Province dummies are included in the RE specifications. Clustered in individual level standard errors are in parentheses., * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. FE and RE denote individual fixed effects and random effects model, respectively.

4.4.2. RIF-WI-OLS regression decomposition.

As a robustness check, Table 4 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 were 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 reinforce this gradient, in particular for obesity.

[9] As the CHNS spans 25 years, the use of a balanced panel implies a very substantial loss of data (only 416 of the 9,313 individuals in our sample replied in every wave from 1991 to 2015). We have however re-run our estimations using unbalanced panel data but restricting the sample to respondents who were surveyed in at least two waves. The results, available on request, are similar to those in Table 3.

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

	Bad SRH	General overweight/obesity	Central obesity	High blood pressure
Mean RIF	0.010	0.149	0.169	0.062
Tap water	-0.052	-0.073**	-0.095***	-0.034
	(0.035)	(0.032)	(0.035)	(0.038)
Indoor flush toilet	-0.002	0.021	-0.042**	-0.043*
	(0.022)	(0.020)	(0.020)	(0.023)
Clean cooking fuel	0.045**	-0.059***	-0.046**	-0.033
	(0.021)	(0.019)	(0.020)	(0.023)
No excreta around dwellings	0.023	-0.071***	-0.078***	-0.055*
	(0.027)	(0.023)	(0.025)	(0.028)
Homeownership	0.040*	0.071***	0.060***	0.033
	(0.022)	(0.021)	(0.022)	(0.026)
N	20029	24829	21998	23978

Notes: Pooled OLS estimates are applied. Robust standard errors appear in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The regressions include the same non-housing control variables as in Table 2.

4.4.3. 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 create a composite index of housing-quality deprivation. This was the sum of deprivation in these four domains, with higher numbers referring to worse housing conditions. The RIF-*EI*-OLS decomposition results using this index appear in Table 5. Consistent with Tables 2 and 3, housing-quality deprivation steepens he objective health gradient, 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 5 RIF-*EI*-OLS decomposition estimates of income-related health inequality for urban adults in China: CHNS 1991-2015

	Bad SRH	General overweight/obesity	Central obesity	High blood pressure
Mean RIF	0.010	0.140	0.168	0.044
Housing-quality deprivation	-0.010	0.030***	0.057***	0.029***
	(0.008)	(0.008)	(0.009)	(0.007)
Homeownership	0.037*	0.067***	0.062***	0.021
	(0.021)	(0.019)	(0.022)	(0.018)
N	20029	24829	21998	23978

Notes: Pooled OLS estimates are applied. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.4. Do cohort effects really matter?

All of the income-related health inequalities we measure are worse for the young. This can reflect either ageing or cohort effects. We could 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 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 Table A2 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.

4.4.5. Short periods.

A lot has changed in China, and quickly during the period of 1991-2015. As such, we separately consider three sub-periods: 1991-1997, 2000-2006 and 2009-2015 (see Table A3). One conception we find that the presence of indoor flush toilets increases the health gradient, especially bad SRH and HBP in 1991-1997. [10] One possible explanation is that, during 1991-1997, better housing conditions especially indoor flush toilet were always accessible in rich households, and thus worsen the income-health gradient. In 2000-2006, tap water had a negative effect on the *EI* values for general overweight/obesity, central obesity and HBP, whereas homeownership worsened income-related inequalities for bad health, except for central obesity and bad SRH, similar to Table 2. In 2009-2015, housing conditions reduced the health gradient, with the exception of HBP.

Perhaps the most important difference between recent years and the whole 1991-2015

[10] The total income-related health inequality for bad SRH is negative (based on the mean RIF value for EI in the first row in Table A3), and the negative coefficient on indoor flush toilets means that this worsens the income-health gradient as it increases the absolute value of EI, and the larger the absolute value of EI, the larger are income-health gradients. Regarding the other three health measures, the mean RIF values of EI (i.e. the total income-related health inequality) are positive, therefore, the negative coefficients suggest that they would reduce the income-health gradients.

period is that in the most-recent period there is no significant effect of homeownership on the income-health gradient in particular for objective health. This might reflect the extremely high rate of homeownership in China in recent years (with an average of around 90 percent in our sample during 2009-2015) that perhaps dissipated its status return (and thus its effect on health).

4.4.6. Results by wave.

To illustrate the changes over time in the relative contributions of housing conditions and homeownership, we carry out the decomposition analysis by wave (see Table A4). The results are similar to those in Table A3. Most housing conditions, especially tap water, indoor flush toilets and non-excreta around dwellings, contribute more to decreasing income-health gradient during the earlier period (1991-2009) than in more-recent data (2011-2015).

4.4.7. Without the income variable.

The income rank, which was one of the determinants of income-related bad health inequalities, is closely related to the income levels. Considering this, we also exclude household income and re-run the estimates (see Table A5). The results are quantitatively similar to those in Table 2.

