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ABSTRACT

Housing Conditions and Health in Urban China

Using longitudinal data from the China Health and Nutrition Survey, we investigate the causal relation between housing conditions (both internal and external) and health among urban adults aged 18+. We find that housing improvement reduces the probability of bad self-reported health by 3.7 percent, with more pronounced impacts among females, older adults, those with lower socioeconomic status (low education and income) and residents of the less developed central and western regions. This beneficial health effect is enhanced by longer treatment periods and consistent across several robustness checks. Housing conditions seemingly operate on health via poor macronutrient intake, physical inactivity, and sleep deprivation.

JEL Classification: D63, I10, I12, R21

Keywords: housing conditions, health, difference-in-differences, urban China

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1. Introduction

In addition to impacting individual well-being, poor health burdens family and public resources, weakens societies, and squanders potential (United Nations in India, 2019). As one of 17 sustainable development goals (SDGs), ensuring healthy lives and well-being for all (SDG 3) is at the center of the global health policy agenda (WHO, 2021). Consequently, understanding the causes of health deprivation is a particular concern worldwide. Given current climate and demographic changes housing is becoming an increasingly important social determinant of health, as well as a major contributor to achieving SDGs, especially SDGs 3 and 11 (sustainable cities and communities) (WHO, 2018). Not only has the COVID-19 pandemic further exacerbated housing-related health disparities – in particular among those with poor housing conditions (Huang et al., 2021; Rogers & Power, 2020) – but 2050 will see the global doubling of a primarily home bound over-60 population needing housing protection from climate extremes (WHO, 2015, 2018).

Nonetheless, despite a growing body of literature documenting the detrimental effect of poor housing on health, this research focuses almost exclusively on developed Western regions like the US (Daysal et al., 2021; Jacob et al., 2015; Katz et al., 2001; Kling et al., 2007; Ludwig et al., 2013), Europe (Angel & Bittschi, 2019; Marsh et al., 2000; Palacios et al., 2021), and Australia (Baker et al., 2020; Mason et al., 2013; Morris, 2018). Hence, causal evidence for developing countries, where housing poverty is more prevalent (WHO, 2018), remains limited. Most existing studies are also based on small-scale interventions in settings not applicable to developing economies like China, which is experiencing an unprecedented demographic transformation and housing reform.

The purpose of this study, therefore, is to use data from the large-scale longitudinal China Health and Nutrition Survey (CHNS) to provide a comprehensive assessment of the causal relation between housing conditions and health in urban China, a unique context for studying the housing-health nexus. First, in the four decades since its 1978 Reform and Opening-Up Policy, China has experienced unprecedented economic growth, with per capita GDP increasing from 385 yuan in 1978 to 10,475 yuan (deflated to 1978) in 2020 (National Bureau of Statistics, 2021) and the urbanization rate rising from 18% to 64% (National Bureau of Statistics, 2021). At the same time, with the rapid privatization of the housing market, homeownership rates among urban households climbed sharply from 20% in the 1990s to more than 90% today (Huang et al., 2021), which has significantly improved average housing conditions. For instance, the average floor area per capita of urban households almost tripled, increasing from 13m^2 in 1992 to 40 m^2 in 2018 (Huang et al., 2021). Yet this increased marketization has led to soaring house prices and thus growing housing inequality (Huang et al., 2021; Huang et al., 2020), which has reshaped the Chinese urban landscape and affected the health and well-being of urban residents (Cheng et al., 2016; Nie et al., 2022). The rapid economic development, therefore, has not been accompanied by equally substantial improvements in health (Baeten et al., 2013; Jiang & Zhang, 2020).

Deriving a clear understanding of how poor housing conditions affect health in such contexts, however, is methodologically challenging because whereas studies based on small-scale interventions may lack external validity, large datasets that comprehensively measure multidimensional housing conditions are generally unavailable (Palacios et al., 2021). Further complicating the issue, housing improvements often accompany economic growth and social welfare changes (e.g., health care program implementation), whose effects on health outcomes are difficult to disentangle from housing-related impacts. Additionally, the outcomes may also be subject to self-selection bias if those with better health enjoy better socioeconomic conditions, which are in turn related to better housing.

Our study thus contributes to the research on the housing-health relation in several ways: First, by using a generalized difference-in-differences (DID) approach, it provides causal evidence on the effects of housing conditions on health. Second, by focusing on multidimensional housing conditions (both internal and external) as well as subjective and objective health outcomes, it paints a far broader picture of the housing-health nexus. Third, unlike prior studies that mostly investigate housing's transitory or short-run impacts on health, it uses longitudinal CHNS data to assess both short- and long-term effects. Fourth, by using the sociodemographic characteristics of age, income, education, and region to explore the heterogeneous effects of housing improvements on health, it offers useful guidance on policies to ameliorate both poor housing conditions and health. Lastly, by including individual macronutrients and health-affecting behaviors (i.e., physical inactivity, sleep deprivation, smoking, and alcohol intake), it goes beyond a sole focus on housing's impact on health to examine the underlying mechanisms of this effect. In doing so, it provides useful insights into the linkage between (improved) housing conditions and health in developing economies.

The remainder of the paper is organized as follows. Section 2 documents China's urban housing reform and reviews the relevant literature on the housing-health link. Section 3 describes the datasets and empirical strategy, after which Section 4 reports the results. Section 5 concludes the paper with a discussion of the housing-health relation and their policy implications.

2. Institutional background and relevant literature

2.1 China's urban housing reform

Between its founding in 1949 and the 1990s, the People's Republic of China administered a purportedly welfare-oriented housing scheme in which urban residents − employed primarily in the public sector – were allocated low-rent dwelling units based on rank and/or seniority (Chen et al., 2020a; Huang et al., 2021; Li et al., 2020; Wang & Murie, 2000). This housing system, however, produced myriad unintended problems, including heavy fiscal and management burdens on government, poor living environments, corruption, and inequality in housing distribution (Chen et al., 2020a; Wang & Murie, 2000). In particular, because the rents failed to cover the cost of basic maintenance, incentives for housing investment and improvement were minimal (Chen et al., 2020a), resulting in continuously deteriorating living conditions (Chen et al., 2020a; Li et al., 2020).

Yet despite initiating a market economy in 1978, China did not begin progressive housing reform until a decade later, and dramatic changes toward housing marketization and commercialization (Wang & Murie, 2000) did not occur until the welfare housing provision terminated in 1998 (Chen et al., 2020a; Huang et al., 2021). After that, employers were prohibited from building or providing housing for their employees, and urban residents had to purchase either public houses from their work units or commercial houses on the market. Thus, China's housing market transformed from a welfare-oriented public housing system to a market-oriented commercial one (Chen et al., 2020a; Li et al., 2020).

Along with housing privatization reform, urbanites' living conditions improved dramatically (Chen et al., 2020a), with per capita residential floor space increasing from $4m^2$ in 1980s to $22m^2$ in 2000 and $40m^2$ in 2018 (Huang et al., 2021; National Bureau of Statistics, 2018). The 42.5% of urban households that were living in collective dormitories with shared bathrooms and kitchens in 1992 decreased sharply by 1998 to 25% and then to 11% in 2009 (Chen et al., 2020a). Living conditions such as a bathroom with shower, flushing toilets, a heater, and clean cooking fuels also improved significantly from 1992 to 2009 (Chen et al., 2020a). Nonetheless, such rapid housing reform also triggered a problem of housing affordability, especially in urban China (Li et al., 2020), where soaring prices in first-tier cities like Beijing began hampering the purchase of decent housing (Li et al., 2020). Hence, although average living conditions improved alongside housing reform, housing inequalities within and between generations, as well as among different socioeconomic groups, worsened (Huang et al., 2021).

2.2 Literature review

As part of the large body of literature assessing the effects of housing conditions on health in Western countries, Marsh et al. (2000) show that in the UK, multiple housing deprivation − including no access to hot water; overcrowding; and lack of an indoor toilet, bath, garden, or yard − is significantly linked to a higher likelihood of ill health. This finding is echoed by Pevalin et al. (2008), who associate an increase in such housing problems as darkness, lack of adequate heating facilities, condensation, leaky roofs, dampness, and rotting window frames or floors with a higher number of reported health problems. Similarly, Navarro et al. (2010) correlate poor housing conditions like no hot running water and heating, leaky roofs, dampness, and overcrowding with a higher probability of being unhealthy among Spanish residents. This observation is further confirmed by Angel and Bittschi (2019), who document that low-level housing conditions like overcrowding and insufficient heating contribute to an increase in the probability of poor self-reported health (SRH) and chronic diseases in 23 European countries. A recent study for Germany likewise shows that individuals living in poor housing conditions are more likely to report worse mental and physical health, and visit the doctor more often (Palacios et al., 2021). Such evidence of the detrimental health effects of poor housing conditions is further reinforced by several studies for the US (Jacob et al., 2015; Katz et al., 2001; Kling et al., 2007; Ludwig et al., 2013), Australia (Baker et al., 2020; Mason et al., 2013; Morris, 2018), and New Zealand (Howden-Chapman et al., 2012; Keall et al., 2010).

