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Sung, Jaesang

Georgia State University

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The Impact of Housing Prices on Health in U.S. Before, During and After the Great Recession

Jaesang Sung[1]

Department of Economics

Andrew Young School of Policy Studies

Georgia State University

April 21, 2017

Abstract

I estimate the effects of U.S. Metropolitan Statistical Area (MSA) housing prices on a variety of health outcomes and risky health behaviors separately for homeowners and tenants. The constructed dataset consists of information on individuals from the 2002 - 2012 Behavioral Risk Factor Surveillance System (BRFSS) combined with homeownership data from the March Current Population Survey (CPS) and housing prices from Freddie Mac. I estimate positive results for homeowners in terms of their health and negative results for tenants. I also find increases in risky behaviors among tenants associated with increases in housing prices, which may be driving the reduction in their health status. Those estimated effects are concentrated on low income homeowners and tenants. The estimated contemporaneous effects do not persist in the long run while the effects of an increase in housing prices on being obese become more pronounced for homeowners, resulting in worse self-reported health.

Keywords: Housing prices, Wealth inequality, Health, Risky behaviors, Homeowners, Tenants

JEL Classification: I12, I14, I18

[1] Corresponding author: Georgia State University, P.O. Box 3992, Atlanta, GA 30302-3992, jsung6@student.gsu.edu.
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1. Introduction

The U.S. Great Recession between 2007 and 2009 is considered to have exerted a strong influence on the cognition, attitudes, and behaviors of individuals over a wide range of social and economic issues. A major cause of the Great Recession was the bursting of a housing price bubble. The average house price in the United States increased 71 percent from January 2002 to July 2006. During this period, many people took advantage of easy mortgage loan accessibility to purchase second and third homes based on the belief that prices would continue to climb.[2] From July 2006 to April 2009, the average house price plunged 33 percent, causing significant financial losses for homeowners. A survey by the University of Michigan showed one of the largest declines in consumer confidence in its survey history between September and November 2008.[3]

This sharp drop in housing values could influence consumption decisions related to various lifestyle choices (food expenditure, smoking, drinking, etc.) and therefore impact health outcomes, given that owner-occupied housing is the primary or only source of wealth for most U.S. households.[4] If a change in housing prices is associated with changes in the affordability of housing, then such changes could also affect tenants' lifestyle choices and health outcomes.[5] On the other hand, fluctuations in housing values could affect mental health through how homeowners feel about a change in the absolute or relative value of their own home equity and how tenants feel about a change in the value of others' equity, which may lead to changes in their risky behaviors and, in turn, health outcomes.

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[2] Mankiw and Ball (2011) provides further discussion in chapter 16, page 443.
[3] Mankiw and Ball (2011) provides further discussion in chapter 19, page 553.
[4] Housing wealth makes up about two thirds of the total wealth of the median household in the United States (Iacoviello, 2011)
[5] With an increase in housing prices, a tenant who wants to buy her own house might have to curtail her spending on other items within her budget. She might have to pay off increased mortgage interest or save more money in order to afford her own house.

In this paper I estimate the effects of U.S. Metropolitan Statistical Area (MSA) housing prices on a variety of health outcomes and many specific risky health behaviors separately for homeowners and tenants. The dataset used to conduct this analysis consists of information on individuals from the 2002 to 2012 waves of the Behavioral Risk Factor Surveillance System (BRFSS) combined with homeownership data from the March Current Population Survey (CPS) and housing prices from Freddie Mac. Using the March CPS, I compute the group homeownership average for each year-MSA-demographic cell from the BRFSS sample. Subsequently, this way of computation is elaborately investigated and proved to be robust. I utilize the Freddie Mac house price index as a proxy for the housing wealth to capture the main channel through which housing values affect health outcomes both for homeowners and tenants. Since the effect of housing value on health outcomes could result from changes in economic conditions that may influence both housing value and health outcomes, I control the unemployment rate as a proxy for the economic performance measure. Inspired by the empirical findings of Mian and Sufi (2014) and Mian et al. (2013), I examine whether the effects of changes in housing prices on health and risky behaviors vary according to the income level of homeowners and tenants. To the best of my knowledge, this study is the first to use micro-data and examine the effects of changes in housing prices both on a broad range of health outcomes and risky health behaviors for both homeowners and tenants of all ages. I am also the first to analyze both the short- and long-term effects of changes in housing prices on health outcomes. In addition, this paper provides an intuition regarding the relationship between wealth inequality and health by investigating how tenants' health outcomes and behaviors vary with respect to changes in housing prices.

I find that there is a statistically significant causal effect of changes in housing prices on health outcomes and risky behaviors both for homeowners and tenants. My results suggest that a

30 percent contemporaneous increase in housing prices reduces the number of mentally unhealthy days by 3.2 percent among homeowners. In contrast, for tenants, the same increase in housing prices increases the probability of reporting poor health by 3.9 percent and increases the number of mentally unhealthy days by 6.8 percent. I also find evidence of statistically significant increases in contemporaneous risky health behaviors among tenants, which may be driving this reduction in their contemporaneous health status. Interestingly, the effects of contemporaneous changes in housing prices on health outcomes are concentrated among low income homeowners and tenants. In the long run, the effects of an increase in housing prices on being obese become more pronounced for homeowners, resulting in worse self-reported health. In addition, the beneficial effect of an increase in home value on the mental health status of homeowners disappears. Finally, the negative effects of an increase in housing prices on tenants' health outcomes do not persist in the long run.

These results suggest that any analysis of changes in housing prices should consider the spillover effects of such prices changes on the health of both homeowners and tenants. In addition, any analysis of the impact of economic changes on health outcomes focusing on the periods of big fluctuations in housing prices should consider the role of changes in housing prices that can impact both health outcomes and risky health behaviors. Accordingly, these findings have some policy implications. Governmental subsidies such as the low-income housing tax credits for providers of housing reserved for low-income tenants and voucher programs that directly subsidize consumers of low-income housing could improve tenants' health. Taking such spillovers into account is one example of a "health-in-all-policies" approach to policymaking.[6]

[6] *"Health in all policies is a collaborative approach to improving the health of all people by incorporating health considerations into decision-making across sectors and policy areas."* (Rudolph et al., 2013)

The rest of the paper is organized as follows: Section 2 summarizes the prior literature and Section 3 provides a conceptual model of the relationship between housing prices and health. Section 4 presents my empirical strategy. Section 5 describes the data used in this paper and presents descriptive statistics. Sections 6 and 7 discuss the main results and some robustness checks. Section 8 presents conclusions and policy implications.

2. Prior literature

Prior to the Great Recession, many studies have consistently shown that economic recessions lead to better health outcomes and healthier behaviors. Ruhm (2000) employs fixed-effect models using aggregate longitudinal data from 1972 to 1991 and finds that mortality rates exhibit pro-cyclical variation (i.e. lower mortality rates during recessions). Ruhm (2003) uses individual level data from the National Health Interview Survey (NHIS) from 1972 to 1981 and shows that most measures of health status deteriorate during an economic expansion. Furthermore, using individual level data from 1987 to 2000 from the BRFSS, Ruhm (2005) investigates the mechanisms underlying the aforementioned pro-cyclical variation in mortality and health status. He demonstrates that smoking and obesity declines and physical activity increases when the economy suffers a downturn. On the other hand, Charles and DeCicca (2008) find that a weak labor market is associated with weight gain and a worsening of mental health among African-American men and less-educated males.

Despite these findings from past time periods, researchers are still debating whether the Great Recession resulted in adverse or favorable health consequences. Using a representative sample of UK households, Griffith et al. (2013) show that there was a reduction in food expenditure and nutritional quality in the U.K. during the Great Recession. The decline in nutritional quality was mainly caused by a switch from fruits and vegetables to sweet and savory foods. Todd (2014) uses data from the National Health and Nutrition Examination Survey (NHANES) to analyze a representative sample of US adults before, during and after the Great Recession. He finds that diet quality improved slightly during the period, with lower intake of calories from fat and saturated fat, and with less consumption of cholesterol.

However, recent research has provided emerging evidence that suggests there may be no significant relationship between recessions, health status, and health-related lifestyle choices. Tekin et al. (2013) use microdata from the BRFSS between 2005 and 2011. They demonstrate that the association between economic downturns and health outcomes and health-related behaviors weakened substantially during the Great Recession.[7] Ruhm (2015) adopts annual average state unemployment rates as proxies for economic conditions and shows that total mortality became weakly associated or unassociated with economic conditions between 1976 and 2010.

With regard to a sharp fall in value of wealth, Cotti et al. (2015) reveals that stock market crashes are related to declines in self-reported mental health and risky health behaviors such as more smoking and drinking. Fiuzat et al. (2010) show that there is a significant correlation between periods of stock market crashes and growth in acute myocardial infarction (AMI) rates. Currie and Tekin (2015) use data on all foreclosures and all hospital and emergency room visits from the four states (Arizona, California, Florida, and New Jersey) that suffered the most from the foreclosure crisis in 2010 and find that a sharp increase in foreclosures is associated with a significant increase in emergency visits for mental health problems, heart disease, and stroke.

[7] Tekin et al. (2013) showed that most measures of health status were not significantly influenced by the unemployment rate. However, smoking and drinking declined, and exercise rose during the Great Recession. The degree of magnitude and significance depend on their specifications.

Meer et al. (2003) and Kim and Ruhm (2012) model inheritances as an exogenous wealth shock and show no significant causal effect of wealth on health outcomes. Apouey and Clark (2015) find that winning the lottery (a positive income shock) has no significant effect on self-reported health status but leads to improvements in mental health. Increased consumption on cigarettes and alcohol due to lottery winnings cancels out the favorable effects on mental health, resulting in no significant effect of lottery winnings on self-reported health.

Several studies have examined the relationship between changes in housing prices and household consumption. Campbell and Cocco (2007) and Goodhart and Hofmann (2008) suggest that changes in housing prices influence behaviors of a household through three mechanisms. One mechanism is a change in households' perceived wealth, another is a change in the degree of household borrowing constraints, and the third is a function of the house price as a proxy for economic conditions. Growth in the value of wealth and easing of borrowing constraints due to increasing housing prices could lead to an increase in consumption. Campbell and Cocco (2007) investigate the effects of a change in housing prices on household consumption using individual-level data from the U.K. They show that the estimated effect of housing prices on consumption for older tenants is positive and significant. Goodhart and Hofmann (2008) find a significant multi-directional relationship between money, credit, house prices and economic conditions using quarterly data for 17 developed countries between 1970 and 2006. Their analysis reveals that shocks to housing prices, credit and money all exercise a profound influence on economic activity.