4.4.8. The WDW decomposition method.

To better understand the difference between the RIF decomposition and other popular methods, we also carry out the commonly-used WDW decomposition (see Table A6). Given that WDW decomposition keeps the weighting function constant, and that EI has a constant weighting function, we here carry out the WDW decomposition based on EI. The WDW decomposition results show the contribution from each covariate to the total income-health gradients. Overall, housing conditions inequalities are major contributors to total health inequalities, especially for objective health. As such, reducing income-related inequalities in housing conditions should reduce the EI of objective heath. But the homeownership result is the opposite. It is also difficult to interpret the WDW results as the key identification assumption - rank ignorability - does not hold in WDW decomposition (Heckley et al., 2016): the covariates such as housing conditions and homeownership that affect health are also related to the income rank. The results based on RIF decomposition are therefore much easier to explain as compared to those from WDW decomposition. Our findings are consistent with Heckley et al. (2016) for Sweden. Although the results from the RIF and WDW decompositions cannot be directly compared due to their different measurement units (Heckley et al., 2016), both do confirm the important role of housing in the income-health gradient.

5. Discussion

We use 1991-2015 CHNS data to consider how housing affects the income-health gradient in urban China. By doing so we extend the existing literature to China, which experiences unprecedented economic growth and distinctive development of its housing market compared to Western economies. Our negative Erreygers index (see Figure 1) 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 might well reflect 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; Yang et al., 2017; Zhao et al., 2018b).

We consider the role of housing in income-health gradient, and show that better housing conditions reduce the income-related inequalities particularly in objective bad health. It might due to the fact that better housing conditions improve the health status of the poor, further decrease the health inequality between the rich and the poor. For example, exposure to household air pollution from inefficient cooking practices using polluting stoves paired with solid fuels and kerosene results in premature death and various other health problems (e.g. lung cancer) (WHO, 2008). Cleaner cooking fuels and improved housing conditions in other dimensions could also reduce the health gap between the rich and the poor. On the contrary, homeownership increase these inequalities for obesity and HBP (although not significantly so for the latter). One potential explanation is that wealth and its distribution are generally associated with health and health inequality (Deaton, 2002; Semyonov et al., 2013). And China's rising health inequality is accompanied by rapid economic growth and a widening wealth distribution (Fang et al., 2010). In particular, homeownership become an important component of household wealth in urban China (Cui et al., 2021). Unlike Western countries where investors have an array of options in which to invest, there are only limited choices, together with the return-rate and risk-averse investment preferences in China for wealth investment. This role of housing, plus China's phenomenal growth over the past four decades, is such that property now accounts for 70 percent of China's household wealth (Gao, 2017; Tan, 2015). The rate of homeownership is higher among the rich than the poor (88.5 percent vs. 76.7 percent) in urban China (Gan et al., 2013). Thus the unequal homeownership rates between the rich and the poor widened income-health gradient. Our findings of a role for both housing conditions and homeownership in the income-health relationship added another dimension to the health-inequality literature and, more importantly, confirmed the emphasis in Gibson et al. (2011) on the role of housing in health inequalities. We also find that the income-health gradient was related to gender, age, marital status, education, per capita household income, medical insurance and household size. Our short period analysis also reveals that with housing conditions and homeownership being more equally distributed among the rich and poor, their effects in income-health gradients shrinks. Therefore some public policies aiming at promoting prevalent access to better housing conditions (e.g. sanitation and infrastructure; and access to improved (uncontaminated) water sources) may mitigate income-health gradient.

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.

Besides housing conditions and homeownership, we also find significant effects of other controls.[11] Income, as a central determinant of health, increases income-related bad health inequalities, as individuals with higher incomes have higher RIF values. This reflects the positive relationship between income and both good SRH and obesity in developing countries (Zhou et al., 2020). In China, those with higher incomes are more likely to have unhealthy diets (with higher levels of fat and sugar), unhealthy behaviors (for example, more sedentary activities (Du et al., 2002; 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 increases 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).[12] Our results also show that higher income is associated with a greater likelihood of HBP for urban residents. Those with higher SES might have higher-salt diets, with a consequent greater probability of HBP (Fang et al., 2015).[13]

The effect of education is non-monotonic: middle-school or high-school or vocational education increases income-related objective bad-health inequalities while university or higher education reduces them. Generally one of the likely benefits of higher

[11] From the formulae of the RIF function of EI/WI (that is, income-related bad-health inequality here), there are two possibilities for a high and positive RIF value: (1) higher income and worse health, and (2) lower income and better health. Likewise, we had a low and negative RIF value for individuals with lower income and worse health or higher income and better health (Kessels and Erreygers, 2019). We follow this argument to explain the effect of covariates on high/low values of EI/WI.

[12] 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 those in Table 2.

[13] As a robustness check, following (Van de Poel et al., 2009; Yang and Land, 2016), we have calculated the equivalent real household income using the inflated household income divided by the square root of the total number of household members, and re-run the estimates. The results are quantitatively similar to these in Table 2.

education is general knowledge (and in particular medical knowledge) that help individuals become more health-conscious and take preventive actions (Costa-Font and Gil, 2008; Martin et al., 2012; Mirowsky and Ross, 2003). In addition, university or higher 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, middle-school or high-school or vocational 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.