In the context of China, however, evidence for housing and health outcomes is relatively sparse. One exception is the work of Wan and Su (2016), who use 2010 district-level data from Shenzhen to construct a composite housing deprivation index that encompasses internal facilities, living space, physical form and structure, attached facilities, affiliated natural amenities, and affordability. These authors identify a significant role for housing deprivation in the development of cardiopathy, chronic pneumonia, and liver cancer. Similarly, drawing on data from the 2011–2015 China Health and Retirement Longitudinal Study, Nie et al. (2021) show that housing poverty (both in quantity and quality) is related to a decline in healthy aging. Additionally, Wang et al. (2019), in an analysis of 2010 China Family Panel Study data, document a link between better housing conditions and improved physical (BMI and daily activity limitations) and SRH. Other work also highlights the positive effect of better water quality on SRH (Lei & Lin, 2021), and the detrimental impact of lack outdoor neighborhood facilities and noise pollution levels on mental health (Shen et al., 2021).

Several aspects of this prior research, however, are worth emphasizing: First, most studies originate in developed regions, especially Europe and the US, whereas evidence for the housing-health relation in China is very limited. Also scarce is empirical evidence on the potentially detrimental impact on health outcomes of both internal and external housing conditions. Second, not only do existing studies come mostly from the fields of epidemiology, medicine, and environmental health, but most adopt a cross-sectional design, rendering a causal interpretation impossible. Third, the findings from small-scale experiments such as those conducted in individual cities are difficult to generalize. Fourth, little is known about either the long-term impacts of housing conditions on health outcomes or the potential mechanisms through which housing conditions operate on health in China. Finally, although it may seem self-evident that improving housing conditions should lead to better health outcomes, current evidence from intervention studies suggests only small or unclear health improvements (Thomson & Thomas, 2015). Hence, a need remains for further investigation that uses large sample micro data (Thomson & Thomas, 2015) to estimate the dose-response effect of improved housing conditions (Thomson et al., 2009).

The above aspects match exactly to this study's contributions: Not only is it one of the first to analyze the causal relation between housing conditions and health in China, it also exploits the longitudinal nature of the large sample data to shed light on housing's short- and long-term effects on health. It also explores the underlying pathways through which housing conditions impact health.

3. Data and methods

3.1 Data and study population

Our analysis is based on data from seven waves of the CHNS (1991, 1993, 1997, 2000, 2004, 2006, and 2015)[1] that capture a range of social, economic, and health characteristics (Zhao et al., 2018) for residents in nine Chinese provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi and Guizhou). The survey adopts a multistage random cluster sampling method (based on different income levels and weighted sampling) that follows two steps: First, after randomly selecting

[1] We exclude the 1998 wave for covering only ages 20-45 and the 2009 and 2011 waves for unavailability of SRH data.

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. Then, using the community as the primary sampling unit, it selects 20 households from each community. The data thus provide a broad coverage of the Chinese population's social, economic, and health situation over both space and time (Zhang et al., 2014).

We restrict our sample to adult urban residents aged 18 or over for whom detailed demographic, socioeconomic, living condition, and anthropometric information is available, with pregnant women excluded. To make full use of the CHNS panel data, we retain respondents interviewed in at least two survey waves. After dropping observations with missing information on health outcomes, housing conditions, and any of our control variables, we meet DID requirements[2] by restricting the sample to respondents who had experienced no defined treatment of housing condition improvement (i.e., were untreated) when the survey began. The resulting sample contains 11,232 individual observations for SRH, 9,720 for general overweight or obesity, 6,828 for central obesity,[3] and 11,490 for having been injured or sick in the 4 weeks preceding interview.

3.2 Health outcomes

As our main health proxy of health, we select SRH for its broad coverage of not only mental and physical health, but also individual satisfaction with health, the subjective experience of acute and chronic diseases, and overall wellbeing (Xie & Mo, 2014). As important, SRH is very closely associated with other health indicators and is an even stronger predictor of mortality than physician assessed health (Mossey & Shapiro, 1982; Van de Poel et al., 2012). In the CHNS data, the SRH variable has four response categories (poor, fair, good, and excellent), which we convert into a binary bad health dummy (1 = fair/poor; 0 = excellent/good).[4]

[2] We also drop a small number of respondents whose housing conditions went from good (treated) to bad (untreated) in our DID analysis.
[3] Central obesity based on waist circumference is only available from 1993 onward.
[4] The 2015 wave uses five SRH categories: Very bad, bad, fair, good, and very good, which we convert into the binary bad health dummy 1 = fair/bad/very bad; 0 = good/very good.

In our robustness checks, we further include self-reported injury or sickness (i.e., a chronic or acute disease) within the 4 weeks previous to interview (1 = yes, 0 = no)[5] and two objective health measures: BMI-based general overweight or obesity and central obesity, as measured by circumference of waist (CW).[6] Our use of clinical measures of individual weight, height, and CW is an advantage in that they eliminate any reporting biases inherent in self-reported weight and height (Nie et al., 2019a, 2019b; Shields et al., 2011), which tend to underestimate obesity (Burkhauser & Cawley, 2008).

3.3 Measure of housing conditions

To comprehensively examine the effects of housing conditions on health, we address both internal and external housing conditions, measuring the first by a set of binary variables for the presence of tap water, an indoor flushing toilet, clean cooking fuels, and an ordinal variable for the number of household electrical appliances, which are related to a convenient and healthy life (Inoue et al., 2019; Mokyr, 2000).[7] For external housing conditions, we use a community level dummy variable for (no) excreta around the dwellings and two indexes for health infrastructure and traditional markets. The health infrastructure index evaluates the availability, type, proximity, and quality of a private, city, or district hospital and the number of pharmacies in the community (Jones-Smith & Popkin, 2010). The higher the index, the greater the access to health facilities and medicines. The traditional market index is based on the presence and operating hours for nine types of markets (grains, oil, meat, vegetables, fish, bean curd, milk, fabric, and fuel) in or nearby the community (Jones-Smith & Popkin, 2010). The higher the index, the better the condition of the community's traditional market.

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[5] Self-reported injury or sickness is measured by two questions: "During the past 4 weeks, have you been sick or injured?" and "Have you suffered from a chronic or acute disease?" The chronic or acute disease variable covers fever, sore throat, cough, diarrhea, stomach ache, asthma, headache, dizziness, joint pain, muscle pain, rash, dermatitis, eye or ear disease, heart disease or chest pain, and other noncommunicable diseases.

[6] General overweight or 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 & the Cooperative Meta-analysis Group of Working Group on Obesity in China, 2002). We 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). These weight criteria are different from those for Westerners, who have a lower percentage of body fat than Chinese with the same BMI (for example, Choo, 2002).

[7] Electrical appliances comprise washing machines, air conditioners, electric fans, refrigerators, microwave ovens, electric cooking pots, sewing machines, color televisions, and cameras.

We then construct a composite housing conditions index by applying a principle component analysis (PCA) to these variables of internal and external household living conditions from the pooled CHNS across all survey waves (ref, Van de Poel et al., 2012; Wan & Su, 2016).[8] Higher values on this index indicate better housing conditions. To verify index validity, we also calculate its correlation to each individual variable, which confirms its significant relation to all our housing condition indicators (see Table A1, column 1).

As in Van de Poel et al. (2012), we define the treatment as improved housing conditions indicated by a change in rank on the composite index. Specifically, we use the median of the index distribution across the pooled data as the cutoff to define the treatment group, defined here as respondents who experience a shift in the housing condition index from the bottom half to the upper half of the distribution. Conversely, the control group comprises those whose housing condition index value remains in the bottom half of the distribution across all waves. In our DID analysis, we retain only those with housing conditions below the distribution median when first interviewed; that is, those who are untreated on first entering the survey wave (Van de Poel et al., 2012). Every respondent can thus either start below the median and end above it (treatment group) or remain below the median (control group). Using this shift in distributional ranking across all waves allows us to track even gradual changes in housing conditions over time.

In addition to this binary treatment, we also explore heterogeneous health effects for different intensities of housing improvement by redefining the treatment variable on the following 3-point scale: 0 = respondents whose housing condition index stays below the median in all waves, 1 = respondents whose housing condition index moves from the bottom half to the third quartile in any subsequent waves, and 2 = respondents whose housing condition index moves from the bottom half to the upper quartile in any subsequent waves. Finally, to avoid an arbitrary choice of cutoff, we copy previous DID

[8] Because the internal and external housing conditions variables are binary, ordinal, or continuous, we perform a polychoric correlation matrix that is more flexible for different types of variables.

estimations (e.g. Chen et al., 2020b; Juhász, 2018) in using the housing condition index directly as a continuous treatment to detect housing's effect on health.

3.4 Control variables

Our models control for the individual and household health-related characteristics (Apouey & Clark, 2015; Molarius et al., 2007) that are important to satisfying the DID estimation's conditional parallel trend assumption. The individual demographic and socioeconomic variables are gender (1 = male, 0 = female), age group (0 = 18-34, 1 = 35-59, and 2 = 60+), marital status (0 = single, 1 = married, and 2 = divorced/widowed/separated), education (0 = low: illiterate, 1 = medium: primary/middle school, and 2 = high: high school/technical/vocational school/university or higher), and a dummy for working status (1 = yes, 0 = no). The household characteristics are household size and per capita annual household income inflated to 2015 and log-transformed to capture any nonlinearities in the health-income relation (Ettner, 1996)

3.5 Mechanism variables

To explore potential mechanisms through which housing conditions operate on health, we introduce individual macronutrients[9] and health-affecting behaviors.[10] The former are low carbon intake (1 = <130g/day; 0 otherwise) (Feng et al., 2021), high fat intake (1 = ⩾65g/day; 0 otherwise) (Van de Poel et al., 2012), and low protein intake (1 = <56g/day for males, 46g/day for females; 0 otherwise) (Feng et al., 2021). The latter include physical inactivity (1 = zero participation in such activities as martial arts, gymnastics, dancing, acrobatics, track and field/swimming, soccer, basketball, or (table) tennis; 0 otherwise), sleep deprivation (1 = sleeps < 7 hours/day; 0 otherwise) (Irwin et al., 2016), smoking (1 = yes; 0 = no), and alcohol use (1 = yes; 0 = no).