Case et al. (2005, 2011) examine the association between housing values, financial assets and household consumption using quarterly panel data of U.S. states from 1978 through 2009. They find a large significant effect of housing values on consumption. The effect is larger than the effect of financial wealth on consumption. Employing U.S. quarterly data between 1960 and 2007, Carroll et al. (2010) also show that the marginal propensity to consume out of housing wealth is substantially larger than the marginal propensity to consume out of financial assets. However, Calomiris et al. (2009) show a small and insignificant effect of housing values on consumption by exploiting state-level Case-Quigley-Shiller data on housing prices for the years 1982-1999 in the U.S.

Interestingly, there has been a recent series of studies examining the effects of housing wealth on consumption across different levels of income. Mian et al. (2013) find that with respect to a change in housing value, the marginal propensity to consume of households living in zip codes with lower average annual income is substantially greater than that of households living in zip codes with higher average annual income between 2006 and 2009. The types of spending considered in their study are autos, durable goods, and non-durable goods including health-related goods such as prescription drugs and groceries. Mian and Sufi (2014) suggest that households in low income zip codes aggressively borrowed money using their homes as collateral and increased consumption substantially when home values rose sharply from 2002 to 2006 whereas households in high income zip codes did not.

Finally, few studies have considered the direct relationship between housing market fluctuations and health outcomes and health related behaviors. Using data from the 2007, 2009, and 2011 waves of the Panel Study of Income and Dynamics (PSID), Yilmazer et al. (2015) find that as housing wealth decreases psychological distress and the self-reported health of homeowners worsen at a small but statistically significant rate. However, there remain some issues related to small sample size, short time periods, and reverse causality in their study.[8] Golberstein et al. (2016)

[8] Conversely, Joshi (2016) finds that housing price reductions lead to more mental distress among tenants, though the validity of his identification of tenants is unclear.

employ the 2001-2013 NHIS and show that a decline in housing prices leads to the deterioration of child and adolescent mental health. Utilizing individual-level data from the Health and Retirement Study (HRS), Hamoudi and Dowd (2014) find that increases in housing prices are associated with a statistically significant reduction in anxiety for women and better performance on some cognitive functioning tests of older American homeowners. This paper includes some analysis of a small sample of tenants, but given their use of the HRS this sample consists of older tenants only. These studies generally focus on the short run effects of housing price changes on homeowners. Therefore, they do not consider longer run effects or the effects of housing price changes on tenants of all ages, both of which are contributions of my work.

3. Conceptual model

How changes in housing prices influence risky behaviors and health outcomes for homeowners and tenants is clearly illustrated by the flow chart of mechanisms in figure 1. This flow chart applies to the specific time period of 2002 through 2006 when U.S. housing prices surged upward, creating a housing bubble.[9] For homeowners, an increase in housing prices could lead to an improvement in mental health because homeowners are likely to be pleased with the increased value in their home equity. In addition, homeowners could increase their spending by taking out a loan using their homes as collateral. Homeowners could also increase consumption in anticipation of the increased value of their lifetime wealth and therefore by loosening their budget constraints.[10] Assuming health-related goods are normal goods, homeowners would tend to spend

[9] This flow chart can also apply to the Great Recession time period when housing prices fell dramatically if I switch the signs of the effects. Here the interpretation would simply be the effects of a reduction in housing prices on risky behaviors and health outcomes, assuming a symmetric effect of increases and reductions in housing prices.
[10] Using data from the PSID from 1968 to 2007, Cooper (2013) finds that U.S. household spending is influenced by changes in housing prices through the borrowing collateral mechanism but not the loosening budget constraints mechanism.

more on such goods out of their increased housing value. However, the effects of an increase in housing prices on overall health and obesity for homeowners are ambiguous because better mental health and increased spending on health-related goods could be offset by increases in risky behaviors. As an example, better mental health might lead to fewer reasons for engaging in risky behaviors such as smoking and drinking, whereas increased wealth could be associated with more spending on unhealthy goods. In other words, with an increase in home value, homeowners might enjoy more junk food, smoking, and drinking while they might also be able to invest in their health through more consumption of healthy food and more medical spending.

Tenants might suffer from worse health due to increases in housing prices, although overall effect of an increase in housing value on the health status and obesity for tenants is also ambiguous. The relative deprivation hypothesis suggests that having lower socioeconomic status, such as lower income than one's neighbors, causes mental distress and anxiety and therefore worsening health.[11] A spike in the value of others' equity could lead to a greater sense of deprivation for tenants, which could result in a deterioration of their mental health and riskier behaviors such as more smoking and drinking. On the other hand, with an increase in housing prices, a tenant who wants to buy her own house might have to curtail her spending on other items within her budget. She might have to pay off increased mortgage interest or save more money in order to afford her own house. A reduction in her budget could cause a decline in both the amount and quality of her consumption. For example, with a more restricted budget, tenants might have to consume less junk food, smoking, and drinking while they might also not be able to afford to invest as much on their own health (i.e.

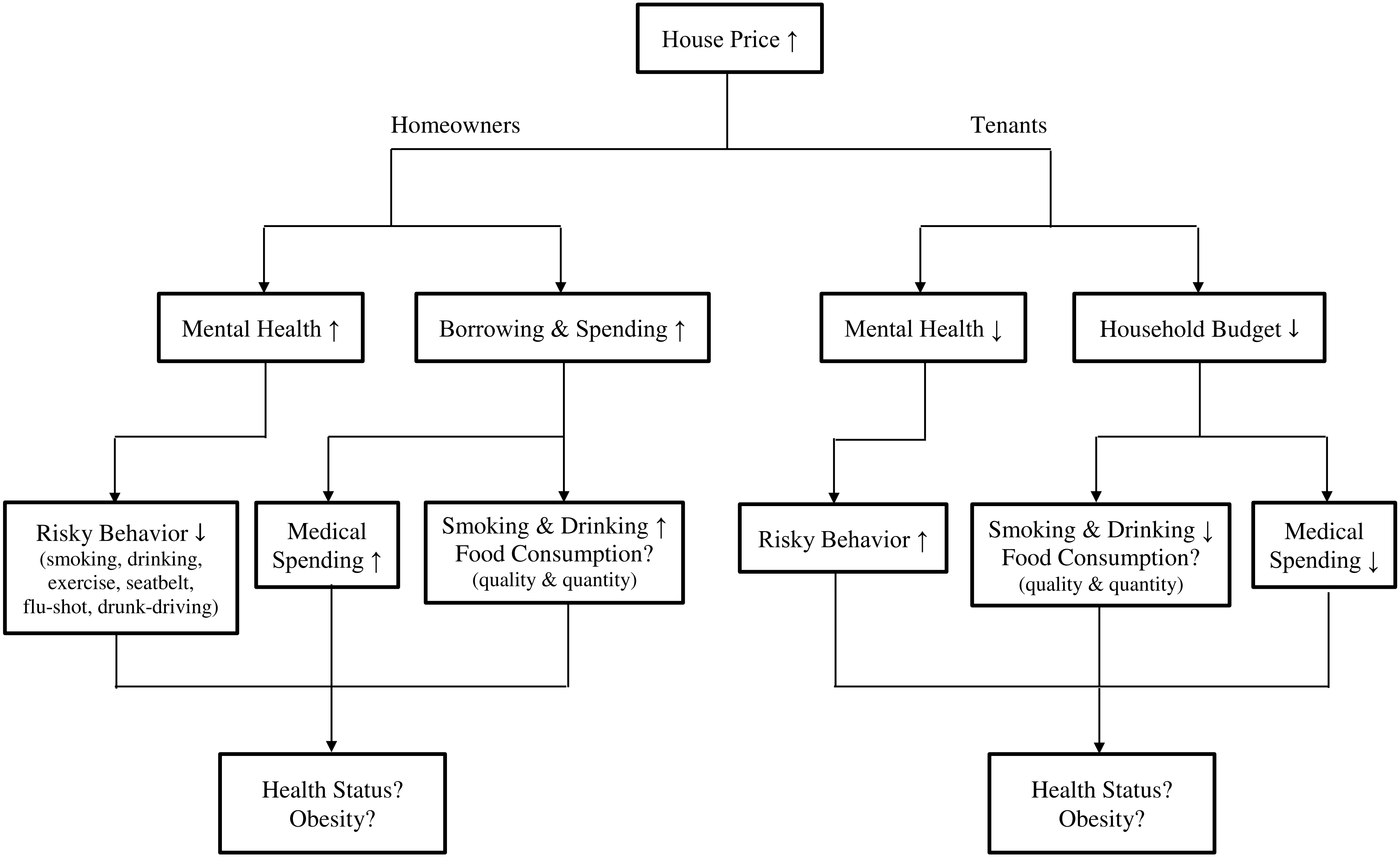
[11] A considerable amount of literature has studied the relationship between relative deprivation and health. For further discussion, see the thorough literature review in Pickett and Wilkinson (2015), as well as Sung, Qiu, and Marton (2017).

less consumption of healthy food and medical spending). In summary, as with homeowners, the effects of an increase in housing prices on overall health and obesity for tenants are not clear.

Another transmission mechanism for the effect of changes in housing prices on health and behaviors operates through the link between house prices and rents. Rent levels might also influence individual health status and risky behaviors, especially among tenants. Therefore, if house prices and rent levels tend to move in the same direction, housing prices can also be used as a proxy for rent levels in my analysis. However, Ellen and Dastrup (2012) show that rent levels rose steadily whereas housing prices plunged during the Great Recession. Therefore, I include rent levels in my analysis separately from housing prices.

I contribute to the literature by providing empirical evidence on the causal effect of changes in housing prices on risky behaviors and health outcomes for homeowners and tenants, which is theoretically ambiguous. As Mian and Sufi (2014) and Mian et al. (2013) suggest, if there exist differential effects of a change in housing prices on consumption across different levels of income, then the effects of a change in housing prices on risky behaviors and health outcomes could also vary depending on individual income. This motivates my sub-sample analysis by income for both homeowners and tenants. Finally, I also differentiate between the short run and long run impact of changes in housing prices, something else not typically done in the previous literature.