The employed have lower RIF *EI* values, which indicating that employment reduces inequalities in bad SRH, central obesity and HBP. In China, the employed are less likely to report poor health than the unemployed (Cai et al., 2017b; Kim and Chung, 2019). One possible explanation is that the employed are less likely to be obese (Zhang et al., 2017) as work-related activities and commuting are associated with increased physical activities (Van Domelen et al., 2011). Physical activity is then an important factor in reducing the risk of health problems such as obesity, hypertension and cardiovascular disease (Zhang et al., 2017). Urban employees are also mostly of high income rank. As they are rich and healthy, they produce lower RIF values and reduce income-related inequality in obesity and HBP.

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 the health inequality in urban China. Specifically, some public policies that promote universal better housing conditions such as tap water, indoor flush toilets, clean cooking fuels and the environment around dwellings may mitigate health inequalities. 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 homeownership, such as better coverage of pension plans and public-health insurance, in order to reduce the role of homeownership and income in determining health outcomes.

Our study does have a number of limitations. First, it is impossible to rule out all of the endogeneity issues that might produce biased estimates of the impact of housing on the health gradient. The assessment of the causality in the nexus between housing and the health gradient thus remains an important subject for research. Second, we mainly focus on housing conditions and homeownership, without taking house prices into account. Given the rapid rise in house prices in urban China, more evidence is needed to explore the impact of house prices on the health gradient. Third, especially regarding homeownership, five major types of housing tenure coexist in housing markets: sole ownership, partial ownership, market rental, rental from a work unit or friends or relatives), and free or inexpensive rental from employers or the state (Chen et al., 2020). However, due to data availability, we were not able to explore how these different types of housing tenure may be related to the health gradient. This is another important topic requiring further investigation.

6. Conclusions

In conclusion, this study analyzes both subjective and objective measures of health to consider changes in the income-health gradient over more than two decades and look at the determinants (including homeownership and housing conditions) of the income-health relationship. To our knowledge, this was the first comprehensive attempt to establish the role of housing characteristics in income-related health inequalities using both subjective and objective health measures. Housing conditions serves to reduce the income-health gradient, especially for objective health. On the contrary, homeownership exacerbates such gradient. Improving housing conditions thus possibly appeared to be an effective way of reducing the income-health gradient. Since China will continue to rapidly urbanize and age, sustainable housing provisions with better housing conditions are urgently needed; these would not only improve the income-health gradient but also bring about significant economic benefits in the future.

Declaration of Competing interest

The authors declare that they have no conflict of interest.

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Authors' contributions

PN, LLD, and AC contributed to the study design. PN and LLD contributed to the data analysis and drafted the manuscript. All authors contributed to interpreting the data, commented on the manuscript, revised the manuscript, and approved the final version for publication.

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Appendix:

Table A1 RIF-EI-OLS decomposition estimates of income-related health inequality for adults 18+: CHNS 1991-2015 (unbalanced panel)