[9] The CHNS assesses individual dietary intake based on 24-hour recall over the same 3 consecutive days, including all food consumed away from and in the home on each of these days (He et al., 2011).

[10] Macronutrient data are unavailable for 2015, physical inactivity information is available from 1997 onward, and sleep deprivation data from 2004 onward.

3.6 Methods

3.6.1 Generalized DID

Linear DID. To estimate the effects of improved housing conditions on health, we employ a quasi-experimental generalized DID approach[11] that leverages the panel variations in housing conditions over time. In our case, this estimation strategy compares the changes in bad SRH for individuals who have experienced housing improvements (treatment group) versus those with no such experience (control group). Specifically, we apply a DID estimation based on the following linear model:

$$y_{it} = \alpha + \beta HCI_{it} + \theta X_{it} + \gamma_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where y_{it} is individual i's bad health outcome at time *t*, HCI_{it} is a binary variable equal to 1 if individual i experiences housing improvement at time *t*, and 0 otherwise. In the linear regression model, β denotes the treatment effects of housing condition improvement on health. To ensure that our DID estimations satisfy the assumption that absent treatment, health outcome trends are parallel for both treatment and control group once a set of confounders is controlled for (Callaway & Sant'Anna, 2021)[12], we also introduce relevant health-related covariates. The first, represented by X_{it}, is individual and household sociodemographic characteristics, to which we add individual fixed effects γ_i to control any preexisting time-invariant individual factors. Given that all CHNS respondents live in the same community during the survey year, γ_i also captures certain time-invariant community-level factors that influence the differences in health outcome between the treatment and control groups. A third covariate, λ_t, captures common trends in health outcome across waves shared by both groups. Lastly, ε_{it} is an error term that we cluster at the individual level to adjust for individual heteroscedasticity and correlation.[13] Because the model includes individual fixed

[11] Unlike the traditional DID inclusion of two groups (control vs. treatment) and two periods (pre- vs. posttreatment), our estimates cover multiple periods and varying treatment timing. We thus use a generalized DID model for panel data, one that includes both individual and time fixed effects.

[12] The parallel trends assumption potentially holds only after conditioning on observed covariates (Callaway & Sant'Anna, 2021).

[13] As a robustness check, we also cluster standard errors at the community level, which yields similar results to clustering at the individual level.

effects, we are unable to provide estimated coefficients for individual time-invariant variables such as gender, which is nonetheless an important determinant of health (Pevalin et al., 2008; Regitz-Zagrosek, 2012). We thus report our results using not only the full sample but also subsamples by gender.

Nonlinear DID. Following Van de Poel et al. (2012), we explore the treatment effects of housing improvements on health using a nonlinear DID logit model:

$$y_{it} = 1(\alpha + \beta HCI_{it} + \theta X_{it} + \gamma_i + \lambda_t + \varepsilon_{it} > 0) \quad (2)$$

where $1(\cdot)$ is an indicator function, variables are defined as in equation (1), and the error term ε_{it} is assumed to be drawn from the logistic distribution.

Based on equation (2), we define the treatment effect of housing improvement on the treatment group (TE) at time of treatment as follows (Puhani, 2012; Wooldridge, 2021b):

$$TE_{i\in T,t\in P} = \Lambda(\alpha + \beta + \theta X_{i\in T,t\in P} + \gamma_{i\in T} + \lambda_{t\in P}) - \Lambda(\alpha + \theta X_{i\in T,t\in P} + \gamma_{i\in T} + \lambda_{t\in P}) \quad (3)$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function, $i \in T$ denotes the individual in the treatment group, and $t \in P$ indicates a particular wave in the post-treatment period. Equation (3) thus estimates the partial effects of HCI evaluated for the individual experiencing improved housing in a post-treatment period. Following Van de Poel et al. (2012) and Wooldridge (2021b), we calculate the average treatment effect on the treated (ATT) by averaging TE over individuals in the treatment group within the treatment period.

3.6.2 Event study

The validity of our DID approach relies on the (conditional) parallel trend assumption of no significant pretreatment differences in health changes between treatment and control groups once we control for confounders. Because in this context the control group can serve as a counterfactual. Although direct testing of this identification assumption is problematic,[14] common preexisting trends in health outcomes is

[14] We cannot test the parallel trends assumption because no counterfactual exists for the treatment group following treatment.

supportable for this identification assumption. Hence, we test pretreatment trends by estimating year-wise changes in the housing condition's effect on health in pre and post treatment, which also facilitates the exploration of long-term treatment effects. Our model for the event study is as follows:

$$y_{it} = \alpha_0 + \sum_{j=-5}^{J} \beta_j L_j + \sum_{k=0}^{K} \beta_k D_k + \theta_0 X_{it} + \mu_i + \eta_t + u_{it} \qquad (4)$$

where X_{it} is controlled individual and household variables; μ_i and η_t are individual and time fixed effects, respectively; u_{it} is an unobserved error term; and L_j and D_k are the lags and leads to the time exposed to treatment. In our sample, $j = -5, -4, -3, -2$ and $k = 0, 1, 2, 3, 4$, respectively, represent the j wave prior to housing improvement treatment in the treatment group and the k wave following such treatment. The omitted (reference) group is the first wave prior to the treatment time; that is, $j = -1$.[15]

4. Main results

4.1 Summary statistics

As the summary statistics show (see Table 1), an average 35.6% of respondents in the full sample reported fair or bad SRH, with the proportion being larger for females than males. This gender difference also manifests in the fractions for general overweight/obesity, central obesity, and sickness or injury in the previous 4 weeks. Regarding housing conditions, 74.8%, 44.7%, 43.0%, and 87.3% of households, respectively, have tap water, an indoor flushing toilet, clean cooking fuels, and no excreta around the dwellings. At the same time, an increasing trend in the composite housing conditions index from 1991 to 2015 (see Figure 1) indicates substantial housing improvements for Chinese urban residents over this period.

[15] Given the relatively small sample size, we combine $j = -5$ and $j = -6$ as $j = -5$, $k = 4$ and $k = 5$ as $k = 4$ to increase estimation power.

Table 1 Summary statistics

	Full sample			Female	Male	Mean differences
	Mean	SD	Obs.	Mean	Mean	
Health measures						
Bad self-reported health (1 = yes, 0 = no)	0.356	0.479	11232	0.385	0.325	0.060***
BMI (kg/m^2)	23.109	3.377	9720	23.149	23.064	0.085
General overweight/obesity (1 = yes, 0 = no)	0.366	0.482	9720	0.371	0.361	0.010
Waist circumference (cm)	81.689	10.630	6826	80.014	83.578	-3.564***
Central obesity (1 = yes, 0 = no)	0.469	0.499	6826	0.495	0.439	0.056***
Sickness or injury in the previous 4 weeks (1 = yes, 0 = no)	0.127	0.333	11490	0.140	0.114	0.026***
Housing poverty measures						
Indoor tap water (1 = yes, 0 = no)	0.748	0.434	11232	0.744	0.753	-0.009
Indoor flushing toilet (1 = yes, 0 = no)	0.447	0.497	11232	0.443	0.451	-0.008
Clean cooking fuels (1 = yes, 0 = no)	0.430	0.495	11232	0.430	0.430	-0.001
No excreta around dwellings (1 = yes, 0 = no)	0.873	0.333	11232	0.871	0.875	-0.004
Number of electrical appliances (0-9)	4.104	1.950	11232	4.088	4.122	-0.034
Community health infrastructure index (0-10)	6.548	1.767	11232	6.537	6.560	-0.023
Traditional market index (0-10)	6.799	2.794	11232	6.779	6.819	-0.040
Composite housing condition index	-0.274	0.629	11232	-0.282	-0.266	-0.016
Demographics and socioeconomics						
Gender (1 = male; 0 = female)	0.480	0.500	11232			
Age (in years)	48.295	16.867	11232	49.222	47.292	1.930***
18-34	0.243	0.429	11232	0.226	0.261	-0.036***
35-59	0.468	0.499	11232	0.469	0.466	0.003
60+	0.289	0.454	11232	0.305	0.272	0.033***
Marital status:						
Single	0.106	0.308	11232	0.085	0.129	-0.044***
Married	0.791	0.406	11232	0.758	0.828	-0.070***
Divorced/widowed/separated	0.103	0.303	11232	0.157	0.043	0.114***
Education level:						
Low	0.254	0.435	11232	0.342	0.159	0.182***
Medium	0.459	0.498	11232	0.429	0.491	-0.062***
High	0.287	0.452	11232	0.230	0.350	-0.120***
Working status (1 = yes, 0 = no)	0.536	0.499	11232	0.453	0.625	-0.172***
Logged per capita household income	8.461	0.999	11232	8.438	8.485	-0.047**
Household size	3.790	1.560	11232	3.751	3.832	-0.080***
Health behaviors and nutrition						
Smoking (1= yes, 0 = no)	0.312	0.463	10531	0.045	0.606	-0.561***
Alcohol use (1= yes, 0 = no)	0.338	0.473	10397	0.106	0.596	-0.490***
Sports-related physical inactivity (1= yes, 0 = no)	0.844	0.363	5950	0.879	0.805	0.074***
Low carbon intake (1 = yes, 0 = no)	0.017	0.129	9704	0.021	0.012	0.010***
High fat intake (1 = yes, 0 = no)	0.520	0.500	9704	0.475	0.570	-0.095***
Low protein intake (1= yes, 0 = no)	0.188	0.391	9704	0.173	0.204	-0.031***
Sleep time (hours/day)	0.097	0.296	2959	0.103	0.092	0.012