Figure 1. Flow Chart of Mechanisms



4. Empirical strategy

The basic empirical specification I employ in this paper is given by equation (1) below:

$$Y_{ijt} = \beta P_{jt} + \theta R_{jt} + \gamma U_{jt} + X_{ijt}\delta + \alpha_j + \lambda_t + \varepsilon_{ijt} \quad (1)$$

where Y is the health status or the presence of a health behavior for individual i living in MSA j interviewed in year-month t (e.g. January 2002), P and R represents the house price index and the median rent estimate in MSA j for year-month t respectively, U represents the seasonally unadjusted unemployment rate as a proxy for economic conditions that may influence both housing values and health outcomes in MSA j for year-month t, X is a vector of individual i's demographic characteristics such as age, gender, race, education, income, and marital status, α represents time-invariant unobserved factors in MSA j (i.e. regional fixed effects), λ represents unobserved factors associated with year-month t (i.e. time fixed effects), and ε represents the error term.[12]

The regional dummies (α) control for time-invariant regional heterogeneity such as differences in health care infrastructure across MSAs. The year-month dummies (λ) account for nationwide trends such as a national change in the taste for cigarettes or soft drinks. As a specification check, I add a vector of MSA-specific linear time trends ($\alpha_j * t$) to my baseline specification given by equation (1) to test for whether or not my results are robust to unobserved factors varying within each MSA over time. These results are reported in section 7.[13]

In my analysis, I first estimate the effects of changes in housing prices on health and risky behaviors for predicted homeowners and tenants respectively. Next I stratify both the homeowner

[12] I take logarithms of income and median rent estimates, considering their diminishing marginal effects on health.
[13] Adding MSA-specific linear time trends enables me to control for unobserved factors varying within each MSA over time, such as the establishment of medical facilities (good for health) or factories (bad for health), which could also influence both health outcomes and housing prices.

and tenant samples by income to test for differential effects of housing prices on these groups by income level. Finally, I analyze the long-term effects of housing prices on health outcomes for both homeowners and tenants.

Depending on the type of dependent variable being analyzed, different estimation strategies are applied. For dichotomous variables (e.g. obese or not), probit models are estimated, for ordered categorical variables (e.g. self-reported health), ordered probit models are estimated, and for count variables (e.g. number of mentally unhealthy days during the past 30 days), negative binomial models are estimated. For continuous variables (e.g. body mass index), linear models are estimated. I use heteroskedasticity-robust standard errors and clustered observations by MSA in all specifications.

5. Data and descriptive statistics

5.1. Outcome variables

Data for health outcomes and risky behaviors are from the Behavior Risk Factor Surveillance System (BRFSS) dataset. The BRFSS is a telephone survey of self-reported health conditions and risky behaviors conducted by state health departments and the Center for Disease Control and Prevention (CDC). The dataset consists of repeated cross-sections of randomly selected individuals, and it does not track the same individuals over time.

For health outcomes, self-assessed health is reported as a five-level ordinal variable (excellent/very good/good/fair/poor). Status of physical and mental health are both reported in the form of count variables (i.e.: the number of physically/mentally unhealthy days during the past 30 days). Obesity and some variables representing health behaviors such as exercise, smoking, binge drinking, health insurance coverage, flu-shot receipt, seatbelt usage, and not being able to afford to see a doctor are all converted to dichotomous variables. Other variables such as the body mass index, average drinks per day, and number of times binge drinking are treated as continuous variables.

5.2. Explanatory variables

I utilize the Freddie Mac house price index as a proxy for home value. Freddie Mac provides their monthly house price index at the Metropolitan Statistical Area (MSA) level.[14] The Freddie Mac House Price Index (FMHPI) is built based on a repeat transaction methodology and house prices are averaged by all counties within a MSA. The FMHPI uses data on transactions involving single-family houses and townhouses serving for mortgages, which has been purchased by Freddie Mac or Fannie Mae.[15] The U.S. Bureau Labor Statistics (BLS) provides monthly MSA-level seasonally unadjusted unemployment rates.[16] As is discussed in section 3, I control for rent levels in my baseline specification given by equation (1). The US Department of Housing and Urban Development (HUD) provides annual median rent estimates at the MSA level.[17]

Since individual health status could impact an individual's income, which raises an endogeneity issue, weighted group averages are adopted for household incomes (Ruhm, 2005). Household incomes are averaged in the MSA and survey year for 16 groups stratified by age (18-

[14] The data is available online [http://www.freddiemac.com/finance/fmhpi/archive.html].
[15] Other possible candidates for the house price index are Case-Shiller index and Federal Housing Finance Agency (FHFA) index. But Case-Shiller home price index is available only in 20 cities, and FHFA house price index is constructed on the basis of Fannie Mae and Freddie Mac mortgages and provides quarterly transactions indexes (that includes both purchase and appraisal data) and monthly purchase-only indexes.
[16] The data is available online [https://fred.stlouisfed.org/search?st=unemployment+rate+metropolitan].
[17] HUD provides each annual median rent estimates across studio, one-bedroom, two-bedroom, three-bedroom, and four-bedroom houses at the MSA level [https://www.huduser.gov/portal/datasets/50per.html] and I take the average of them in each year and MSA to represent an estimate of annual MSA median rent levels.

24, 25-54, 55-64, 65-99), gender (female versus male), and education (some college or higher versus high school graduate or less).[18]

Because the BRFSS did not begin to provide information on homeownership until 2009, I utilize information acquired from the Current Population Survey (CPS) March Supplement to calculate weighted group averages of predicted homeownership for individuals with similar characteristics in both the CPS and the BRFSS.[19] Specifically, I first calculate weighted group averages of predicted homeownership based on a stratification of demographic characteristics within a MSA for a survey year, using the March CPS.[20] Here are the five demographic categories, which yield a total of 96 bins (3*2*2*2*4 = 96):

- Age (3): 18-34, 35-54, 55 or above;
- Race (2): White, or other;
- Marital status (2): Married, or not;
- Education (2): College graduate or higher, or less than college graduate;
- Income quartiles (4);

Therefore, individuals in the CPS who have similar demographic characteristics in the same MSA in the same survey year share the same predicted homeownership in the MSA in the year which is between 0 and 1 (binary representation of homeownership: homeowners=1, tenants=0). This

[18] Empirical results that control for weighted group average income are similar to the results that control for individual household income. The latter results are provided in the Appendix tables A1 and A2.

[19] The BRFSS actually only provides adequate homeownership data starting in 2011, because response rates for the homeownership questions over 2009-2010 are less than 10 percent.

[20] Bostic et al. (2009) matched two datasets of Consumer Expenditure Survey (CEX) and Survey of Consumer Finances (SCF) in a similar way (stratification based on age, race, marital status, education, and income) in constructing micro data to examine the causal relationship between wealth and consumption. Ruhm (2005) matched weekly work hours from the CPS Outgoing Rotation Group data into the BRFSS in the respondent's state-gender-age-education bins.

predicted homeownership measure from the March CPS is then matched into the BRFSS sample so that the respondents in the BRFSS who have similar demographic characteristics with the respondents in the CPS in the same MSA in the same survey year share the same group-average homeownership predicted probability.[21]

Table 1 provides the percentage of homeowners across different demographic characteristics in the CPS. For those aged 18 to 34, the share of homeowners is only 53 percent whereas the share of homeowners is as large as 81 percent for those aged 55 or above. Whites, married individuals, and with a college degree or more education appear to be much more likely to be homeowners. Homeownership also appears to increase with income.

Table 1. Percent of homeowners in the March CPS

Categories	% Homeowners
Age	
18-34	53%
35-54	73%
55 or above	81%
Race	
White	78%
Other	54%
Marital Status	
Married	80%
Other	56%
Education	
College graduate or higher	77%
Less than college graduate	65%
Income Quartile	
1st (Lowest income)	47%
2nd	63%
3rd	77%
4th (Highest income)	89%

Notes: Percent of homeowners across different demographic characteristics are calculated from the 2002-2012 March CPS after being matched with the 2002-2012 BRFSS.

[21] After the match between the datasets, the sample size of the CPS and the BRFSS totals 983,260 and 1,777,070 respectively.

I arrange the assigned individual predicted homeownership values in order within the BRFSS sample and define the highest 70 percent to be homeowners and the bottom 30 percent to be tenants, given that the share of homeowners in the March CPS is about 70 percent.[22] The matching rate between my predicted homeownership indicator and actual homeownership is 80 percent in the CPS sample, while the matching rate between my predicted homeownership indication and the actual homeownership over 2009-2012 is 77 percent in the BRFSS sample.[23]

Rather than combing predicted homeowners and tenants into one sample and controlling for predicted homeownership, I conduct all of my analysis for homeowners and tenants separately. This is because some demographic factors associated with constructing my predicted homeownership indicator such as income quartiles could lead to a reverse causality problem. In a combined regression, controlling for predicted homeownership could bias the estimated effects of changes of housing prices on health outcomes because health outcomes could affect income levels and income influences predicted homeownership.[24]

5.3. Descriptive statistics

Weighted descriptive statistics of the variables from the BRFSS and CPS used in my analysis are summarized in tables 2-5. Table 2 shows that both the BRFSS and CPS samples consist larger shares of those who are white, aged 25 to 54, those with some college or graduates, married, and homeowners. Average annual household income in the CPS sample is more than $82,000 which is higher than that of the BRFSS sample, where average annual income is around

[22] I test the sensitivity of my results to different cut-offs, such as 75:25 and 65:35.
[23] In section 7.3, I elaborately investigate the extent to which these differences influence my estimated effects of changes in housing prices on health outcomes.
[24] However, utilizing income quartiles instead of individual income in constructing my predicted homeownership indicator might reduce this concern to some degree.

$63,000. This could be because those two datasets measure income in different ways. The BRFSS asks about household income in ranges (less than $10,000, $10,000-14,999, $15,000-19,999, $20,000-24,999, $25,000-34,999, $35,000-49,999, $50,000-74,999 and $75,000 or above) while the CPS asks about exact amounts of household income.[25] As Ruhm (2005) suggests, I take the midpoint of each income range from the BRFSS, and I take 150 percent of the highest income category that is unbounded above $75,000, which may underestimate the average annual income in the BRFSS. I deflate income using the 2009 Personal Consumption Expenditure Price Index (PCEPI).[26] Finally, according to the summary statistics, approximately 70 percent of the households are homeowners in both samples.

Table 3 provides average figures for the economic indices across MSAs between 2002 and 2012. The weighted mean value of the MSA house price index adjusted for inflation is 144 (for instance, if the average housing price in a MSA is $288,000, the value of one unit of the house price index is around $2,000), and the weighted mean value of the MSA unemployment rate is 6.7 percent. The weighed mean value of MSA median rent level adjusted for inflation is $1,100. Table 4 shows the weighted means for my health outcomes of interest. In the BRFSS, 56 percent of the MSA respondents regard their health as excellent or very good while 61 percent of the respondents in the CPS report their health as so. Other measures of health outcomes and behaviors are available only in the BRFSS. The average number of physically and mentally unhealthy days during the past 30 days for adults living in a MSA are 3.39 and 3.48 days, respectively. The average body mass index (BMI) of adults living in a MSA is 27 and one-fourth are obese.[27] Table 5 shows that nearly

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[25] This explains why I prefer to use (relative) income quartiles as opposed to (absolute) exact income in stratifying demographic groups when calculating group average predicted homeownership to match between the BRFSS and the CPS.