	Bad SRH		General overweight/obesity		Central obesity		High blood pressure	
	FE	RE	FE	RE	FE	RE	FE	RE
Mean RIF	0.010		0.140		0.168		0.044	
Tap water	-0.066	-0.053	0.020	-0.016	-0.004	-0.067*	0.009	-0.004
	(0.049)	(0.035)	(0.041)	(0.032)	(0.046)	(0.035)	(0.037)	(0.029)
Indoor flush toilet	0.021	0.000	0.005	0.013	-0.013	-0.042**	-0.030	-0.029*
	(0.033)	(0.021)	(0.027)	(0.020)	(0.030)	(0.021)	(0.025)	(0.017)
Clean cooking fuels	0.009	0.032	-0.100***	-0.075***	-0.107***	-0.071***	-0.056***	-0.035**
	(0.026)	(0.020)	(0.022)	(0.018)	(0.025)	(0.020)	(0.021)	(0.017)
No excreta around dwellings	0.066**	0.031	-0.026	-0.046**	-0.017	-0.055**	0.012	-0.025
	(0.033)	(0.026)	(0.027)	(0.023)	(0.032)	(0.026)	(0.026)	(0.020)
Homeownership	0.089**	0.037*	0.075**	0.068***	0.066*	0.058**	0.032	0.023
	(0.035)	(0.022)	(0.033)	(0.022)	(0.035)	(0.024)	(0.030)	(0.019)
Female	-	-0.016	-	-0.129***	-	-0.108***	-	-0.026
	-	(0.023)	-	(0.023)	-	(0.023)	-	(0.020)
35-59	-0.075*	-0.080***	-0.113***	-0.052**	-0.224***	-0.122***	-0.214***	-0.132***
	(0.040)	(0.022)	(0.038)	(0.023)	(0.043)	(0.025)	(0.028)	(0.016)
60+	0.012	-0.078**	-0.037	0.019	-0.110*	-0.068**	-0.132**	-0.095***
	(0.072)	(0.034)	(0.058)	(0.032)	(0.066)	(0.034)	(0.053)	(0.029)
Married	-0.012	0.025	-0.063	0.000	-0.037	0.053*	-0.072*	0.052***
	(0.055)	(0.027)	(0.046)	(0.026)	(0.056)	(0.031)	(0.039)	(0.019)
Widowed/separated/divorced	0.149*	-0.023	-0.078	0.024	0.123	0.093**	0.070	-0.009
	(0.088)	(0.046)	(0.069)	(0.042)	(0.079)	(0.046)	(0.062)	(0.037)
Middle	-0.016	0.081***	0.044	0.051**	0.072	0.110***	-0.016	0.081***
	(0.068)	(0.022)	(0.044)	(0.021)	(0.047)	(0.022)	(0.044)	(0.019)
Tertiary	-0.242**	-0.168***	0.060	-0.058	0.008	-0.044	-0.193***	-0.108***
	(0.102)	(0.038)	(0.074)	(0.038)	(0.078)	(0.038)	(0.064)	(0.031)
Employed	-0.065**	-0.051**	-0.031	-0.015	-0.053*	-0.052**	-0.025	-0.030*
	(0.030)	(0.021)	(0.025)	(0.019)	(0.028)	(0.020)	(0.023)	(0.017)
Per capita household income	0.146***	0.093***	0.051***	0.045***	0.086***	0.073***	0.061***	0.054***
	(0.019)	(0.015)	(0.018)	(0.015)	(0.019)	(0.015)	(0.016)	(0.013)
Smoking	0.013	-0.020	-0.022	0.020	-0.035	-0.012	0.006	-0.009
	(0.037)	(0.023)	(0.030)	(0.021)	(0.035)	(0.023)	(0.030)	(0.021)
Alcohol drinking	-0.031	-0.011	-0.011	0.003	0.069**	0.062**	-0.026	-0.011
	(0.035)	(0.024)	(0.030)	(0.023)	(0.033)	(0.025)	(0.029)	(0.022)
Medical insurance coverage	-0.029	-0.000	-0.037	-0.045**	-0.044*	-0.043**	-0.068***	-0.029*
	(0.028)	(0.019)	(0.023)	(0.018)	(0.025)	(0.019)	(0.021)	(0.016)
Household size	-0.004	0.010	-0.015	-0.012*	-0.010	-0.015**	0.008	-0.007
	(0.012)	(0.007)	(0.010)	(0.007)	(0.011)	(0.007)	(0.010)	(0.006)
1993	-0.046*	-0.034	-0.138***	-0.128***			-0.086***	-0.065***
	(0.028)	(0.026)	(0.023)	(0.021)			(0.023)	(0.022)
1997	-0.192***	-0.132***	-0.198***	-0.193***	-0.073**	-0.037	-0.146***	-0.069***
	(0.036)	(0.028)	(0.032)	(0.027)	(0.036)	(0.030)	(0.031)	(0.025)
2000	-0.342***	-0.263***	-0.197***	-0.220***	-0.160***	-0.142***	-0.123***	-0.067***
	(0.041)	(0.030)	(0.036)	(0.028)	(0.038)	(0.030)	(0.033)	(0.025)
2004	-0.335***	-0.213***	-0.207***	-0.237***	-0.203***	-0.179***	-0.126***	-0.056**
	(0.049)	(0.033)	(0.042)	(0.030)	(0.043)	(0.032)	(0.039)	(0.028)
2006	-0.389***	-0.272***	-0.231***	-0.258***	-0.286***	-0.242***	-0.159***	-0.098***
	(0.051)	(0.033)	(0.044)	(0.031)	(0.046)	(0.032)	(0.040)	(0.028)
2009			-0.194***	-0.223***	-0.245***	-0.193***	-0.086*	-0.033
			(0.050)	(0.032)	(0.052)	(0.034)	(0.048)	(0.030)

2011			-0.190***	-0.219***	-0.227***	-0.170***	-0.142***	-0.107***
			(0.054)	(0.034)	(0.056)	(0.035)	(0.051)	(0.031)
2015	-0.440***	-0.275***	-0.055	-0.091**	-0.026	0.020	-0.027	0.013
	(0.075)	(0.040)	(0.063)	(0.040)	(0.065)	(0.040)	(0.060)	(0.036)
Constant	-0.979***	-0.721***	0.047	0.015	-0.189	-0.149	-0.142	-0.218*
	(0.193)	(0.144)	(0.178)	(0.144)	(0.188)	(0.149)	(0.155)	(0.125)
N	20029	20029	24829	24829	21998	21998	23978	23978

Notes: Pooled OLS estimates are applied. Province dummies are included in the RE specifications. Robust standard errors are in parentheses., * p < 0.1, ** p < 0.05, *** p < 0.01. FE and RE denote individual fixed effects and random effects model, respectively.