Notes: For 2015, SRH is defined as 1 = very good/good; 0 = fair/bad/very bad, general overweight/obesity as BMI⩾24kg/m^2, and central obesity as waist circumference⩾80 for females and ⩾85 for males (Zhou & the Cooperative Meta-analysis Group of Working Group on Obesity in China, 2002). The health infrastructure index evaluates the availability, type, proximity, and quality of a private, city, or district hospital and the number of pharmacies in the community. The traditional markets index indicates the presence and operating hours for nine types of markets (grains, oil, meat, vegetables, fish, bean curd, milk, fabric, and fuel) in or near the community. The higher these housing-related indices, the better and more convenient the housing. Education level is ranked as low (illiterate), medium (primary/middle school), or high (high school/technical/vocational school/university or higher). The per capita household income is inflated to 2015 and then translated to log form. Sports-related physical participation encompasses martial arts, gymnastics, dancing, acrobatics, running, swimming, soccer, basketball, (table) tennis, badminton, and volleyball.

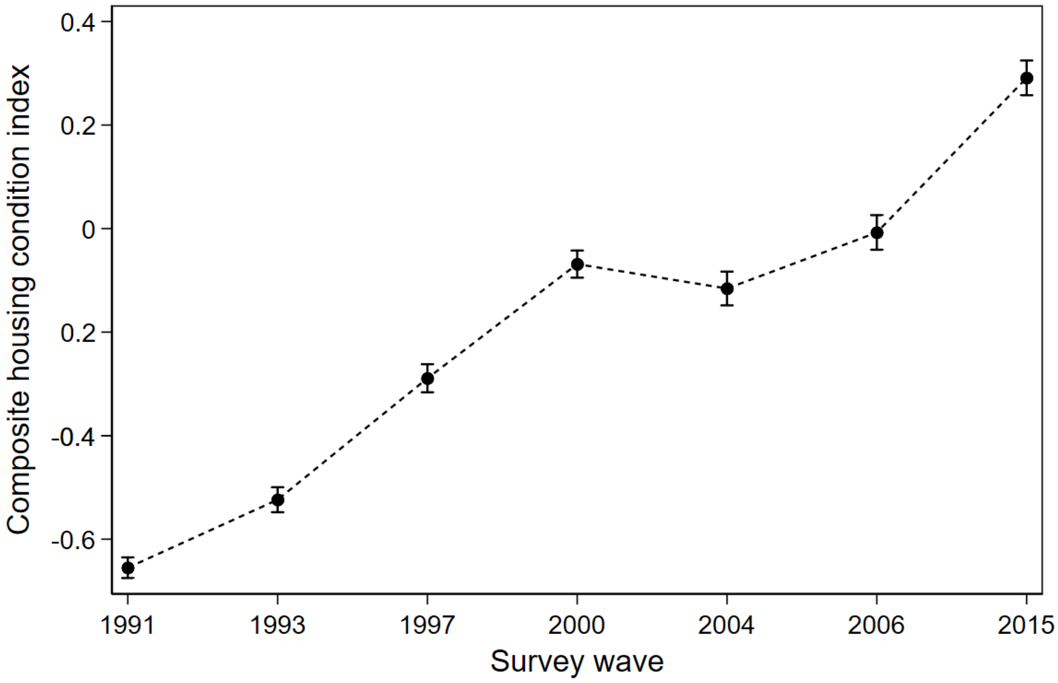

Figure 1 Composite housing condition index by wave (CHNS, 1991-2015)

When we list the mean individual and household health determinants by wave for both the treatment and control group (see Table A2), however, clear intergroup differences emerge: Treated individuals not only have a higher likelihood of being married, highly educated, and employed, but also a higher household income. We could thus eliminate such discrepancies, which may violate the parallel trend assumption, in the DID estimates by including controls for these covariates. Additionally, treated individuals also consistently enjoy significantly better housing conditions on both the individual and composite measures, suggesting that the housing conditions and housing improvement treatment included in our DID estimations clearly distinguish between the two groups. Overall, the substantial improvement on the composite housing condition index from -0.66 in 1991 to 0.29 in 2015 shifted 6,560 of the 11,232 (58%) individuals in our sample to the upper half of the index distribution.

4.2 The effect of housing improvement on bad SRH

This increase on the composite housing condition index from below to above the distribution median mirrors the average treatment effects of improved housing conditions on the SRH of the treated. Whereas the specifications in the odd columns in Table 2 control only for individual and year fixed effects, those in the even columns also add in time-variant individual and household controls. Panels A and B show the DID results for the linear probability and logit models, respectively. Based on the significantly negative coefficients in Panel A, column 2, improving housing conditions decreases the probability of bad SRH by 3.7 percentage points, or 10% of the average rate (0.037/0.356 = 10%). However, such significant negative impacts occur mainly among females, which is consistent with prior evidence showing that poor housing conditions predominantly affect women (Pevalin et al., 2008; Vásquez-Vera et al., 2022). One possible explanation is that females, being more likely than males to engage in such household chores as laundry, cooking, and shopping (Cerrato & Cifre, 2018), benefit more from such improvements as clean cooking fuels and indoor tap water. Another possibility is that females in damp and overcrowding housing are more likely than males to experience emotional strain thereby poor mental health (Howden-Chapman, 2004).

The nonlinear DID results are similar to those in the Panel A linear estimations, confirming that our main results are robust to different specifications.[16] Moreover, when we employ these same time-variant individual and household controls in our tests for housing improvement's effects on health, the results are quite similar to those without such controls, suggesting that these characteristics exert a negligible influence on the treatment effects.[17]

Table 2 Average treatment effects on the treated (ATT) of improved housing conditions on bad SRH

	Full sample		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear probability DID model						
ATT of improved housing conditions	-0.040***	-0.037**	-0.063***	-0.062***	-0.015	-0.011

[16] The sample size for the nonlinear DID logit estimations is smaller because the fixed effects logit model only uses observations with variations in the dependent variable during the survey periods.
[17] When we cluster standard errors at the community level, the results remain similar to those in Table 2. Moreover, we control for community time-variant unobserved factors by re-estimating equation (1) with the interaction of community ID and wave dummies included, and the magnitude of the treatment effects is not only significant but quantitatively larger than in Table 2.

	(0.015)	(0.015)	(0.020)	(0.020)	(0.022)	(0.022)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Adjusted R^2	0.229	0.229	0.234	0.236	0.217	0.218
N	11232	11232	5837	5837	5395	5395
Panel B: Nonlinear logit DID model [a]						
ATT of improved housing conditions	-0.034**	-0.037*	-0.059**	-0.052**	-0.007	-0.007
	(0.017)	(0.019)	(0.024)	(0.025)	(0.024)	(0.030)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Pseudo R^2	0.073	0.074	0.073	0.078	0.075	0.079
N	6853	6853	3642	3642	3211	3211

Notes: The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (0 = no, 1 = yes), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] ATT calculated from fixed effects logit model is the partial effects of improved housing conditions for individuals who experience such improvement in the post-treatment period.

4.3 Dynamic effects of improved housing conditions on bad SRH

The estimated coefficients from the event study (see Figure 2) capture the effects of the housing improvement treatment relative to the prepreatment values for the first wave pior to the treatment. Two key findings are worth emphasizing: First, in support of the conditional parallel trends assumption, before the treatment of improved housing there are no significantly negatively differences between the treatement and control groups, confirming that the treated and control groups follow similar time trends over waves prior to treatment. Second, the results indicate dynamic treatment effects of the housing condition improvements; in particular, a gradually increasing magnitude of the already statistically significant negative post-treatment coefficients, especially following initial treatment in the third and fourth waves. According to this latter, the longer individuals experience improved housing conditions, the less likely they are to report bad health, indicating that housing conditions cause not only transient but also long-term effects on SRH.