[26] This data is available online [https://fred.stlouisfed.org/series/PCEPI].

[27] BMI is calculated by the BRFSS as weight in kilograms divided by square of height in meters. Adults with BMI of 30 or more are considered to be obese.

80 percent exercised in the past 30 days, almost one-fifth report being a current smoker, and 71 percent of them smoke every day. The number of drinks on average on days of drinking is about 2.4 and 17 percent engage in binge drinking.[28] Among adults living in a MSA, 85 percent are covered by some type of health insurance, 34 percent got flu-shots during the past 12 months, and 86 percent always use seatbelts while driving. The number of times engaged in drunken driving in the past 30 days is 0.14 and 14 percent of the sample could not afford to see a doctor in the past 12 months.

[28] Binge drinking is measured in binary form: whether or not a person consumed 5 (4) or more drinks for men (women) on an occasion during the past 30 days.

Table 2. Summary Statistics of Demographic Characteristics [a]

Variable	BRFSS(N=1,777,070)	CPS(N=983,260)
Gender		
Female	0.50 (0.50)	0.52 (0.50)
Race		
White	0.65 (0.48)	0.63 (0.48)
Black	0.12 (0.32)	0.13 (0.34)
Hispanic	0.16 (0.36)	0.17 (0.37)
Other Race	0.08 (0.27)	0.07 (0.26)
Age		
Age from 18 to 24	0.11 (0.31)	0.13 (0.34)
Age from 25 to 34	0.20 (0.40)	0.19 (0.39)
Age from 35 to 44	0.21 (0.41)	0.20 (0.40)
Age from 45 to 54	0.20 (0.40)	0.19 (0.39)
Age from 55 to 64	0.14 (0.35)	0.14 (0.35)
Age from 65 to 99	0.15 (0.35)	0.15 (0.36)
Education		
Not high school graduate	0.11 (0.31)	0.14 (0.35)
High school graduate	0.26 (0.44)	0.29 (0.45)
Take some college	0.27 (0.45)	0.27 (0.45)
College graduate	0.36 (0.48)	0.30 (0.46)
Marital Status		
Married	0.58 (0.49)	0.54 (0.50)
Home Ownership		
Home Owner	0.67 (0.47) [b]	0.69 (0.46)
Income (adjusted by 2009$)		
Individual Household Income ($)	$63,047 (40,964)	$82,014 (81,583)

Notes: These descriptive statistics are calculated based on the MSA-level samples of 1,777,070 over the 2002-2012 BRFSS and samples of 983,260 over the 2002-2012 March CPS respectively and they are each sampling weighted.

[a] Summary statistics are expressed in terms of weighted mean (weighted standard error).

[b] Data on actual ownership from the BRFSS is available only from 2009 to 2012.

Table 3. Summary Statistics of Economic Conditions[a]

Variable	Weighted Mean
MSA House Price Index	143.96 (34.93)
MSA Unemployment Rate (%)	6.67 (2.37)
MSA Median Rent ($)	$1100.68 (292.44)

Notes: Freddie Mace House price index, seasonally unadjusted unemployment rate, and the HUD MSA median rent level are used. They are all adjusted to sampling weight between 2002 and 2012.

[a] Summary statistics are expressed in terms of weighted mean (weighted standard error).

Table 4. Summary Statistics of Health Outcomes[a]

Variable	BRFSS	CPS
Self-reported Health (Ordinal)		
"Excellent"	0.22 (0.41)	0.29 (0.45)
"Very good"	0.34 (0.47)	0.32 (0.47)
"Good"	0.29 (0.46)	0.26 (0.44)
"Fair"	0.11 (0.32)	0.09 (0.29)
"Poor"	0.04 (0.19)	0.04 (0.19)
Physical Health and Mental Health (Count)		
Number of physically unhealthy days during the past 30 days	3.39 (7.61)	-
Number of mentally unhealthy days during the past 30 days	3.48 (7.51)	-
Obesity Status		
Body Mass Index (Continuous)	27.22 (5.79)	-
Obese (Binary)	0.25 (0.43)	-

Notes: CPS provides only self-reported health data.

[a] Summary statistics are expressed in terms of weighted mean (weighted standard error).

Table 5. Summary Statistics of Risky Health Behaviors[a]

Variable	BRFSS	CPS
Exercise (Binary)		
Any exercise in the past 30 days	0.77 (0.42)	-
Any moderate physical activity for more than 10 minutes in a week	0.87 (0.34)	-
Any vigorous physical activity for more than 10 minutes in a week	0.49 (0.50)	-
Smoking (Binary)		
Current smoker	0.19 (0.39)	-
Smoke everyday among current smoker	0.71 (0.46)	-
Drinking		
Number of drinks on average on the days of drink (Continuous)	2.44 (2.62)	-
Number of times of binge drinking in the past 30 days (Continuous)	1.15 (3.42)	-
Binge drinking (Binary)	0.17 (0.37)	-
Other Risky Behaviors		
Any health insurance (Binary)	0.85 (0.36)	-
Flu-shot (Binary)	0.34 (0.47)	-
Seatbelt (Binary)	0.86 (0.34)	
Number of times of drunken driving in the past 30 days (Continuous)	0.14 (0.98)	-
Unaffordability of seeing a doctor in the past 12 months (Binary)	0.14 (0.35)	-

Notes: CPS doesn't provide the data of health related behaviors.

[a] Summary statistics are expressed in terms of weighted mean (weighted standard error).

6. Results

6.1. Contemporaneous results

Table 6 reports the estimated effects of changes in housing prices on contemporaneous health status for homeowners based on my baseline specification given by equation (1). The first column shows the predicted effect of a one unit change in the house price index on the dependent variables, with all the explanatory variables measured at their average values. The second column provides p-values, which is the observed level of significance at which a null hypothesis that the effect of changes in housing prices on health status is zero can be rejected. The third column displays the percent change in each outcome given a one unit change in the house price index, which is obtained by dividing the predicted effect (from the first column) by the weighted mean of the dependent variable and multiplying by 100 percent. The final column reports the percent change in each outcome variable in response to a one percent change in the house price index, which is calculated by dividing the third column by a reciprocal of the weighted mean of the house price index multiplied by 100 percent.

For instance, the statistically significant predicted effect of a one unit change in the house price index on the contemporaneous number of days that homeowners suffer from mental distress during the past 30 days is -0.002234. Since the weighted mean number of mentally unhealthy days during the past 30 days for predicted homeowners is 3.0027, a one unit increase in the house price index leads to a decline in the number of days that homeowners suffer from mental distress by 0.0744 percent ($= -\frac{0.002234}{3.0027} \times 100\%$). Finally, a one percent increase in the house price index leads to a decline in the number of days that homeowners suffer from mental distress by 0.1062 percent ($= -\frac{0.0744\%}{\frac{1}{142.74} \times 100\%}$) where the weighted mean house price index for predicted homeowners is 142.74. In other words, a 30 percent increase in housing prices statistically significantly reduces the number of days that homeowners suffer from mental distress by 3.2 percent.[29] I find no statistically significant effects of changes in housing prices on other contemporaneous health outcomes, including self-reported health status.[30]

Table 6. Estimated effects of changes in house price on health status for predicted homeowners

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000058 (0.000056)	0.301	-0.0250%	-0.0356%
Very good	-0.000019 (0.000019)	0.304	-0.0053%	-0.0076%
Good	0.000040 (0.000039)	0.303	0.0144%	0.0205%
Fair	0.000026 (0.000026)	0.302	0.0273%	0.0389%
Poor	0.000011 (0.000010)	0.299	0.0319%	0.0456%
# Physically Unhealthy Days (NB)	-0.000943 (0.001275)	0.459	-0.0290%	-0.0414%
# Mentally Unhealthy Days (NB)	-0.002234** (0.000950)	0.019	-0.0744%	-0.1062%
BMI (OLS)	0.000812 (0.000800)	0.311	0.0030%	0.0043%
Obese (Probit)	0.000080 (0.000072)	0.270	0.0324%	0.0463%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

[29] This empirical finding is consistent with prior literature in that increases (decreases) in wealth lead to better (worse) mental health in the following contexts: stock market (Cotti et al., 2015), foreclosure (Currie and Tekin, 2015), lottery (Apouey and Clark, 2015), housing value (Yilmazer et al.,2015; Golberstein et al., 2016; Hamoudi and Dowd, 2014).
[30] A 30 percent increase in housing prices increases the probability of being obese by 1.4 percent among homeowners, although this estimate is not statistically significant.

Table 7. Estimated effects of changes in house price on lifestyle behaviors for predicted homeowners

Lifestyles	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Exercise (Probit)				
Any exercise	-0.000062 (0.000090)	0.489	-0.0078%	-0.0112%
Moderate Exercise	-0.000041 (0.000047)	0.386	-0.0046%	-0.0066%
Vigorous Exercise	0.000052 (0.000108)	0.628	0.0104%	0.0149%
Smoking (Probit)				
Current Smoker	0.000096* (0.000057)	0.091	0.0586%	0.0837%
Smoke Everyday	-0.000085 (0.000157)	0.590	-0.0117%	-0.0167%
Drinking				
# Average Drinks (OLS)	0.000783 (0.000755)	0.301	0.0354%	0.0505%
# Times Binge Drinking (OLS)	0.000556 (0.000589)	0.346	0.0565%	0.0807%
Binge drinking (Probit)	-0.000006 (0.000049)	0.902	-0.0039%	-0.0055%
Other Risky Behaviors				
Health Insurance (Probit)	-0.000053 (0.000055)	0.338	-0.0058%	-0.0083%
Flu Shot (Probit)	-0.000032 (0.000098)	0.743	-0.0084%	-0.0120%
Always Seatbelt (Probit)	0.000010 (0.000065)	0.882	0.0011%	0.0016%
# Times Drunken Driving (OLS)	0.000082 (0.000267)	0.760	0.0679%	0.0969%
Doctor Unaffordability (Probit)	-0.000121*** (0.000042)	0.004	-0.1281%	-0.1829%

Abbreviations: Probit, binary probit; OLS, ordinary least square; Any exercise, any exercise in the past 30 days; Moderate (Vigorous) Exercise, any moderate (vigorous) physical activity for more than 10 minutes in a week; # Average Drinks, number of drinks on average on the days of drink; # Times Binge Drinking, number of times of binge drinking in the past 30 days; Doctor Unaffordability, inability to afford seeing a doctor in the past 12 months.

Note: Standard errors, clustered by MSA, are in parenthesis.