Table A2 HAPC-CCREM estimation based on RIF-EI-OLS decomposition estimates of income-related health inequality for urban adults 18+: CHNS 1991-2015

	Bad SRH	General overweight/obesity	Central obesity	High blood pressure
Mean RIF	0.010	0.140	0.168	0.044
Fixed effects				
Tap water	-0.052	-0.021	-0.072**	-0.009
	(0.032)	(0.030)	(0.035)	(0.028)
Indoor flush toilet	-0.003	0.016	-0.039*	-0.026
	(0.022)	(0.019)	(0.021)	(0.018)
Clean cooking fuel	0.035*	-0.077***	-0.071***	-0.034**
	(0.021)	(0.018)	(0.020)	(0.017)
No excreta around dwellings	0.031	-0.048**	-0.055**	-0.019
	(0.024)	(0.022)	(0.025)	(0.020)
Homeownership	0.028	0.057***	0.049**	0.018
	(0.022)	(0.021)	(0.023)	(0.018)
Female	-0.029	-0.131***	-0.113***	-0.033*
	(0.022)	(0.022)	(0.023)	(0.019)
35-59	-0.118***	-0.102***	-0.205***	-0.258***
	(0.031)	(0.027)	(0.031)	(0.024)
60+	-0.028	0.027	-0.085*	-0.135***
	(0.048)	(0.041)	(0.046)	(0.038)
Married	-0.020	-0.063**	-0.027	-0.058**
	(0.031)	(0.030)	(0.034)	(0.027)
Widowed/separated/divorced	-0.030	-0.032	0.036	-0.033
	(0.045)	(0.042)	(0.046)	(0.038)
Education: Medium	0.058***	0.024	0.090***	0.062***
	(0.022)	(0.021)	(0.022)	(0.019)
Education: High	-0.152***	-0.055	-0.033	-0.073**
	(0.035)	(0.033)	(0.035)	(0.029)
Employed	-0.069***	-0.027	-0.062***	-0.042**
	(0.021)	(0.018)	(0.020)	(0.016)
Per capita household income	0.086***	0.045***	0.071***	0.052***
	(0.009)	(0.008)	(0.009)	(0.007)
Smoking	-0.031	0.014	-0.019	-0.019
	(0.023)	(0.021)	(0.023)	(0.019)
Heavy drinking	-0.011	0.002	0.059**	-0.010
	(0.025)	(0.022)	(0.024)	(0.020)
Medical insurance	0.003	-0.043**	-0.043**	-0.034**
	(0.020)	(0.018)	(0.019)	(0.016)
Household size	0.016***	-0.009	-0.011*	0.001
	(0.006)	(0.006)	(0.007)	(0.005)
Constant	-0.879***	-0.108	-0.206*	-0.297**

	(0.124)	(0.110)	(0.120)	(0.123)
Random effects				
Period				
1991	0.164***	0.150***		0.034*
	(0.038)	(0.029)		(0.020)
1993	0.129***	0.032	0.097***	-0.017
	(0.038)	(0.029)	(0.034)	(0.021)
1997	0.031	-0.025	0.064**	-0.024
	(0.037)	(0.029)	(0.033)	(0.020)
2000	-0.089***	-0.044	-0.028	-0.015
	(0.038)	(0.028)	(0.033)	(0.020)
2004	-0.036	-0.052*	-0.054*	0.003
	(0.037)	(0.028)	(0.032)	(0.020)
2006	-0.096***	-0.072**	-0.114***	-0.033*
	(0.037)	(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***
	(0.037)	(0.029)	(0.033)	(0.020)
Cohorts				
1895-1909	-0.168	0.093	0.044	-0.157
	(0.124)	(0.120)	(0.131)	(0.156)
1910-1919	-0.250***	0.096	-0.057	-0.470***
	(0.068)	(0.070)	(0.080)	(0.064)
1920-1929	-0.103**	-0.059	-0.084*	-0.140***
	(0.046)	(0.043)	(0.048)	(0.035)
1930-1939	0.039	-0.077**	0.013	0.174***
	(0.040)	(0.034)	(0.037)	(0.025)
1940-1949	0.165***	0.056*	0.100***	0.343***
	(0.039)	(0.032)	(0.035)	(0.023)
1950-1959	0.172***	0.149***	0.178***	0.345***
	(0.036)	(0.029)	(0.032)	(0.020)
1960-1969	0.163***	0.116***	0.156***	0.241***
	(0.037)	(0.029)	(0.033)	(0.020)
1970-1979	0.098***	0.059*	0.053	0.095***
	(0.039)	(0.031)	(0.035)	(0.023)
1980-1989	-0.077	-0.164***	-0.144***	-0.142***
	(0.049)	(0.040)	(0.042)	(0.033)
1990-1997	-0.040	-0.270***	-0.260***	-0.290***
	(0.087)	(0.076)	(0.078)	(0.076)
Variance component				
Period	0.012*	0.006**	0.008**	0.001
	(0.007)	(0.003)	(0.004)	(0.001)
Cohort	0.024*	0.020*	0.021*	0.074**
	(0.014)	(0.012)	(0.012)	(0.035)
Individual	0.070***	0.287***	0.222***	0.139***
	(0.009)	(0.010)	(0.011)	(0.007)
N	20029	24829	21998	23978

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

Table A3 RIF-EI-OLS decomposition estimates of income-related health inequality for adults 18+: CHNS 1991-2015 (pooled cross-sectional)