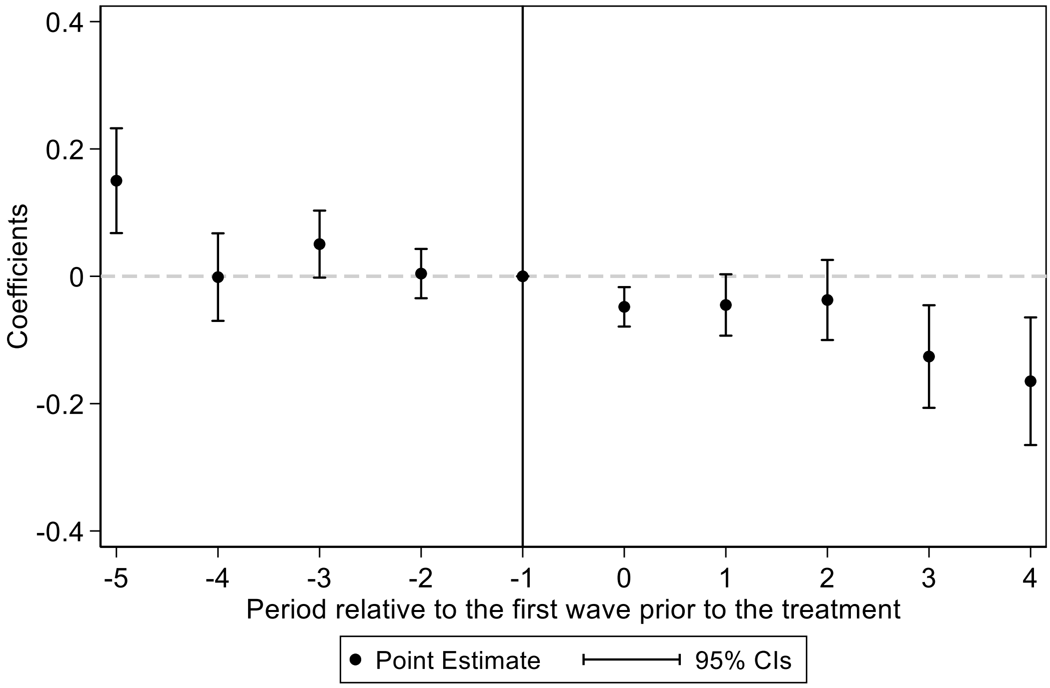

Figure 2 The dynamic effects of improved housing conditions on bad SRH

4.4 Robustness checks

Our robustness checks address four important empirical aspects, the first is results verification via intensity- and continuity-based redefinitions of the housing improvement treatment. The second is the treatment effect on a set of alternative health measures, including general overweight/obesity, central obesity, and injury/sickness in the prior 4 weeks, and the third assesses the validity of the DID specification by using a variety of strategies. The last is potential identification problems, such as the homogenous treatment assumption in the traditional TWFE, addressed using de Chaisemartin and D'Haultfœuille (2020) heterogeneous two-way fixed effects (TWFE) model.

4.4.1 Effects of different intensities of housing improvement

To explore whether health effects vary with the intensity of housing improvements, we redefine our housing improvement treatment on a 3-point scale that partitions smaller and larger movements up the housing improvement index distribution: 0 = housing condition index stays below the median in all waves, 1 = index moves from bottom half to third quartile in any subsequent waves, and 2 = index moves from bottom half to upper quartile in any subsequent waves. As Table 3 shows, the treatment effects of moving from the bottom half to the third quartile are consistently smaller than those of moving from the bottom half to the top quartile regardless of whether we use the full sample or the female subgroup. In the full sample, a higher intensity of housing improvements decreases the probability of bad SRH by about 5 percentage points, equivalent to 14% of the average bad SRH rate in the full sample. As in our main results, such effects are larger for females but insignificant for males.[18]

Table 3 Average treatment effect on bad SRH: Varying intensity of housing improvement

	Full sample		Female		Male	
Bottom half to third quartile of HI	-0.036**	-0.033**	-0.057***	-0.057***	-0.013	-0.009
	(0.016)	(0.016)	(0.022)	(0.022)	(0.023)	(0.023)
Bottom half to top quartile of HI	-0.050**	-0.045**	-0.077***	-0.074***	-0.020	-0.014
	(0.020)	(0.020)	(0.027)	(0.027)	(0.028)	(0.028)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Adjusted R^2	0.229	0.229	0.234	0.235	0.217	0.218
N	11232	11232	5837	5837	5395	5395

Notes: HI = housing index. The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (1 = yes, 0 = no), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.2 Effects of continuous housing improvement treatment

To avoid an arbitrarily selected cutoff in defining the housing improvement treatment, we use the composite index of housing conditions as a continuous treatment. As Table 4 shows, a one-standard deviation (SD) increase in the housing improvement index significantly reduces the probability of bad SRH by 3.1 and 5.3 percentage points for the full and female samples, respectively.

[18] The results from the nonlinear logit DID model are similar to those from the linear probability model (see Table 3).

Table 4 Average treatment effect on bad SRH: Continuous housing improvement treatment

	Full sample		Female		Male	
Continuous housing improvement	-0.033***	-0.031***	-0.054***	-0.053***	-0.010	-0.008
	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.013)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Adjusted R^2	0.230	0.230	0.236	0.237	0.217	0.218
N	11232	11232	5837	5837	5395	5395

Notes: The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (0 = no, 1 = yes), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.3 Alternative health measures

In addition to bad SRH, we also assess the housing improvement treatment effects, as measured by movement from the bottom half to the upper half of the composite index distribution, on general overweight/obesity, central obesity, and being injured/sick in the previous 4 weeks (see Table 5). The treatment effects on all three health measures are negative, albeit only significant for central obesity in the full and female samples (Panel B), with a 3.1% probability reduction equivalent to 6.6% of the average central obesity rate. As in the baseline results (see Table 2), the treatment effects are stronger for females than for males.

Table 5 Average treatment effect of improved housing conditions on alternative health outcomes

	Full sample		Female		Male	
Panel A: General overweight/obesity						
ATT of housing improvement	-0.003	-0.009	-0.004	-0.009	-0.005	-0.010
	(0.012)	(0.012)	(0.016)	(0.016)	(0.018)	(0.018)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Adjusted R^2	0.580	0.585	0.590	0.593	0.571	0.578
N	9720	9720	5160	5160	4560	4560
Panel B: Central obesity						
ATT of housing improvement	-0.026	-0.031*	-0.048**	-0.053**	-0.002	-0.004
	(0.016)	(0.016)	(0.021)	(0.021)	(0.024)	(0.024)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y

Adjusted R^2	0.461	0.465	0.470	0.473	0.446	0.450
N	6826	6826	3619	3619	3207	3207
Panel C: Injured/sick (suffering a chronic or acute disease) within the previous 4 weeks						
ATT of housing improvement	-0.010	-0.008	-0.012	-0.010	-0.007	-0.006
	(0.010)	(0.010)	(0.015)	(0.015)	(0.014)	(0.014)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Adjusted R^2	0.153	0.155	0.144	0.147	0.161	0.161
N	11490	11490	5953	5953	5537	5537

Notes: ATT = average treatment effects on the treated. The dependent variables are general overweight/obesity (1 = yes, 0 = no), being injured/sick or suffering from a chronic or acute disease in the previous 4 weeks (1 = yes, 0 = no) and central obesity (1 = yes, 0 = no), defined as waist circumference ⩾80 for females and ⩾85 for males. The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (0 = no, 1 = yes), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.4 DID based on a matched sample

Although the DID method does not require random assignment of treatment and control groups, the common trend assumption is essential. Given the intergroup differences in sociodemographic characteristics (i.e., age, education, and income) (see Table A2), one possible concern is that the groups may exhibit different health patterns prior to treatment. If so, it would violate the core assumption of parallel counterfactual trends. To address this concern, we match individuals in the treatment group to a subset of individuals in the control group to ensure that sociodemographic characteristics in the first are similar to those in the second, thereby and further validating the parallel trend assumption. As shown in Table 6, our DID estimates employ two different pairing methods: radius matching and Mahalanobis distance matching.[19] After matching, the control variables between the two groups are close to being balanced (see Figures A1 and A2). In the radius matched sample, the improved housing effects on bad SRH are significantly negative (see Panel A), with a 3.0 percentage point probability reduction for the full sample (8.4% of the average: 0.030/0/356) and a 6.2 percentage point

[19] To avoid weakening external validity by losing too many observations, instead of one-to-one matching, we use two techniques that allow the pairing of one control individual with several treated individuals and then apply matching weights to the regressions.

reduction for females (16.1% of the average: 0.062/0.385). The Mahalanobis distance matching yields similar results (see Panel B).

Table 6 Average treatment effect of improved housing on bad SRH: Matched sample

	Full sample		Female		Male	
Panel A: Radius matching [a]						
ATT of housing improvement	-0.032**	-0.030*	-0.061***	-0.062***	-0.003	0.002
	(0.016)	(0.016)	(0.022)	(0.022)	(0.024)	(0.023)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Adjusted R^2	0.257	0.258	0.259	0.262	0.253	0.254
N	11185	11185	5809	5809	5376	5376
Panel B: Mahalanobis distance matching [b]						
ATT of housing improvement	-0.044**	-0.042**	-0.094***	-0.095***	0.005	0.009
	(0.021)	(0.021)	(0.030)	(0.030)	(0.030)	(0.029)
Individual and year FE	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	N	Y	N	Y	N	Y
Pseudo R^2	0.310	0.312	0.321	0.321	0.298	0.306
N	6225	6225	3148	3148	3077	3077

Notes: ATT = average treatment effects on the treated. Panels A and B show the results for the linear probability DID model. The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (1 = yes, 0 = no), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[a] For the radius matching, we use logit model to perform the propensity score matching, with a 1% caliper.

[b] In the Mahalanobis distance analysis, we calculate distances based on the six covariates of age, marital status, education level, labor status, per capita household income, and household size and then match each treatment group to its five nearest control group neighbors.