*** represents statistical significance at the 1% level.

** represents statistical significance at the 5% level.

* represents statistical significance at the 10% level.

Table 7 reports the estimated effects of changes in housing prices on health-related behaviors for homeowners. There is no statistically significant relationship between changes in housing prices and risky behaviors, except for smoking and the inability to afford seeing a doctor in the past 12 months. A one percent increase in the house price index increases the probability of being smoker by 0.08 percent and decreases the probability of reporting the inability to afford seeing a doctor by 0.18 percent. According to the conceptual model in section 3, this may imply that increases in the affordability of smoking (bad for health) could be offset by increases in the affordability of medical spending (good for health), leading to no significant effect of housing prices on overall health status (as reported in table 6). In addition, the fact that I find no significant effects of changes in housing values on other contemporaneous health-related behaviors such as exercise, drinking and risky behaviors also supports my earlier finding of no significant effect of changes in housing values on contemporaneous self-reported health.[31]

Tables 8 and 9 report the estimated effects of changes in housing prices on contemporaneous health status and health related behaviors for tenants. The estimated effects for tenants are very different from the ones for homeowners. Table 8 reports that a one percent increase in the house price index leads to a statistically significant increase in the number of days that tenants suffer from mental distress by 0.23 percent. Therefore, a 30 percent increase in the house price index leads to a 6.8 percent increase in the number of days that tenants suffer from mental distress. Table 9 shows that with a one percent increase in housing values, the probability that tenants do any exercise decreases by 0.11 percent and the probability they smoke increases by 0.18

[31] I find a statistically significant association between higher housing prices and better mental health but no significant relationship between changes in housing prices and self-reported health for homeowners. This is consistent with the findings from Apouey and Clark (2015) who show that winning the lottery is associated with more smoking and better mental health, but no net change in general health as these two effects tend to offset each other.

percent. Tenants also increase the number of drinks on average on the days they drink by 0.23 percent. In addition, a one percent increase in housing values leads to a decrease in the probability of having health insurance by 0.1 percent. It also leads to an increase in the probability of reporting the inability to afford seeing a doctor by 0.18 percent.

Table 8. Estimated effects of changes in house price on health status for predicted tenants

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000147* (0.000077)	0.057	-0.0776%	-0.1140%
Very good	-0.000088* (0.000046)	0.055	-0.0310%	-0.0456%
Good	0.000085* (0.000044)	0.055	0.0256%	0.0376%
Fair	0.000111* (0.000059)	0.061	0.0732%	0.1075%
Poor	0.000039** (0.000020)	0.045	0.0886%	0.1301%
# Physically Unhealthy Days (NB)	0.001065 (0.002193)	0.627	0.0287%	0.0421%
# Mentally Unhealthy Days (NB)	0.007098** (0.003046)	0.020	0.1544%	0.2267%
BMI (OLS)	-0.002591 (0.002368)	0.224	-0.0095%	-0.0140%
Obese (Probit)	0.000066 (0.000092)	0.472	0.0255%	0.0375%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 9. Estimated effects of changes in house price on lifestyle behaviors for predicted tenants

Lifestyles	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Exercise (Probit)				
Any exercise	-0.000548*** (0.000194)	0.005	-0.0755%	-0.1108%
Moderate Exercise	-0.000294* (0.000154)	0.056	-0.0350%	-0.0515%
Vigorous Exercise	-0.000154 (0.000287)	0.592	-0.0340%	-0.0499%
Smoking (Probit)				
Current Smoker	0.000299*** (0.000110)	0.007	0.1232%	0.1809%
Smoke Everyday	-0.000085 (0.000220)	0.699	-0.0126%	-0.0185%
Drinking				
# Average Drinks (OLS)	0.004877** (0.001899)	0.011	0.1587%	0.2330%
# Times Binge Drinking (OLS)	0.001929 (0.001393)	0.168	0.1197%	0.1758%
Binge drinking (Probit)	0.000180 (0.000123)	0.146	0.0895%	0.1314%
Other Risky Behaviors				
Health Insurance (Probit)	-0.000455*** (0.000133)	0.001	-0.0650%	-0.0954%
Flu Shot (Probit)	-0.000009 (0.000161)	0.955	-0.0036%	-0.0053%
Always Seatbelt (Probit)	-0.000094 (0.000107)	0.380	-0.0112%	-0.0164%
# Times Drunken Driving (OLS)	0.000260 (0.000768)	0.736	0.1313%	0.1929%
Doctor Unaffordability (Probit)	0.000300** (0.000145)	0.038	0.1208%	0.1774%

Abbreviations: Probit, binary probit; OLS, ordinary least square; Any exercise, any exercise in the past 30 days; Moderate (Vigorous) Exercise, any moderate (vigorous) physical activity for more than 10 minutes in a week; # Average Drinks, number of drinks on average on the days of drink; # Times Binge Drinking, number of times of binge drinking in the past 30 days; Doctor Unaffordability, inability to afford seeing a doctor in the past 12 months.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

These estimated effects of changes in housing prices on risky behaviors are all statistically significant and could result in worse contemporaneous health for tenants. For example, table 8 suggests that with a one percent increase in housing values, tenants are 0.13 percent more likely to report being in poor health. In other words, a 30 percent increase in housing prices statistically significantly increases the probability for tenants to be in poor health by 3.9 percent. Tenant's tendencies to suffer from mental distress and engage in risky behaviors (i.e. more drinking and smoking) due to increases in the value of others' equity could be explained by the relative deprivation hypothesis discussed in section 3 and lead to worse overall health. On the other hand, as is also discussed in section 3, with an increase in housing prices, a tenant who wants to buy her own house might have to curtail her spending on other items such as cigarettes and alcohol. She might have to pay off increased mortgage interest or save more money in order to afford her own house. My empirical findings suggesting that tenants increase the net amount of smoking and drinking they engage in, thus support the relative deprivation story rather than the constrained budget story.[32]

6.2. Subgroup analysis of different income level

Tables 10 – 13 report the estimated effects of changes in housing prices on contemporaneous health status across different income levels for homeowners and tenants. Homeowners and tenants are each simply divided by the size of their income into two categories: high income homeowners (tenants) and low income homeowners (tenants), where I use median income as the dividing line for each group. The sample size of the low income sub-sample is

[32] I also examine the contemporaneous effects of MSA unemployment rates on health outcomes and risky behaviors separately for homeowners and tenants. I find no statistically significant effects of unemployment rates on them. The estimated coefficients of unemployment rates are available from the author upon request.

1,116,694 individuals, while for the high income sub-sample it is 655,780 individuals.[33] Table 10 shows that changes in home values are not statistically significantly related to the contemporaneous health status of high income homeowners. However, I find that changes in housing prices have a statistically significant causal relationship with low income homeowners' mental health and obesity, which is shown in table 11. For low income homeowners, a one percent increase in the house price index leads to both a 0.17 percent decline in the number of days suffering from mental distress and a 0.08 percent increase in the probability of being obese. Because these magnitudes and levels of statistical significance are larger than those reported for the full sample of homeowners in table 6, I conclude that the health effects of contemporaneous changes in housing prices are concentrated among low income homeowners.

This result is consistent with the empirical findings of Mian and Sufi (2014) and Mian et al. (2013). They find that households in low income zip codes aggressively borrow money using their homes as collateral and increase consumption substantially when home values rise. Increases in spending on cars and groceries, which are the representative consumption goods in their analysis, may increase the likelihood of being obese among homeowners, considering that many prior studies support a positive association between vehicle travel and obesity (Frank et al., 2004; Courtemanche, 2011).[34] Meanwhile, I find no statistically significant effects of changes in housing prices on other health outcomes, such as self-reported health status, for low income homeowners.

[33] The sample size of low income individuals in the BRFSS is larger than that of high income. This is because the BRFSS asks about household income in ranges and thus I take midpoint of each income range as individual household income, which makes many of the sample clustered at median income as the dividing line share the same income. I arbitrarily assign them to be low income households. Also, non-respondents to income level questionnaires are excluded from the sample size in this analysis.

[34] McCormack and Virk (2014) provide a literature review on the relationship between driving time and distance and weight status.

Table 12 shows that changes in home values have no statistically significant effects on the health outcomes of high income tenants. Conversely, table 13 illustrates that changes in housing prices lead to statistically significant changes in mental health and self-reported general health for low income tenants. For such tenants, a 30 percent increase in the house price index leads to a 7.1 percent increase in the number of days in which they suffer from mental distress and a 5.8 percent increase in the probability of reporting poor health.

Table 10. Estimated effects of changes in house price on health status for high income predicted homeowners

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000050 (0.000102)	0.624	-0.0168%	-0.0240%
Very good	-0.000000 (0.000000)	0.614	-0.0000%	-0.0000%
Good	0.000034 (0.000070)	0.623	0.0144%	0.0206%
Fair	0.000013 (0.000026)	0.624	0.0261%	0.0373%
Poor	0.000004 (0.000007)	0.623	0.0356%	0.0508%
# Physically Unhealthy Days (NB)	0.000006 (0.000859)	0.995	0.0003%	0.0004%
# Mentally Unhealthy Days (NB)	-0.000354 (0.001275)	0.781	-0.0150%	-0.0215%
BMI (OLS)	-0.000021 (0.001168)	0.986	-0.0001%	-0.0001%
Obese (Probit)	-0.000001 (0.000099)	0.993	-0.0005%	-0.0006%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 11. Estimated effects of changes in house price on health status for low income predicted homeowners

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000033 (0.000059)	0.581	-0.0210%	-0.0300%
Very good	-0.000026 (0.000046)	0.581	-0.0085%	-0.0122%
Good	0.000018 (0.000033)	0.581	0.0055%	0.0078%
Fair	0.000026 (0.000046)	0.581	0.0175%	0.0250%
Poor	0.000015 (0.000027)	0.581	0.0244%	0.0349%
# Physically Unhealthy Days (NB)	-0.002022 (0.002504)	0.419	-0.0442%	-0.0630%
# Mentally Unhealthy Days (NB)	-0.004453** (0.001782)	0.012	-0.1183%	-0.1687%
BMI (OLS)	0.001384 (0.001125)	0.220	0.0050%	0.0071%
Obese (Probit)	0.000147* (0.000075)	0.051	0.0528%	0.0754%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 12. Estimated effects of changes in house price on health status for high income predicted tenants