	Bad SRH	Overweight/obesity	Central obesity	High blood pressure
Panel A: 1991-1997				
Mean RIF	-0.023	0.054	0.022	-0.024
Tap water	-0.028	-0.012	-0.066	0.009
	(0.045)	(0.042)	(0.057)	(0.040)
Indoor flush toilet	-0.060**	0.031	-0.010	-0.058**
	(0.030)	(0.031)	(0.039)	(0.029)
Clean cooking fuels	0.011	-0.002	0.021	-0.032
	(0.030)	(0.031)	(0.038)	(0.028)
No excreta around dwellings	-0.012	-0.016	0.001	0.025
	(0.034)	(0.032)	(0.043)	(0.029)
Homeownership	-0.034	0.030	0.031	-0.034
	(0.029)	(0.030)	(0.040)	(0.027)
N	8088	7681	4918	7468
Panel B: 2000-2006				
Mean RIF	-0.068	0.081	0.101	0.027
Tap water	-0.056	-0.106**	-0.152***	-0.117**
	(0.055)	(0.053)	(0.055)	(0.046)
Indoor flush toilet	0.001	-0.002	-0.048	-0.026
	(0.031)	(0.031)	(0.032)	(0.027)
Clean cooking fuels	0.019	-0.038	0.024	-0.002
	(0.031)	(0.031)	(0.032)	(0.027)
No excreta around dwellings	-0.026	-0.032	-0.135***	-0.053
	(0.043)	(0.041)	(0.043)	(0.037)
Homeownership	0.100***	0.085**	0.044	0.059*
	(0.037)	(0.038)	(0.039)	(0.036)
N	8915	8562	8542	8392
Panel C: 2009-2015				
Mean RIF	-0.259	0.062	0.086	0.020
Tap water	-0.121	0.059	0.004	0.140**
	(0.108)	(0.073)	(0.076)	(0.069)
Indoor flush toilet	0.170***	-0.022	-0.007	-0.061*
	(0.066)	(0.038)	(0.038)	(0.034)
Clean cooking fuels	-0.008	-0.037	-0.049	-0.054
	(0.079)	(0.042)	(0.043)	(0.040)
No excreta around dwellings	0.005	-0.051	-0.080*	0.078*
	(0.070)	(0.046)	(0.047)	(0.043)
Homeownership	-0.127*	0.013	0.034	0.053
	(0.071)	(0.043)	(0.043)	(0.040)
N	3026	8586	8538	8118

Notes: Pooled OLS estimates are applied. Wave and Province dummies are controlled. Robust standard errors are in parentheses., * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Due to data available in CHNS, in panel A, the pooled survey period for central obesity is 1993-1997. In panel C, the pooled survey period for bad SRH is 2015. The regressions include the same non-housing control variables as in Table 2.

Table A4 RIF-EI-OLS decomposition estimates of income-related SRH inequality for adults 18+ by waves