4.4.5 Attrition bias

Because they are unbalanced, our CHNS panel data are subject to attrition bias[20] from individuals with poor SRH being more likely to drop out of the sample. To test for such bias, we employ a variable addition test (Jones et al., 2006; Verbeek & Nijman, 1992) with the total number of survey waves in which each respondent is represented as the added variable. In our case this latter is insignificant at *p-value* = 0.448 (see Table A3),

[20] In our final sample, 39.31% of the respondents are interviewed twice, 23.08% three times, 16.08% four times, 10.04% five times, 8.37% six times, and only 3.16% represented in all waves.

indicating the absence of attrition bias.

4.4.6 Placebo test using randomly generated housing improvement

If housing improvements are endogenously determined by unobserved characteristics (omitted variables) associated with health, the resulting estimates may be biased. To check for this possibility, we perform a placebo test that randomly assigns housing improvement to individual respondents. If no severe endogeneity exists, the absolute value of β should be much smaller than the estimates for the actual housing improvement treatment. To increase this test's identification power, we reiterate this randomization 500 times and graph both the false coefficient and true benchmark estimate distributions in Figure 3. If our baseline results are caused by housing improvements rather than omitted variables, the false treatment effect coefficient should be close to zero and the baseline results outside the distribution. As Figure 3 illustrates, such is indeed the case, implying that the benchmark results are unlikely to be biased by omitted variables.

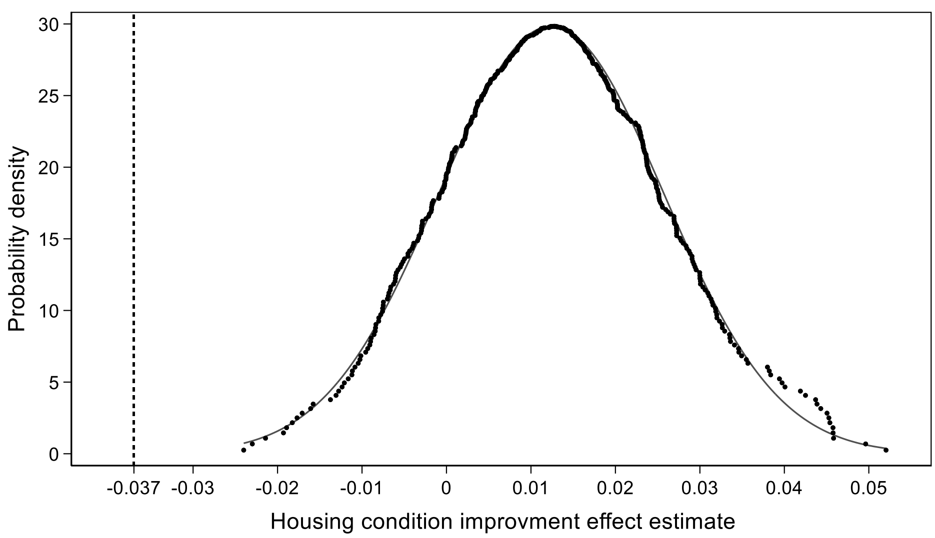

Figure 3 Distribution of estimated coefficients of falsification test. The figure displays the density of estimated coefficients from 500 simulations of randomly assigning the improved housing treatment. The vertical dashed line represents the true estimated causal effects from Table 2.

4.4.7 Alternative estimation method: Heterogenous TWFE

Although the TWFE specification in equation (1) is an effective DID indicator widely used in empirical work (Lin et al., 2021; Wooldridge, 2021a), several scholars argue it can lead to biased estimates when treatment timing varies across observations and treatment effects are heterogeneous across treatment intensity, calendar time, and covariates (de Chaisemartin & D'Haultfœuille, 2020; Wooldridge, 2021a). Hence, to reduce this estimation bias from a homogeneous treatment assumption, we adopt a heterogeneous TWFE model that uses a weighted average of DID estimators to compare the outcome evolution of two groups: Those whose treatment changes from 0 to 1 between t-1 and t, and those whose treatment is equal to 0 on both dates (de Chaisemartin & D'Haultfœuille, 2020). This model is unbiased even when the treatment effect is heterogeneous across groups or over time as long as the treatment is binary and the design staggered (de Chaisemartin & D'Haultfœuille, 2020). In line with our main results (see Table 2), these heterogeneous TWFE estimates show significantly negative effects of the housing improvement treatment on bad SRH, which are more pronounced for females than males (see Table 7). An additional three placebo tests further confirm the validity of the parallel trends assumption prior to the treatment.

Table 7 Heterogeneous two-way fixed effects estimates of housing improvement's effects on bad SRH

	Full sample	Female	Male
ATT of housing improvement	-0.063***	-0.106***	-0.012
	(0.020)	(0.029)	(0.034)
Placebo test (t = -1) [a]	0.028	0.066	-0.015
	(0.024)	(0.035)	(0.031)
Placebo test (t = -2)	-0.063	-0.089	-0.040
	(0.045)	(0.058)	(0.067)
Placebo test (t = -3)	0.200	0.142	0.306
	(0.080)	(0.100)	(0.127)
Individual and year FE	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y

Notes: ATT = average treatment effects on the treated. The time-variant individual controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (1 = yes, 0 = no), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[a] Placebo tests t = −1, −2, and −3, respectively, refer to the weighted average of DID estimators comparing the t −2 to t −1, t –3 to t –2, and t −4 to t −3 outcome evolution between the treatment and control groups.

4.5 Heterogeneity analysis

To provide more pragmatic guidance for housing and health policy, we perform heterogeneity analyses that more directly measure treatment effect differences across our subgroups. To do so, we modify our specifications to include the interaction between the housing improvement treatment and four important sociodemographics; namely, age, income, education, and region.

By age group. Here we divide our samples by age (0 = 18-34, 1 = 35-59, 2 = 60+). As in the baseline results, the treatment still has a significantly negative effect on bad SRH for full and female samples (see Table 8, Panel A). Nonetheless, a joint test of linear combination shows this significant treatment effect to be larger for individuals aged 60+ than for those aged 18-34, implying that seniors benefit more from improved housing conditions than the young. Two possible explanations are that age-related health deterioration makes seniors more susceptible to the detrimental effects of poor housing and that being out of the workforce increases their time at home (Jones-Smith & Popkin, 2010) and thus their exposure to poor conditions (Palacios et al., 2021).

By income level. The treatment effect is also much stronger for low-income than high-income individuals (see Table 8, Panel B), which we attribute to the affluent being better able to cope with adverse health shocks (Hallegatte et al., 2020; Marmot, 2002). For example, the rich may be able to afford the costs associated with the health issues linked to poor housing conditions.

By education level. As regards treatment effect heterogeneity by educational level (see Table 8, Panel C), the joint test of linear combination shows that these effects are more pronounced among the lower than the higher educated. Possible explanations are that the latter generally have a healthier lifestyle and better health-related knowledge, making them more health conscious and more likely to take preventive action (Cutler & Lleras-Muney, 2010).

By region. The need to analyze treatment effect heterogeneity by region stems from the notable geographic differences in China's economic development and health resources.

According to our joint test of linear combination, relative to citizens in eastern China, those residing in the center and west benefit more from housing improvements (Table 8, Panel D), probably because the east is more economically developed (Meng et al., 2012). In particular, the east has better health care resources and services, including higher density and better quality of primary health care (Meng et al., 2012; Tao et al., 2020; Zhang et al., 2018). The east's financial revenue is thus also likely to be higher, increasing its public infrastructure investments in living environment (e.g., transportation, green space, outdoor facilities) (Fan et al., 2011). The marginal effects associated with improved housing conditions are thus larger in central and western China than in the east, a finding that underscores the important role of economic development in housing poverty alleviation policies aimed at also promoting health. The heterogeneity analysis overall thus confirms that improved housing conditions especially benefit those who are older, have lower socioeconomic status (low education and income), and reside in less developed regions.

Table 8 Heterogeneity of the effects of improved housing conditions on bad SRH

	Full sample (1)	Female (2)	Male (3)
Panel A: By age group			
Improved housing conditions (IHC)	-0.051**	-0.061*	-0.039
	(0.024)	(0.033)	(0.035)
IHC × aged 35-59	0.039	0.025	0.054
	(0.028)	(0.038)	(0.041)
IHC × aged 60+	-0.020	-0.040	0.002
	(0.034)	(0.046)	(0.052)
Linear combination [a]			
ATT of IHC for aged 35-59	-0.012	-0.036	0.015
ATT of IHC for aged 60+	-0.071***	-0.101**	-0.037
Individual and year FE	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y
Adjusted R^2	0.230	0.236	0.218
N	11232	5837	5395
Panel B: By income level			
IHC	-0.031*	-0.051**	-0.010
	(0.017)	(0.023)	(0.024)
IHC × low income	-0.023	-0.035	-0.007
	(0.025)	(0.034)	(0.036)
Linear combination			

ATT of IHC for low income	-0.054**	-0.086***	-0.017
Individual and year FE	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y
Adjusted R^2	0.229	0.236	0.217
N	11232	5837	5395
Panel C: By education level			
IHC	-0.027	-0.032	-0.020
	(0.020)	(0.030)	(0.026)
IHC × medium education	0.003	-0.011	0.017
	(0.025)	(0.037)	(0.034)
IHC × low education	-0.057	-0.093**	0.018
	(0.036)	(0.046)	(0.060)
Linear combination			
ATT of IHC for medium education	-0.024	-0.043	-0.003
ATT of IHC for low education level	-0.084***	-0.125***	-0.002
Individual and year FE	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y
Adjusted R^2	0.230	0.236	0.218
N	11232	5837	5395
Panel D: By region [b]			
IHC in eastern region	-0.035	-0.049	-0.021
	(0.028)	(0.039)	(0.039)
IHC in central region	-0.045*	-0.083***	-0.003
	(0.023)	(0.031)	(0.034)
IHC in western region	-0.045*	-0.070*	-0.023
	(0.027)	(0.038)	(0.040)
Individual and year FE	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y
N (East region)	3089	1612	1477
N (Central region)	4879	2540	2339
N (Western region)	3264	1685	1579

Notes: ATT = average treatment effects on the treated. The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group, not included in Panel A), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (0 = no, 1 = yes), logged per capita household income, and household size. We define the different income levels based on the median of logged per capita household income. Standard errors clustered at the individual level are in parentheses. Eastern region = Jiangsu, Shandong, and Liaoning provinces; central region = Henan, Hubei, Hunan, and Heilongjiang provinces; western region = Guangxi and Guizhou provinces. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] The joint test of linear combination (i.e., the sum of the IHC coefficients and each interaction) uses a Wald test.