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	0.000081 (0.000282)	0.773	0.0253%	0.0375%
Very good	-0.000006 (0.000020)	0.774	-0.0015%	-0.0022%
Good	-0.000054 (0.000188)	0.773	-0.0242%	-0.0359%
Fair	-0.000018 (0.000062)	0.772	-0.0409%	-0.0606%
Poor	-0.000003 (0.000012)	0.775	-0.0418%	-0.0621%
# Physically Unhealthy Days (NB)	0.002514 (0.002807)	0.370	0.1376%	0.2041%
# Mentally Unhealthy Days (NB)	0.005970 (0.005115)	0.243	0.2059%	0.3055%
BMI (OLS)	-0.000009 (0.003634)	0.998	-0.0000%	-0.0001%
Obese (Probit)	0.000272 (0.000311)	0.383	0.1493%	0.2215%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 13. Estimated effects of changes in house price on health status for low income predicted tenants

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000199** (0.000079)	0.012	-0.1154%	-0.1693%
Very good	-0.000135** (0.000053)	0.011	-0.0504%	-0.0739%
Good	0.000101** (0.000040)	0.011	0.0292%	0.0429%
Fair	0.000169** (0.000069)	0.015	0.1021%	0.1497%
Poor	0.000064*** (0.000024)	0.007	0.1312%	0.1924%
# Physically Unhealthy Days (NB)	0.001132 (0.002843)	0.691	0.0286%	0.0419%
# Mentally Unhealthy Days (NB)	0.007806** (0.003521)	0.027	0.1619%	0.2375%
BMI (OLS)	-0.003071 (0.002604)	0.240	-0.0112%	-0.0164%
Obese (Probit)	0.000044 (0.000109)	0.686	0.0164%	0.0240%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

In order to investigate further the mechanisms behind this reduction in the health of low income tenants, I replicate the analysis on the health behaviors of tenants presented in table 9 for the sub-set of low income tenants and report those results in table 14. According to table 14, among low income tenants, a one percent increase in housing prices leads to a 0.13 percent reduction in the likelihood of doing any exercise, a 0.21 percent increase in the probability of being smoker, a 0.26 percent increase in the number of drinks on average on days of drinking, and a 0.16 percent increase in the probability of being binge drinker. A one percent increase in housing values also result in a 0.12 percent reduction in the probability of having health insurance, and a 0.19 percent increase in the probability of not being able to afford seeing a doctor. These estimated effects are all statistically significant and suggest that increases in risky behaviors is one mechanism through which increases in home values result in worse health for low income tenants. A comparison of table 13 with table 8 suggests that the estimated effects of housing price changes on the health of tenants are concentrated among low income tenants, as was the case with homeowners. These findings are all the more supportive of the relative deprivation story because low income tenants might have a greater sense of deprivation relative to high income tenants with respect to increases in housing values.

One concern is that low income homeowners and tenants tend to live in areas with lower house prices within an MSA. If the house prices in these sub-areas (i.e. counties) move in the opposite direction of the MSA house price, then my empirical results for low income homeowners and tenants might be of incorrect sign. Using the county-level Zillow home value index, I plot Z scores of both average home values across all counties and average home values in the counties of the lowest quartile of time-average home values over time which are displayed in the Appendix figure A1.[35] Z scores provide normalized variations of the home values with a mean of 0 and a standard deviation of 1. Appendix figure A1 shows that both fluctuations in average home values across all counties and average home values in the counties of the lowest quartile of time-average home values move in the same direction during my study period.

[35] The Zillow Home Value Index (ZHVI) is available online [http://www.zillow.com/research/data/#median-home-value].

Table 14. Estimated effects of changes in house price on lifestyle behaviors for low income predicted tenants

Lifestyles	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Exercise (Probit)				
Any exercise	-0.000615*** (0.000210)	0.003	-0.0868%	-0.1272%
Moderate Exercise	-0.000367** (0.000176)	0.037	-0.0443%	-0.0650%
Vigorous Exercise	-0.000269 (0.000227)	0.237	-0.0614%	-0.0901%
Smoking (Probit)				
Current Smoker	0.000360*** (0.000127)	0.005	0.1415%	0.2075%
Smoke Everyday	-0.000123 (0.000224)	0.583	-0.0181%	-0.0265%
Drinking				
# Average Drinks (OLS)	0.005632*** (0.002118)	0.009	0.1792%	0.2628%
# Times Binge Drinking (OLS)	0.001996 (0.001457)	0.173	0.1215%	0.1782%
Binge drinking (Probit)	0.000211* (0.000120)	0.079	0.1092%	0.1601%
Other Risky Behaviors				
Health Insurance (Probit)	-0.000556*** (0.000123)	0.000	-0.0826%	-0.1212%
Flu Shot (Probit)	-0.000037 (0.000172)	0.830	-0.0152%	-0.0222%
Always Seatbelt (Probit)	-0.000142 (0.000120)	0.239	-0.0169%	-0.0248%
# Times Drunken Driving (OLS)	0.000106 (0.000384)	0.784	0.0567%	0.0831%
Doctor Unaffordability (Probit)	0.000352** (0.000152)	0.020	0.1305%	0.1914%

Abbreviations: Probit, binary probit; OLS, ordinary least square; Any exercise, any exercise in the past 30 days; Moderate (Vigorous) Exercise, any moderate (vigorous) physical activity for more than 10 minutes in a week; # Average Drinks, number of drinks on average on the days of drink; # Times Binge Drinking, number of times of binge drinking in the past 30 days; Doctor Unaffordability, inability to afford seeing a doctor in the past 12 months.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

6.3. Long-term effects

I next examine long-term (rather than contemporaneous) effects of changes in a given period's housing prices on future health outcomes controlling for 36 months' lagged terms of housing prices.[36] I find that the maximum long-term effect on self-reported health is realized at about 36 months. However, the maximum long-term effect on obesity is realized earlier at about 24 months. Therefore, I also estimate long-term effects of housing prices on obesity controlling for 24 months' lagged terms of housing prices. Table 15 provides the predicted long-term effect of a one unit change in the house price index on the health outcomes of both homeowners and tenants.[37] Contemporaneous effects displayed in the first columns of table 15 for homeowners and tenants simply restate results from tables 6 and 8 respectively. Compared to the contemporaneous effects, the effects of an increase in housing prices on being obese become stronger for homeowners over time, resulting in worse self-reported health in the long run with a one-year time lag. Both the magnitudes and the levels of statistical significances of those effects are larger in the long term. In addition, the beneficial effect of an increase in home prices on the mental health of homeowners disappears in the long run. On the other hand, the negative effects of an increase in home values on tenants' health outcomes do not persist in the long run either. The negative effects of contemporaneous increases in housing prices on metal distress and self-reported health status of tenants lose strength and statistical significance in the long run. Both the magnitudes and the levels of statistical significances of those effects are smaller in the long term.

[36] In other words, I include not only a contemporaneous housing price variable in this regression, but also 36 additional variables representing housing prices in each of the previous 36 months.
[37] The estimated long-term effects are calculated by using the STATA syntax *lincome*, which provides linear combination of the estimated coefficients on housing prices across all the terms.

Table 15. Estimated long-term effects of changes in house price (predicted effect with respect to a 1 unit change in HPI) on health status for predicted homeowners and predicted tenants (36 months)

Health Outcomes	Predicted Homeowners				Predicted Tenants			
	Contemporaneous	P - value	36 months	P - value	Contemporaneous	P - value	36 months	P - value
Self-reported health (OProbit)								
Excellent	-0.000058 (0.000056)	0.301	-0.000232** (0.000096)	0.015	-0.000147* (0.000077)	0.057	-0.000083 (0.000179)	0.642
Very good	-0.000019 (0.000019)	0.304	-0.000081** (0.000034)	0.017	-0.000088* (0.000046)	0.055	-0.000051 (0.000110)	0.642
Good	0.000040 (0.000039)	0.303	0.000161** (0.000067)	0.016	0.000085* (0.000044)	0.055	0.000047 (0.000101)	0.642
Fair	0.000026 (0.000026)	0.302	0.000108** (0.000045)	0.015	0.000111* (0.000059)	0.061	0.000065 (0.000138)	0.641
Poor	0.000011 (0.000010)	0.299	0.000044** (0.000018)	0.015	0.000039** (0.000020)	0.045	0.000023 (0.000050)	0.645
# Physically Unhealthy Days (NB)	-0.000943 (0.001275)	0.459	0.003707 (0.002303)	0.108	0.001065 (0.002193)	0.627	-0.005291 (0.004909)	0.281
# Mentally Unhealthy Days (NB)	-0.002234** (0.000950)	0.019	0.000557 (0.002085)	0.789	0.007098** (0.003046)	0.020	0.001549 (0.008808)	0.860
BMI (OLS)	0.000812 (0.000800)	0.311	0.001629 (0.001350)	0.229	-0.002591 (0.002368)	0.224	-0.000051 (0.003312)	0.988
Obese (Probit)	0.000080 (0.000072)	0.270	0.000125 (0.000089)	0.158	0.000066 (0.000092)	0.472	-0.000048 (0.000245)	0.844
Obese (Probit) – 24 months			0.000198** (0.000095)	0.038			0.000031 (0.000182)	0.863

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

7. Robustness checks

7.1 Specification Check

As a specification check, I add a vector of MSA-specific linear time trends ($\alpha_j * t$) to my baseline specification given by equation (1) to test for whether or not my results are robust to unobserved factors varying within each MSA over time. The estimated effects of changes in housing prices on contemporaneous health status for homeowners and tenants with the MSA-specific linear time trends are shown in tables 16 and 17, and they turn out to be similar to the estimated results provided in tables 6 and 8 from my baseline specification. The magnitudes, the levels of statistical significance, and the signs of the estimated effects are very similar, which shows that my empirical results are robust to this specification change.