Panel A: Bad SRH	1991	1993	1997	2000	2004	2006	2009	2011	2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tap water	-0.021	-0.284***	0.201**	-0.194**	-0.041	0.172			-0.121
	(0.081)	(0.075)	(0.078)	(0.095)	(0.089)	(0.108)			(0.108)
Indoor flush toilet	-0.021	-0.081	-0.099**	-0.003	0.003	-0.018			0.170***
	(0.061)	(0.055)	(0.048)	(0.054)	(0.056)	(0.056)			(0.066)
Clean cooking fuels	0.144**	0.029	-0.041	0.003	0.050	0.021			-0.008
	(0.057)	(0.054)	(0.048)	(0.057)	(0.052)	(0.054)			(0.079)
No excreta around dwellings	-0.120**	0.068	0.034	-0.017	-0.112	0.039			0.005
	(0.060)	(0.060)	(0.061)	(0.074)	(0.072)	(0.082)			(0.070)
Homeownership	-0.025	-0.038	-0.017	0.183***	0.069	0.058			-0.127*
	(0.052)	(0.054)	(0.052)	(0.062)	(0.068)	(0.069)			(0.071)
Constant	-0.708	-0.634	-0.613	-0.738*	-0.422	-1.168***			-0.240
	(0.450)	(0.451)	(0.389)	(0.404)	(0.350)	(0.361)			(0.356)
N	2704	2406	2978	2652	3153	3110			3026
Panel B: General overweight/obesity	1991	1993	1997	2000	2004	2006	2009	2011	2015
Tap water	0.075	-0.008	-0.212***	-0.197**	-0.087	-0.051	0.024	-0.210	0.230**
	(0.070)	(0.072)	(0.082)	(0.089)	(0.086)	(0.110)	(0.118)	(0.151)	(0.115)
Indoor flush toilet	-0.021	0.005	0.060	0.034	0.026	-0.048	-0.011	-0.028	0.078
	(0.057)	(0.056)	(0.052)	(0.053)	(0.057)	(0.058)	(0.064)	(0.062)	(0.073)
Clean cooking fuels	0.127**	-0.022	-0.055	0.016	-0.076	-0.051	0.003	-0.081	-0.060
	(0.053)	(0.056)	(0.051)	(0.056)	(0.051)	(0.055)	(0.062)	(0.078)	(0.091)
No excreta around dwellings	0.036	0.050	-0.083	-0.056	-0.088	0.075	-0.009	0.049	-0.087
	(0.054)	(0.055)	(0.061)	(0.070)	(0.067)	(0.081)	(0.077)	(0.088)	(0.077)
Homeownership	0.074	0.128**	-0.113**	0.046	0.060	0.107	0.033	0.010	0.043
	(0.052)	(0.055)	(0.056)	(0.063)	(0.068)	(0.072)	(0.074)	(0.073)	(0.078)
Constant	0.291	0.767**	0.154	-0.658	0.618*	0.665*	-0.107	-0.046	-0.160
	(0.385)	(0.380)	(0.409)	(0.407)	(0.333)	(0.360)	(0.357)	(0.395)	(0.397)
N	2656	2388	2637	2670	2996	2896	3003	2973	2610
Panel C: Central obesity	1991	1993	1997	2000	2004	2006	2009	2011	2015
Tap water		-0.061	-0.127	-0.123	-0.215**	-0.070	0.133	-0.361**	-0.016
		(0.074)	(0.087)	(0.091)	(0.086)	(0.114)	(0.124)	(0.157)	(0.119)
Indoor flush toilet		-0.023	0.013	-0.015	0.008	-0.115*	0.083	-0.029	0.002
		(0.061)	(0.052)	(0.055)	(0.058)	(0.059)	(0.066)	(0.062)	(0.069)
Clean cooking fuels		-0.012	0.031	0.016	-0.005	0.054	-0.070	-0.004	-0.003
		(0.058)	(0.052)	(0.059)	(0.053)	(0.057)	(0.065)	(0.077)	(0.087)
No excreta around dwellings		0.098	-0.089	-0.072	-0.257***	-0.024	-0.091	0.084	-0.101
		(0.060)	(0.063)	(0.073)	(0.070)	(0.084)	(0.080)	(0.092)	(0.075)
Homeownership		0.129**	-0.051	0.115*	-0.053	0.112	0.089	0.009	0.042
		(0.060)	(0.056)	(0.064)	(0.069)	(0.073)	(0.074)	(0.071)	(0.072)
Constant		0.098	0.485	-0.930**	0.892**	0.317	0.160	-0.469	0.248
		(0.448)	(0.415)	(0.409)	(0.348)	(0.381)	(0.367)	(0.394)	(0.394)
N		2278	2640	2651	2989	2902	3000	2997	2541
Panel D: HBP	1991	1993	1997	2000	2004	2006	2009	2011	2015
Tap water	0.086	-0.105	0.012	-0.132*	-0.117	-0.149*	-0.045	0.338**	0.096
	(0.065)	(0.066)	(0.079)	(0.074)	(0.085)	(0.085)	(0.125)	(0.147)	(0.102)
Indoor flush toilet	-0.085*	-0.095*	-0.047	-0.014	0.011	-0.062	-0.134**	0.010	-0.042
	(0.050)	(0.054)	(0.047)	(0.045)	(0.050)	(0.051)	(0.063)	(0.053)	(0.067)
Clean cooking fuels	-0.042	0.057	-0.084*	-0.015	0.013	-0.001	-0.055	0.004	-0.096
	(0.046)	(0.051)	(0.048)	(0.047)	(0.046)	(0.048)	(0.062)	(0.071)	(0.083)

No excreta around dwellings	-0.007	0.082	0.021	-0.024	-0.112*	-0.039	0.052	0.142*	0.100
	(0.048)	(0.051)	(0.054)	(0.060)	(0.064)	(0.070)	(0.076)	(0.080)	(0.073)
Homeownership	-0.001	-0.010	-0.093*	0.051	-0.020	0.111	0.055	0.085	-0.003
	(0.047)	(0.053)	(0.050)	(0.055)	(0.066)	(0.070)	(0.068)	(0.062)	(0.076)
Constant	-0.248	0.127	-1.583***	-0.795**	0.451	0.508*	-0.257	-0.907**	-0.265
	(0.391)	(0.379)	(0.412)	(0.372)	(0.289)	(0.296)	(0.370)	(0.368)	(0.364)
N	2689	2252	2527	2665	2854	2873	2581	2917	2620

Notes: Province levels have been controlled. Robust standard errors are in parentheses., * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 RIF-EI-OLS decomposition estimates of income-related health inequality for urban adults in China: CHNS 1991-2015 (excluding household income)