[b] The regressions in Panel D are estimated separately for the east, central, and west subgroups because the time invariant nature of the province of residence variable prevents inclusion of the treatment effect-regional dummy interaction in the individual fixed effects estimates of heterogeneity effect.

4.6 Potential mechanisms

To explore the underlying pathways through which housing conditions operate on health, we test their relation to five potential mechanisms: macronutrient intake, physical activity (PA), sleep deprivation, and the risk-taking behaviors of smoking and alcohol use. As regards the first, we assume that housing improvements imply better markets access to the nutrient rich foods whose balanced intake is vital to individual good health (Solon-Biet et al., 2015). Because our composite housing condition index captures such access (specifically, to grains, oil, meat, vegetables, fish, bean curd, and milk), we test whether improved housing influences intake of the three macronutrients: carbon, fat, and protein. According to the results, better housing conditions do appear to reduce the likelihood of an imbalanced intake – in particular, low protein and (statistically insignificantly) low carbon – especially among females (see Table 9, Panel A).

As regards whether a livable housing environment (e.g., neighborhood green spaces, outdoor facilities) encourages PA (e.g. Humpel et al., 2002; Jongeneel-Grimen et al., 2014), another important predictor of individual good health, our analysis confirms the negative association between improved housing and physical inactivity (see Table 9, Panel B). Likewise, housing improvement decreases the probability of sleep deprivation[21] (defined as sleep time less than 7 hours/day) (Irwin et al., 2016), albeit with insignificant coefficients (see Panel C). This finding thus provides support for previous findings of an association between disadvantaged neighborhood environments and poor household conditions (e.g., uncomfortable temperatures) and insufficient sleep and sleep disorders (e.g. Johnson et al., 2018). Unsurprisingly, we find no effect of housing improvements on the risk-taking behaviors of smoking and alcohol use.

[21] Both quality and quantity of sleep are important for good health.

Table 9 Average treatment effect of improved housing conditions on health-related factors

Panel A: Macronutrients	Low carbon			High fat intake			Low protein intake		
	Full sample	Female	Male	Full sample	Female	Male	Full sample	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT of housing improvement	-0.005	-0.007	-0.002	-0.0001	0.029	-0.034	-0.035**	-0.047**	-0.024
	(0.007)	(0.011)	(0.008)	(0.022)	(0.032)	(0.032)	(0.016)	(0.022)	(0.024)
Individual and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.103	0.095	0.118	0.241	0.221	0.212	0.237	0.219	0.214
N	9675	5082	4593	9675	5082	4593	9675	5082	4593
Panel B: Physical inactivity	Self-reported physical inactivity								
	Full sample	Female	Male						
ATT of housing improvement	-0.060***	-0.051**	-0.073**						
	(0.021)	(0.026)	(0.034)						
Individual and year FE	Y	Y	Y						
Time-variant individual and household controls	Y	Y	Y						
Adjusted R^2	0.221	0.184	0.201						
N	5910	3071	2839						
Panel C: Health behaviors	Sleep deprivation [a]			Smoking			Alcohol use		
	Full sample	Female	Male	Full sample	Female	Male	Full sample	Female	Male
ATT of housing improvement	-0.017	-0.047	0.020	0.019	0.004	0.031	0.011	0.005	0.018
	(0.027)	(0.036)	(0.041)	(0.012)	(0.009)	(0.023)	(0.015)	(0.016)	(0.027)
Individual and year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.149	0.106	0.104	0.677	0.519	0.486	0.535	0.337	0.374
N	2930	1576	1354	10496	5514	4982	10363	5465	4898

Notes: ATT = average treatment effects on the treated. The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (0 = no, 1 = yes), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] Data on sleep time is only available in the 2004, 2006, and 2015. Sleep deprivation is defined as sleep time less than 7 hours/day (Irwin et al., 2016).

5. Conclusions

This study makes three important contributions to the research on housing's role in health outcomes: It extends the focus on housing's transitory impacts to its longitudinal influences, assesses the causal relation between living environment and health, and explores the mechanisms underlying this dynamic. In particular, by using large-scale longitudinal CHNS data from 1991 to 2015 and a generalized DID approach, it provides a thorough assessment of the effects that both internal and external housing conditions cause to health in urban China, a country unique in its unprecedented economic growth and distinct housing market development (Chen et al., 2020a; Huang et al., 2021; Nie et al., 2022).

The first of the study's major findings is that a consistent increase in the composite housing index over the 1991–2015 period studied indicates that housing conditions for Chinese urban residents have improved substantially under housing privatization. An increase of composite housing condition index from the bottom half to the upper half of the distribution induces a 3.7 percentage point reduction in the probability of reporting bad health, a 10% reduction of the full sample average. Not only do these effects appear consistently throughout a battery of robustness checks, but, according to our event study, they are cumulative, implying that the longer individuals are exposed to improved housing conditions, the less likely they are to report bad health. We thus provide evidence that housing conditions have not only transient but also long-term effects on health.

Our analysis of treatment effect also identifies two major channels through which improved housing appears to operate on health: macronutrient intake and the health-affecting behaviors of physical (in)activity and sleep (deprivation). That is, when better housing conditions include greater access to healthy foods and outdoor activities, they reduce the tendency to bad health by promoting a more balanced diet and healthier lifestyles. This analysis also indicates that housing improvements are of most benefits to older residents, those of lower socioeconomic status (based on income and education level), and those living in the less developed central and western regions.

These findings have several important policy implications; in particular, the need for housing intervention programs to address both internal and external aspects of the living environment, including clean cooking fuels and water, indoor flushing toilets, and convenient access to well-supplied food markets, as well as health and recreational facilities. These latter are tied to the important role in health of macronutrient (im)balance and physical (in)activity and speak to the need to solve the urban food desert problem by facilitating healthy nutrition while also encouraging sports and exercise. Such provision, it should be noted, would address two major goals of the "Health China 2030" initiative; namely, improving nationwide health and controlling major risk factors.[22] Policy makers should also consider the sociodemographic heterogeneities in the housing-health relation by prioritizing such vulnerable groups as seniors, lower income citizens, and residents of less developed regions. Overall, given our evidence of housing improvement's long-term benefits for individual health, a sustainable scheme for increasing housing quality as well as quantity would not only improve national health outcomes but bring notable economic benefits in the future.

Conflicts of interest

None.

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[22] The "Healthy China 2030" initiative, implemented in 2016, makes public health a key benchmark for assessing economic and social initiatives based on five goals: Improving nationwide health; controlling major risk factors; increasing health service capacity; enlarging the health industry; and perfecting the health service system.

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Appendix

Table A1 Correlations between the composite housing condition index and individual housing condition variables

	Housing condition index	Tap water	Indoor flushing toilet	Clean cooking fuels	No excreta around dwellings	Electrical appliance	Health infrastructure	Traditional market
Housing condition index	1.000							
Tap water	**0.679***	1.000						
Indoor flushing toilet	**0.799***	0.681*	1.000					
Clean cooking fuels	**0.804***	0.495*	0.688*	1.000				
No excreta around dwellings	**0.604***	0.436*	0.545*	0.514*	1.000			
Electrical appliance	**0.770***	0.366*	0.549*	0.576*	0.404*	1.000		
Health infrastructure	**0.411***	0.212*	0.129*	0.172*	0.241*	0.141*	1.000	
Traditional market	**0.347***	0.020	0.068*	0.045*	0.007	0.026*	-0.003	1.000

Notes: Estimation methods = Pearson correlation for two continuous variables; polyserial correlation for one binary variable and one continuous variable; and polychoric correlation for two binary variables. * $p < 0.01$.