Table 16. Estimated effects of changes in house price on health status for predicted homeowners based on a specification adding MSA-specific linear time trends

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000040 (0.000081)	0.623	-0.0172%	-0.0246%
Very good	-0.000013 (0.000027)	0.624	-0.0036%	-0.0052%
Good	0.000027 (0.000056)	0.623	0.0097%	0.0138%
Fair	0.000018 (0.000037)	0.623	0.0189%	0.0269%
Poor	0.000007 (0.000015)	0.622	0.0203%	0.0290%
# Physically Unhealthy Days (NB)	-0.001487 (0.001295)	0.251	-0.0457%	-0.0653%
# Mentally Unhealthy Days (NB)	-0.002588** (0.001059)	0.015	-0.0862%	-0.1230%
BMI (OLS)	0.000756 (0.008709)	0.386	0.0028%	0.0040%
Obese (Probit)	0.000095 (0.000079)	0.228	0.0385%	0.0549%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 17. Estimated effects of changes in house price on health status for predicted tenants based on a specification adding MSA-specific linear time trends

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000193** (0.000096)	0.045	-0.1019%	-0.1497%
Very good	-0.000116** (0.000058)	0.045	-0.0409%	-0.0601%
Good	0.000111** (0.000055)	0.044	0.0335%	0.0492%
Fair	0.000146* (0.000075)	0.051	0.0963%	0.1414%
Poor	0.000051** (0.000024)	0.032	0.1158%	0.1701%
# Physically Unhealthy Days (NB)	0.000997 (0.001721)	0.562	0.0268%	0.0394%
# Mentally Unhealthy Days (NB)	0.007073** (0.003474)	0.042	0.1538%	0.2259%
BMI (OLS)	-0.003525 (0.002468)	0.155	-0.0129%	-0.0190%
Obese (Probit)	0.000073 (0.000086)	0.399	0.0282%	0.0415%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

7.2. Sensitivity Test

Recall that my homeowner indicator is set equal to 1 for individuals in my BRFSS sample with predicted homeownership values of 70 percent or higher and 0 otherwise. All of those with a 0 for the homeowner indicator are defined to be tenants. This 70 percent rule came from the fact that the share of homeowners in my March CPS sample is about 70 percent. As a sensitivity test, I instead take the highest 75 (65) percent as homeowners and take the lowest 25 (35) percent as tenants and then estimate the effects of changes in housing prices on health status. Tables 18 and 20 provide the estimated effects of changes in housing prices on health outcomes for homeowners based on the 75:25 and 65:35 ratios. Those results appear similar to my baseline homeowner results reported in table 6. For example, a one percent increase in the house price index leads to a decline in the number of days that homeowners suffer from mental distress by a range of 0.11 to 0.12 percent at significance levels that range from 1 to 2 percent across the different specifications. A one percent increase in the house price index also causes an increase in the probability of homeowners' being obese by a range of 0.04 to 0.05 percent at significance levels that range between 16 and 33 percent across the different specifications.

Tables 19 and 21 provide the estimated effects of changes in housing prices on health outcomes for tenants based on the 75:25 and 65:35 ratios. Again, I find the results that appear similar to my baseline tenant results reported in table 8. For instance, a one percent increase in the house price index leads to an increase in the number of days that tenants suffer from mental distress by a range of 0.17 to 0.31 percent at significance levels that range from 1 to 6 percent across the different specifications. A one percent increase in the house price index also causes an increase in the probability of tenants' being poor health by a range of 0.11 to 0.17 percent at significance levels that range from 3 to 5 percent across the different specifications. Interestingly, as the percentage assigned as tenants increases, the negative effects on mental health and self-reported health tend to fall in magnitude and statistical significance. As I move along the distribution of predicted homeownership from assigning the bottom 25 percent to be tenants to the bottom 35 percent, I am likely classifying more homeowners as tenants. This likely attenuates the negative effects on mental health and self-reported health for tenants, which supports my empirical finding that homeowners' mental health tends to improve and their self-reported health is not likely to be influenced by increases in housing prices. Taken together, these results suggest that my baseline findings are not being driven by my cutoff choice in the construction of my homeowner / tenant indicator.

Table 18. Estimated effects of changes in house price on health status for predicted homeowners based on 75:25 ratio of homeownership indicator

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000054 (0.000053)	0.314	-0.0235%	-0.0336%
Very good	-0.000019 (0.000019)	0.317	-0.0053%	-0.0076%
Good	0.000037 (0.000037)	0.316	0.0132%	0.0188%
Fair	0.000025 (0.000025)	0.315	0.0255%	0.0364%
Poor	0.000010 (0.000010)	0.312	0.0284%	0.0406%
# Physically Unhealthy Days (NB)	-0.000747 (0.001174)	0.525	-0.0227%	-0.0325%
# Mentally Unhealthy Days (NB)	-0.002554*** (0.000927)	0.006	-0.0827%	-0.1183%
BMI (OLS)	0.000612 (0.000765)	0.425	0.0022%	0.0032%
Obese (Probit)	0.000091 (0.000065)	0.163	0.0367%	0.0525%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 19. Estimated effects of changes in house price on health status for predicted tenants based on 75:25 ratio of homeownership indicator

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000191* (0.000098)	0.052	-0.1018%	-0.1493%
Very good	-0.000116* (0.000060)	0.052	-0.0415%	-0.0609%
Good	0.000109* (0.000056)	0.052	0.0325%	0.0478%
Fair	0.000148* (0.000078)	0.058	0.0958%	0.1406%
Poor	0.000050** (0.000024)	0.039	0.1152%	0.1690%
# Physically Unhealthy Days (NB)	0.000749 (0.002348)	0.750	0.0203%	0.0298%
# Mentally Unhealthy Days (NB)	0.009715*** (0.003312)	0.003	0.2084%	0.3058%
BMI (OLS)	-0.002749 (0.003089)	0.375	-0.0101%	-0.0148%
Obese (Probit)	0.000042 (0.000132)	0.752	0.0163%	0.0239%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 20. Estimated effects of changes in house price on health status for predicted homeowners based on 65:35 ratio of homeownership indicator

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000044 (0.000066)	0.500	-0.0187%	-0.0266%
Very good	-0.000014 (0.000021)	0.502	-0.0039%	-0.0055%
Good	0.000031 (0.000046)	0.501	0.0112%	0.0160%
Fair	0.000020 (0.000029)	0.501	0.0216%	0.0307%
Poor	0.000008 (0.000012)	0.499	0.0241%	0.0343%
# Physically Unhealthy Days (NB)	-0.001504 (0.001295)	0.245	-0.0472%	-0.0671%
# Mentally Unhealthy Days (NB)	-0.002244** (0.000931)	0.016	-0.0770%	-0.1096%
BMI (OLS)	0.000357 (0.000853)	0.676	0.0013%	0.0019%
Obese (Probit)	0.000072 (0.000074)	0.333	0.0293%	0.0417%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table 21. Estimated effects of changes in house price on health status for predicted tenants based on 65:35 ratio of homeownership indicator

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000125** (0.000060)	0.039	-0.0658%	-0.0968%
Very good	-0.000075** (0.000036)	0.038	-0.0261%	-0.0385%
Good	0.000073** (0.000035)	0.038	0.0222%	0.0326%
Fair	0.000093** (0.000045)	0.041	0.0625%	0.0920%
Poor	0.000034** (0.000016)	0.032	0.0755%	0.1110%
# Physically Unhealthy Days (NB)	0.001385 (0.002094)	0.508	0.0368%	0.0542%
# Mentally Unhealthy Days (NB)	0.005375* (0.002845)	0.059	0.1185%	0.1743%
BMI (OLS)	-0.001738 (0.002225)	0.436	-0.0064%	-0.0094%
Obese (Probit)	0.000063 (0.000090)	0.481	0.0243%	0.0358%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

7.3. Predicted homeownership vs. actual homeownership

As discussed in section 5.2, the matching rate between my predicted homeownership indicator and actual homeownership is 80 percent in my CPS sample while the matching rate between my predicted homeownership indicator and actual homeownership over 2009-2012 is 77 percent in my BRFSS sample. In this sub-section I investigate the extent to which these differences influence my estimated effects of changes in housing prices on health outcomes.

Table 22 provides the estimated percent change in excellent health with respect to a one percent change in housing prices for homeowners and tenants across different income levels using different homeownership information (actual vs. predicted) and different datasets (CPS vs. BRFSS). I compare my baseline results provided in tables 10 – 13 and summarized in column (4) in table 22 to the estimated results based on the actual CPS homeownership indicator using the CPS sample, which is summarized in column (1) in table 22.[38] This comparison is possible because the March CPS also reports self-reported health status of respondents.

There are some minor differences between column (1) and (4) and these differences may be occurring for several reasons. First, the CPS actual homeownership indicator and my predicted homeownership indicator are not exactly the same, as mentioned above. The matching rate between them is not 100 percent but about 80 percent, which could cause a discrepancy between the estimated results in column (1) and the ones in column (4). Second, the March CPS and BRFSS employed in each regressions of column (1) and (4) are different datasets. The CPS focuses on income and employment status of households, although it also surveys self-reported health status whereas the BRFSS focuses on a variety of health outcomes and health behaviors of respondents. In addition, the CPS is an annual survey data whereas the BRFSS is a monthly survey data and the sample size of the BRFSS is almost twice the sample size of the CPS. Therefore, the differences in the estimated effects of housing prices on health outcomes between column (1) and (4) could also result from differences in these datasets.

Given this discussion, it would be informative to separate the differences in these estimates that come from differences in different types of dataset (second reason) from the differences that

[38] The estimated results provided in column (1) are based on the empirical specification of equation (1). The CPS is an annual survey data and thus the time unit for *t* in equation (1) becomes years rather than months. Consequently, the annual house price index and annual unemployment rate are used in the estimation of the results in column (1).

come from differences between actual homeownership and my predicted homeownership indicator (first reason). In order to do that, I first annualize my BRFSS dataset then separately estimate the impact of housing prices on excellent health for both my annualized BRFSS sample (column (3)) and my already annual CPS sample (column (2)). In both columns (2) and (3) I use my predicted homeownership indicator.[39] Thus, the differences in estimates between columns (1) and (2) may be due to the differences between actual homeownership information and my predicted homeownership indicator. The differences in estimates between column (2) and (3) may be due to the differences in the dataset (CPS VS BRFSS). The differences between column (3) and (4) may result from differences in survey periods (monthly vs. annual).

A comparison of columns (1), (2), (3) and (4) allows me to ascertain whether or not my BRFSS results with my predicted homeownership indicator are similar to what I would have found if I had instead used the CPS with either my predicted homeownership indicator or actual homeowner information in the CPS. The fact that the results for low income homeowners and tenants, where most of the action in my analysis appeared to be, are qualitatively similar across these columns suggests that my choice of importing predicted homeownership information from the CPS into the BRFSS is a reasonable one. Use of the BRFSS allows me to analyze mental distress and risky health behaviors that serve potential mechanisms connecting changes in housing prices to changes in overall health. The BRFSS also allows for the use of larger sample sizes, and thus more precise estimates.

[39] The annual BRFSS data for the regressions in column (3) are simply averaged over all monthly BRFSS data within each year.