	Bad SRH	General overweight/obesity	Central obesity	High blood pressure
Mean RIF	0.010	0.140	0.168	0.044
Tap water	-0.041	-0.059**	-0.087**	-0.014
	(0.033)	(0.029)	(0.034)	(0.027)
Indoor flush toilet	0.011	0.032*	-0.029	-0.020
	(0.020)	(0.018)	(0.020)	(0.016)
Clean cooking fuel	0.055***	-0.046**	-0.035*	-0.017
	(0.020)	(0.018)	(0.020)	(0.016)
No excreta around dwellings	0.024	-0.062***	-0.073***	-0.037*
	(0.025)	(0.022)	(0.025)	(0.020)
Homeownership	0.061***	0.076***	0.081***	0.038**
	(0.021)	(0.019)	(0.022)	(0.018)
Female	-0.019	-0.111***	-0.097***	-0.019
	(0.021)	(0.019)	(0.020)	(0.017)
35-59	-0.066***	-0.031	-0.097***	-0.101***
	(0.021)	(0.019)	(0.023)	(0.015)
60+	-0.074**	0.019	-0.051	-0.063**
	(0.032)	(0.028)	(0.031)	(0.025)
Married	0.028	0.006	0.059**	0.050***
	(0.025)	(0.023)	(0.028)	(0.017)
Widowed/separated/divorced	-0.063	0.046	0.060	-0.043
	(0.043)	(0.036)	(0.041)	(0.034)
Education: Medium	0.087***	0.053***	0.116***	0.081***
	(0.020)	(0.018)	(0.019)	(0.016)
Education: High	-0.128***	-0.067**	-0.020	-0.084***
	(0.035)	(0.031)	(0.033)	(0.027)
Employed	-0.033	0.016	-0.031	-0.017
	(0.021)	(0.018)	(0.019)	(0.016)
Smoking	-0.029	0.024	-0.009	-0.006
	(0.022)	(0.020)	(0.021)	(0.019)
Heavy drinking	-0.011	0.016	0.067***	-0.006
	(0.024)	(0.021)	(0.023)	(0.021)
Medical insurance	0.026	-0.033**	-0.025	-0.005
	(0.018)	(0.017)	(0.018)	(0.015)
Household size	0.008	-0.018***	-0.024***	-0.012**
	(0.006)	(0.006)	(0.006)	(0.005)
1993	-0.022	-0.119***		-0.055**
	(0.027)	(0.027)		(0.025)
1997	-0.118***	-0.181***	-0.032	-0.049*
	(0.028)	(0.028)	(0.031)	(0.026)
2000	-0.232***	-0.215***	-0.137***	-0.043*
	(0.030)	(0.028)	(0.031)	(0.025)
2004	-0.155***	-0.217***	-0.157***	-0.015
	(0.032)	(0.030)	(0.032)	(0.027)
2006	-0.213***	-0.237***	-0.212***	-0.057**
	(0.032)	(0.030)	(0.033)	(0.027)
2009		-0.194***	-0.149***	0.016
		(0.031)	(0.033)	(0.029)
2011		-0.187***	-0.117***	-0.056*
		(0.033)	(0.034)	(0.029)
2015	-0.170***	-0.046	0.087**	0.076**
	(0.037)	(0.037)	(0.038)	(0.034)
Constant	0.024	0.406***	0.469***	0.222***
	(0.063)	(0.056)	(0.063)	(0.051)
N	20029	24829	21998	23978

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

Table A6 WDW decomposition estimates of income-related health inequality for urban adults in China: CHNS 1991-2015

Variables	Bad SRH	General overweight/obesity	Central obesity	High blood pressure
Tap water	-0.0002	0.0031***	0.0034***	0.0027***
Indoor flush toilet	-0.0066*	0.0115***	0.0132***	0.0047*
Clean cooking fuel	0.0093***	0.0081***	0.0119***	-0.0030
No excreta around dwellings	-0.0043**	0.0035**	0.0066***	0.0005
Homeownership	-0.0041**	-0.0060***	-0.0036**	-0.0029**
N	20029	24829	21998	23978

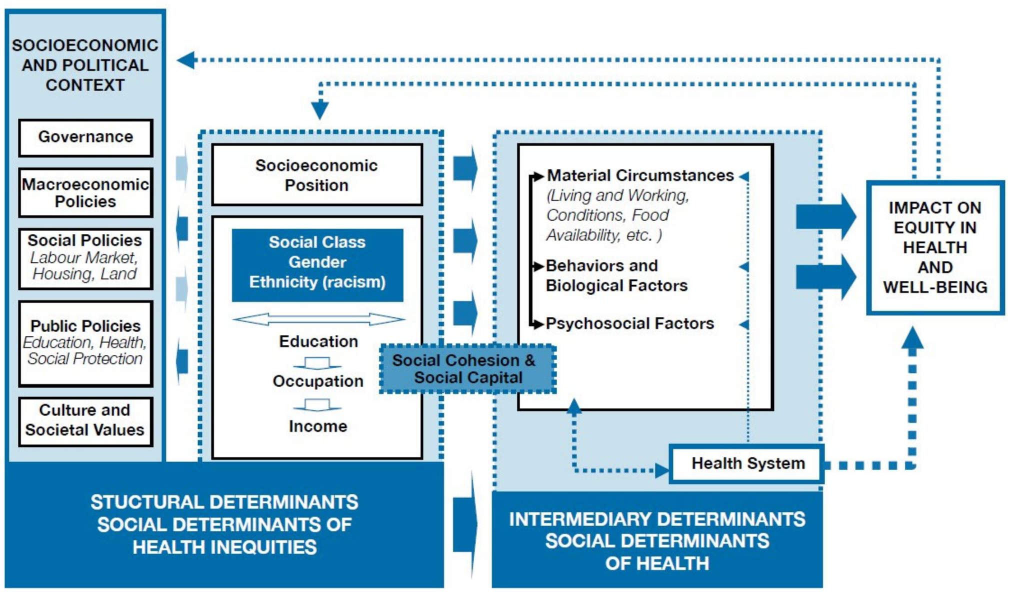

Figure A1. The CSDH's conceptual framework

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