Table A2 Control and housing condition variable means: By wave and treated/control group

Variables	1991		1993		1997		2000		2004		2006		2015	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
Control variables														
Gender (1 = male; 0 = female)	0.487	0.485	0.489	0.480	0.499	0.476	0.476	0.466	0.482	0.465	0.478	0.458	0.477	0.462
Age (in years)	41.708	44.950	42.972	46.215	45.427	49.181	47.650	51.215	51.256	52.427	52.303	53.773	58.820	56.951
Age group:														
18-34	0.389	0.338	0.332	0.331	0.285	0.293	0.204	0.213	0.154	0.194	0.102	0.133	0.023	0.043
35-59	0.460	0.403	0.486	0.372	0.495	0.344	0.543	0.412	0.524	0.423	0.574	0.485	0.525	0.527
60+	0.151	0.259	0.182	0.297	0.220	0.363	0.253	0.375	0.322	0.383	0.323	0.381	0.452	0.429
Marital status:														
Single	0.096	0.195	0.091	0.187	0.106	0.169	0.102	0.147	0.054	0.090	0.031	0.055	0.008	0.016
Married	0.858	0.708	0.856	0.699	0.818	0.699	0.821	0.710	0.839	0.737	0.852	0.771	0.871	0.810
Divorced/widowed/separated	0.046	0.096	0.052	0.114	0.076	0.132	0.077	0.143	0.107	0.173	0.116	0.174	0.121	0.174
Education level:														
Low	0.270	0.378	0.236	0.332	0.217	0.370	0.170	0.337	0.161	0.263	0.182	0.309	0.120	0.163
Medium	0.480	0.451	0.483	0.466	0.469	0.452	0.443	0.443	0.440	0.497	0.400	0.458	0.469	0.560
High	0.250	0.172	0.282	0.202	0.314	0.179	0.388	0.219	0.399	0.240	0.418	0.233	0.411	0.277
Working status (1 = yes, 0 = no)	0.696	0.598	0.694	0.568	0.647	0.513	0.558	0.400	0.442	0.352	0.444	0.379	0.371	0.359
Per capita household income (logged)	8.189	7.991	8.256	8.021	8.447	8.032	8.690	8.218	8.889	8.318	8.986	8.329	9.757	9.191
Household size	4.408	4.231	4.295	4.193	3.869	3.738	3.634	3.505	3.221	3.331	3.210	3.470	3.244	3.685
Housing conditions variables														
Indoor tap water (1 = yes, 0 = no)	0.761	0.572	0.814	0.623	0.847	0.577	0.897	0.588	0.893	0.583	0.908	0.566	0.946	0.609
Indoor flushing toilet (1 = yes, 0 = no)	0.278	0.090	0.413	0.126	0.556	0.183	0.688	0.271	0.761	0.328	0.870	0.392	0.908	0.435
Clean cooking fuels (1 = yes, 0 = no)	0.201	0.100	0.413	0.134	0.611	0.262	0.664	0.269	0.639	0.261	0.755	0.290	0.960	0.728
No excreta around dwellings (1 = yes, 0 = no)	0.800	0.720	0.874	0.822	0.893	0.794	0.958	0.834	0.967	0.891	0.969	0.886	0.974	0.951
Number of electrical appliances (0-9)	3.610	2.623	4.039	2.808	4.522	3.022	4.960	3.321	5.319	3.587	5.594	3.716	6.217	4.967
Community health infrastructure index (0-10)	6.864	6.710	6.890	6.786	6.814	6.499	6.553	6.312	6.450	5.201	6.481	5.485	7.228	4.817
Traditional market index (0-10)	5.976	6.615	6.042	6.154	6.920	6.975	7.967	7.635	7.364	6.711	7.635	6.139	7.294	3.844
Composite housing condition index	-0.510	-0.781	-0.303	-0.720	-0.058	-0.620	0.145	-0.505	0.154	-0.611	0.289	-0.590	0.507	-0.465
Above the median of housing condition index (%)	0	0	30.8%	0	38.9%	0	56.0%	0	64.0%	0	76.8%	0	100%	0
Obs.	985	1131	1030	1160	1025	717	985	483	963	525	928	472	644	184

Notes: Treatment group = individuals whose composite housing conditions index is ever in the upper median of the (all wave pooled) index distribution.

Table A3 Attrition bias: Variable addition test

	Full sample	Female	Male
ATT of improved housing conditions	-0.021*	-0.028*	-0.013
	(0.012)	(0.016)	(0.017)
Total number of observed waves in panel	-0.002	-0.003	-0.002
	(0.003)	(0.005)	(0.004)
Year FE	Y	Y	Y
Time-variant individual and household controls	Y	Y	Y
Adjusted R^2	0.131	0.128	0.127
N	11232	5837	5395

Notes: ATT = average treatment effect on the treated. The DID estimates are based on the linear probability model. Because the total number of observed waves in the panel data is constant for every individual, the variable addition test includes no fixed individual effects. The time-variant individual and household controls include age group (0 = 18-34, 1 = 35-59, 2 = 60+, 0 as the reference group), marital status (0 = never married, 1 = married, 2 = divorced/widowed/separated, 0 as the reference group), education (0 = low: illiterate, 1 = medium: primary/middle school, 2 = high: high school/technical/vocational or above, 0 as the reference group), working status (0 = no, 1 = yes), logged per capita household income, and household size. Standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

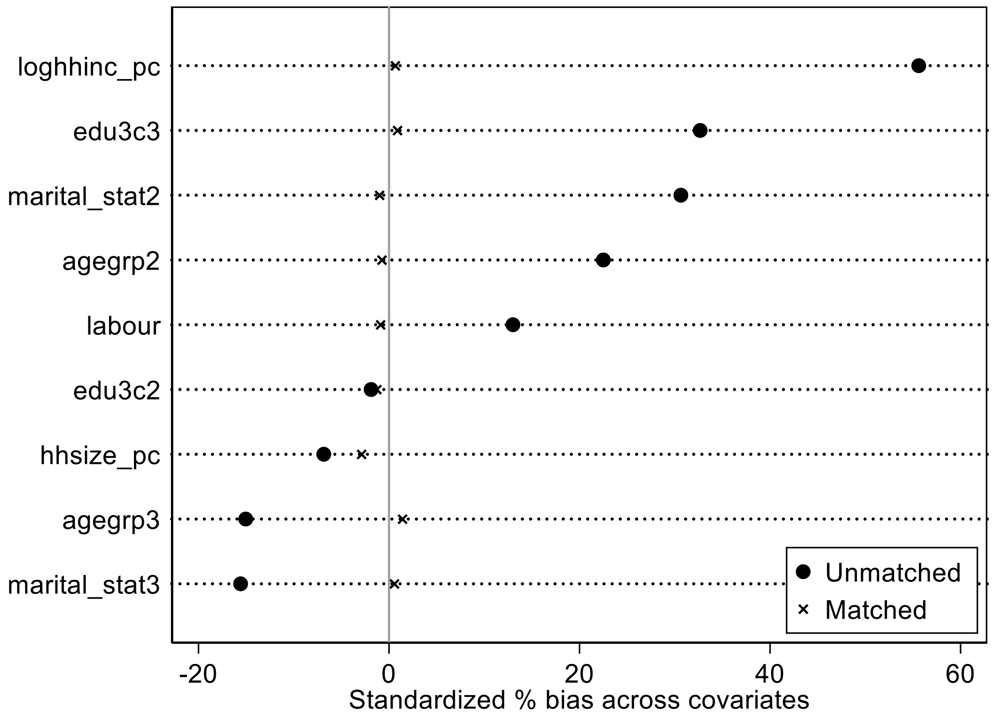

Figure A1 Standardized differences in control variables before and after radius matching

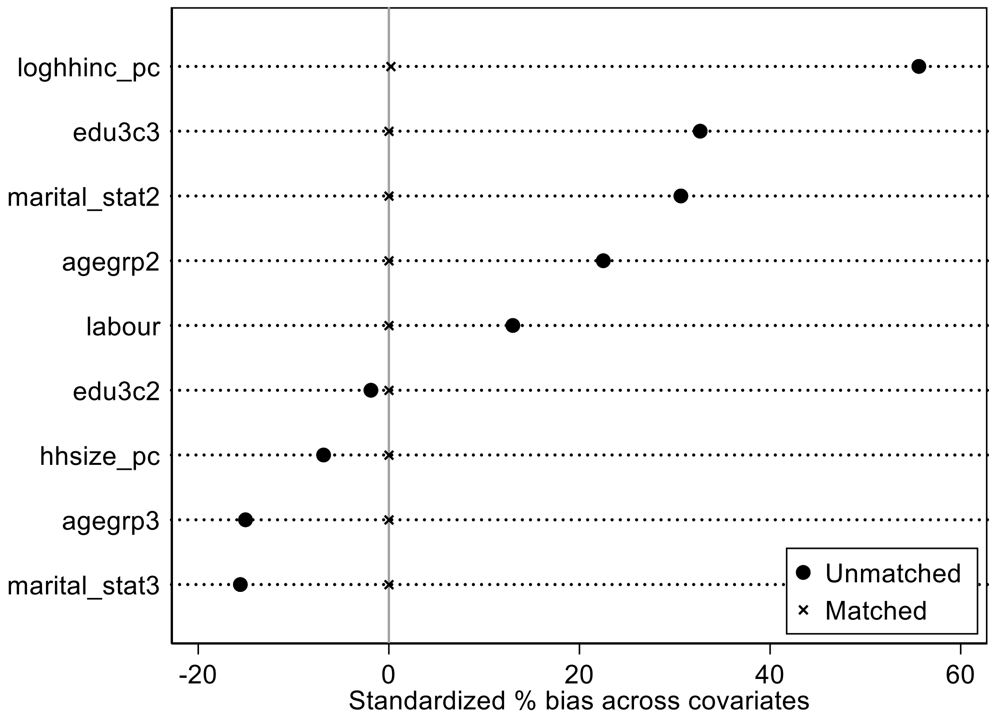

Figure A2 Standardized differences in control variables before and after Mahalanobis distance matching