Table 22. Estimated percent change on being excellent health with respect to a one percent change in house price for high/low income predicted homeowners/tenants using actual/predicted homeownership data from annual/monthly CPS/BRFSS

	CPS		BRFSS	
	(1) **Annual** **Actual Homeownership indicator**	**(2)** **Annual** **Predicted Homeownership indicator**	**(3)** **Annual** **Predicted Homeownership indicator**	**(4)** **Monthly** **Predicted Homeownership indicator**
High Income Homeowners	-0.0112% (p=0.795) [N=419,300]	0.0008% (p=0.983) [N=450,312]	-0.0269% (p=0.578) [N=618,475]	-0.0240% (p=0.624) [N=618,475]
Low Income Homeowners	-0.0707% (p=0.130) [N=266,220]	-0.0448% (p=0.442) [N=238,819]	-0.0193% (p=0.748) [N=760,956]	-0.0300% (p=0.581) [N=760,956]
High Income Tenants	0.0872% (p=0.378) [N=76,370]	0.0206% (p=0.855) [N=45,358]	0.1357% (p=0.360) [N=36,689]	0.0375% (p=0.773) [N=36,689]
Low Income Tenants	-0.1047%** (p=0.045) [N=221,370]	-0.1435%** (p=0.011) [N=248,771]	-0.1616%*** (p=0.006) [N=354,826]	-0.1693%** (p=0.012) [N=354,826]

Notes: 1. CPS provides actual homeownership data but BRFSS doesn't until 2009 whereas BRFSS provides monthly data but CPS doesn't.
2. Numbers in parenthesis are (p) value as a measure of statistical significance and sample size [N] respectively.
3. Non-respondents to self-reported health questionnaires are excluded from the sample size in this analysis.

8. Conclusion

In this paper I estimate the effects of housing prices on a variety of health outcomes and many specific risky health behaviors separately for U.S. homeowners and tenants during the time period before, during, and after the Great Recession. I find positive contemporaneous results for homeowners in terms of their health and negative results for tenants. I also find evidence of statistically significant increases in contemporaneous risky health behaviors associated with increases in home values among tenants, which may be driving the reduction in their contemporaneous health status. Interestingly, my results suggest that most of the action in terms of health and behaviors are concentrated among low income homeowners and tenants. In the long run, the effects of an increase in housing prices on being obese become more pronounced for homeowners, resulting in worse self-reported health. In addition, the beneficial effect of an increase in home value on the mental health status of homeowners disappears. Finally, the negative effects of an increase in housing prices on tenants' health outcomes do not persist in the long run.

These results suggest that any analysis of changes in housing prices should consider the spillover effects of such prices changes on the health of both homeowners and tenants. In addition, any analysis of the impact of economic changes on health outcomes should consider the role of changes in housing prices that can impact both health outcomes and risky health behaviors. Such an analysis is especially appropriate during my study period since it includes both the run up and the bursting of the housing bubble during the Great Recession. Accordingly, these findings have some policy implications. Governmental subsidies such as the low-income housing tax credits for providers of housing reserved for low income tenants and voucher programs that directly subsidize consumers of low-income housing could improve tenants' health. Taking such spillovers into account is one example of a "health-in-all-policies" approach to policymaking.

My analysis contributes to the literature in several ways. First, I consider the impact of housing price changes on both homeowners and tenants. This is important to note since I find negative short run health impacts for tenants, despite the fact that they are typically ignored in the literature in favor of a focus on homeowners. Second, I consider both short run and longer run health impacts of housing price changes. This is important given that negative health impacts for homeowners only manifest themselves in the long run, while the negative health impacts on tenants tend to disappear in the long run.

Of course, this work is subject to some limitations. The BRFSS is not a panel but rather a repeated cross sectional dataset that does not track the same individuals over time. Therefore, migration bias could occur if a substantial number of people moved to a different metropolitan area just prior to being surveyed. MSA-level analysis could mitigate the issue relative to county-level analysis because the metro-to-metro migration rate is smaller than the county-to-county migration rate.[40] In addition, the BRFSS does not survey non-housing wealth and individuals' debt such as mortgage liability, which restricts my ability to do a more comprehensive study of how different types of equity and debt influence individuals' risky behaviors and health outcomes.

My empirical findings regarding the significant effects of changes in housing prices on risky behaviors and health outcomes for low income tenants provide reasonable evidence to support a strong and negative association between relative deprivation in wealth and health. Therefore, my future research will focus on how changes in housing values interact with varying predicted homeownership values and influence individuals' risky behaviors and health outcomes within different regional reference groups. This will enable me to shed light on the relationship

[40] According to US Census (2015), 8.5 million people moved to a different metropolitan area whereas 16.7 million people moved to a different county in 2014 which is approximately 2.6 percent and 5.2 percent of the US population respectively [https://www.census.gov/newsroom/press-releases/2015/cb15-145.html].

between wealth inequality and health, a relationship that has been recognized as important but has not yet been quantified.

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Appendix

Table A1. Estimated effects of changes in house price on health status for predicted homeowners in a specification controlling for individual income

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000051 (0.000054)	0.339	-0.0219%	-0.0313%
Very good	-0.000018 (0.000019)	0.342	-0.0050%	-0.0072%
Good	0.000037 (0.000039)	0.340	0.0133%	0.0189%
Fair	0.000024 (0.000025)	0.339	0.0252%	0.0359%
Poor	0.000009 (0.000009)	0.338	0.0261%	0.0373%
# Physically Unhealthy Days (NB)	-0.001116 (0.001263)	0.377	-0.0343%	-0.0490%
# Mentally Unhealthy Days (NB)	-0.001887* (0.000985)	0.055	-0.0628%	-0.0897%
BMI (OLS)	0.000687 (0.000810)	0.398	0.0025%	0.0036%
Obese (Probit)	0.000074 (0.000073)	0.306	0.0300%	0.0428%

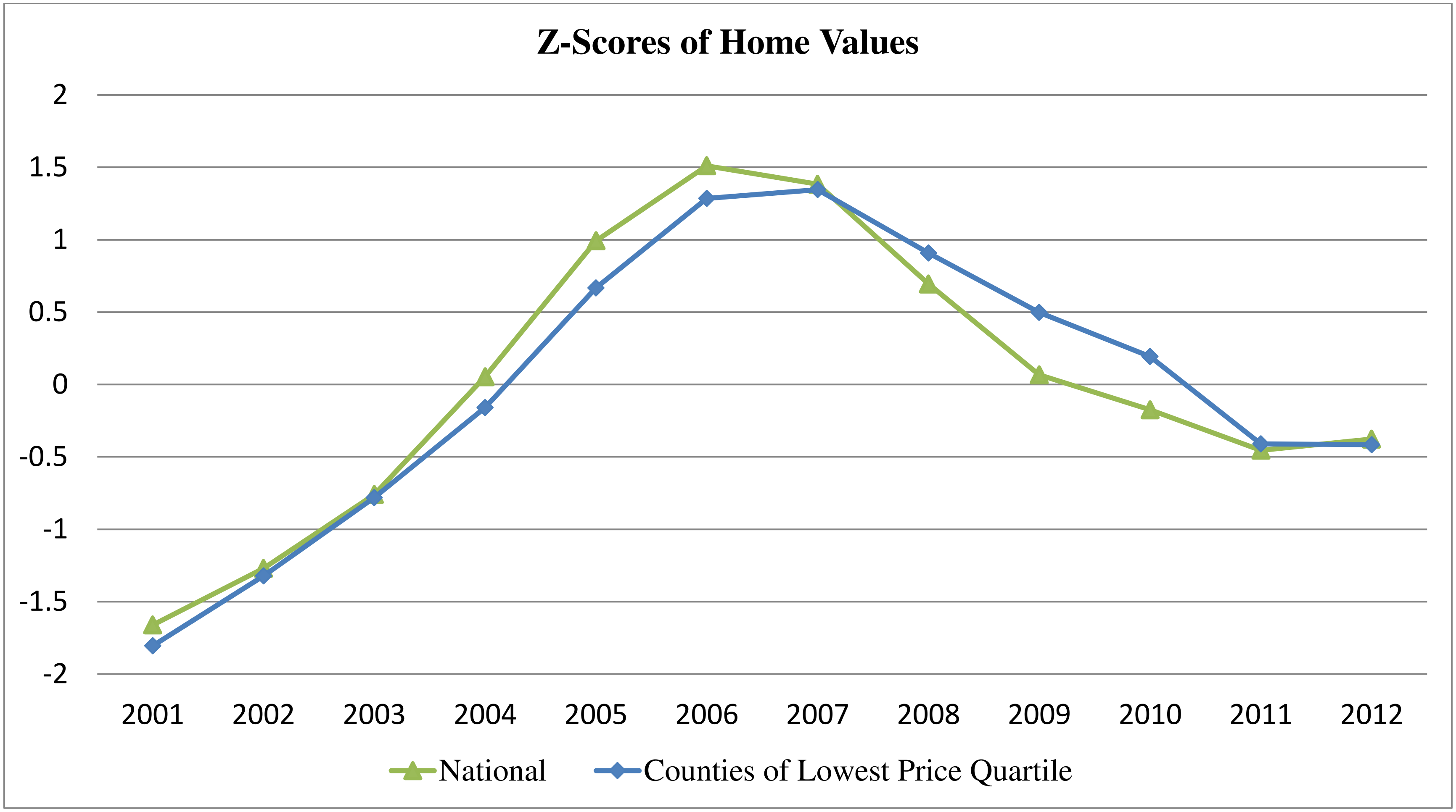
Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Table A2. Estimated effects of changes in house price on health status for predicted tenants in a specification controlling for individual income

Health Outcomes	Predicted effect (1 unit change in HPI)	P-value	Percent change (1 unit change in HPI)	Percent change (1% change in HPI)
Self-reported health (OProbit)				
Excellent	-0.000147* (0.000078)	0.060	-0.0776%	-0.1140%
Very good	-0.000092* (0.000049)	0.058	-0.0325%	-0.0477%
Good	0.000088* (0.000047)	0.058	0.0265%	0.0390%
Fair	0.000114* (0.000062)	0.065	0.0752%	0.1104%
Poor	0.000037** (0.000019)	0.046	0.0840%	0.1234%
# Physically Unhealthy Days (NB)	0.000358 (0.002071)	0.863	0.0096%	0.0142%
# Mentally Unhealthy Days (NB)	0.006770** (0.002950)	0.022	0.1472%	0.2162%
BMI (OLS)	-0.002892 (0.002276)	0.206	-0.0106%	-0.0156%
Obese (Probit)	0.000066 (0.000092)	0.474	0.0255%	0.0375%

Abbreviations: OProbit, ordered probit; NB, negative binomial; OLS, ordinary least square; Probit, binary probit; # Physically (Mentally) Unhealthy Days, number of physically (mentally) unhealthy days during the past 30 days, BMI; body mass index.
Note: Standard errors, clustered by MSA, are in parenthesis.
*** represents statistical significance at the 1% level.
** represents statistical significance at the 5% level.
* represents statistical significance at the 10% level.

Figure A1. Fluctuations in Average Home Values across All Counties VS. Fluctuations in Average Home Values in the Counties of the Lowest Quartile of Time-Average Home Values



Source: Zillow Home Value Index (ZHVI)