Housing Wealth, Health and Deaths of Despair*

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Abstract

We use household-level data to study the causal effects of exogenous changes in housing wealth on health and the drug crisis in the US attributed to "deaths of despair". We find that a one standard deviation positive shock in housing wealth increases the probability of an improvement in self-reported health (mental health) by 1.0 (1.10) percentage points and decreases the change in drug-related mortality rate by 4.3 percent. We also find that the impact of housing wealth on health varies across socioeconomic groups and is more pronounced in MSAs in which housing supply is more inelastic, which explains the differential effect of economic cycles across geographical areas. Our results suggest that housing-related policies could have important implications for general health outcomes as well as for the opioid crisis.

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1 Introduction

Do housing shocks affect population health? If so, does housing wealth play a role in the US opioid crisis that has tripled the drug-related death rate since 1999?[1] Although the relationship between wealth and health has been extensively reported in the literature, little is known about its causality. The attention on this relationship has been magnified by the recent dramatic increase in "deaths of despair", that is the increase in drug overdoses and alcohol-related deaths that have shortened the lifespan of white non-Hispanic Americans for the first time after decades of progress.[2] In this paper, we use unexpected shocks in housing wealth as an important unexplored driver that explains the effect of wealth on different measures of health such as self-reported health (SRH), limitations in activities of daily living (ADLs), drug-related mortality rates, suicide rates, and alcoholic-related liver mortality rates, as well as their socioeconomic and geographic differences.

We use household-level data from the Panel Study of Income Dynamics (PSID) to exploit a quasi-natural experiment to analyze the causal relationship between wealth and health. We use the fact that housing wealth is the most important part of households wealth. It accounts for almost two thirds of the total wealth of the median household in the US (Federal Reserve Board) where the home ownership rate is 64.2% (Federal Reserve Bank of St Louis). To determine causality, we create a measure of unexpected shocks in housing wealth. This measure builds upon the fact that households tend to misestimate the value of their houses and they only discover their true market value when they sell them.[3] Therefore, households that overvalue (undervalue) their houses experience an unexpected negative (positive) shock in their housing wealth when they sell their houses. This unexpected shock in housing wealth is what we define as the realization of housing wealth misestimation (RHWM). The magnitude of this shock is very large: 25% of the households in our sample overvalue their house by 9% or more, while 25% of the households undervalue their houses by at least 11%.[4]

[1] Hedegaard et al. (2017) document that the age-adjusted rate of drug-overdose has increased from 6.1 per 100,000 in 1999 to 19.8 per 100,000 in 2016.

[2] Case and Deaton (2015, 2017) named this crisis "deaths of despair". They suggest that this increase has been due to difficult social and economic environments that have led to cumulative disadvantage over time.

[3] See Kish and Lansing (1954); Follain and Malpezzi (1981); Goodman Jr and Ittner (1992); Agarwal (2007); Benítez-Silva et al. (2015); Kuzmenko and Timmins (2011); Corradin et al. (2017).

[4] Housing wealth misestimation is large, even with the proliferation of online real estate appraisals such as Zillow, as well as the existence of real estate municipal tax assessments and appraisals for extracting home equity value. Zillow documents that 45.6% (25.5%) of Zillows estimates are off by 5% (10%) or more (see https://www.zillow.com/zestimate). Moreover, the geographical variation is sizable. For example, 32.7% (14.7%)

There could be three types of concerns related to the causal interpretation of a RHWM shock. First, one might worry that our results are driven by households that decide to move for health reasons. To address this concern, we perform a two sample t-test and find that those who move do not have a statistically different health status from those who do not move. Moreover, we control for the health of the head of the household in all our specifications. Second, these unexpected wealth shocks must be truly unexpected. Maybe households that significantly overestimate their houses may not sell them because they are loss averse. Therefore, we test whether households only realize their house wealth misestimation when they sell their house and we show that RHWM is actually an unexpected shock. Third, unexpected wealth shocks must be independent of any unobserved heterogeneity in health changes. For this reason, we control for variables such as initial health, housing wealth, number of family members in the household, and employment status to address reverse causality concerns. Moreover, house market changes may not only affect house prices but also correlate with prices of other wealth holdings. We show that our results are robust when controlling for the fraction of wealth held in stocks and in housing. Finally, it could be that those who move and sell their house at a large discount are different for those who move and sell at a profit. For example, those who loose their jobs might be forced to move and sell their house at a large discount and, therefore, have a negative wealth shock. We have performed tests to show that there are no significant differences among socioeconomic and demographic characteristics between households that experience a positive or negative wealth shock when moving. Overall, our results suggest that there is causality between housing wealth and health outcomes.

We find that housing is an important channel to understand the causal effects of wealth on a broad range of health outcomes.[5] Our results show that a one standard deviation positive shock in housing wealth increases the probability of an improvement in SRH by 1.0 percentage points. A shock of the same size leads to a 1.10 percentage points decrease in the probability of increasing the number of limitations in mental ADLs suffered by an individual. Moreover, we find that a one standard deviation positive change in housing wealth decreases the change in drug-related mortality rate by 4.3 percent. We do not find significant equivalent results for alcohol or suicide death rates.

of Zillows estimates are off by 5% (10%) or more in Phoenix, while 62.1% (44.9%) of Zillows estimates are off by 5% (10%) or more in New York.

[5]We define change in health outcome as the difference in health from two years after the unexpected wealth shock to the year of the wealth shock (i.e., when the household moves). This definition addresses a potential concern related to the fact that health shocks might trigger moving houses.

We also show that these effects are different across geographical areas. Specifically, the impact of wealth on health is higher in Metropolitan Statistical Areas (MSAs) in which housing supply is more inelastic because unexpected shocks in housing wealth tend to be greater in those MSAs.

Our approach contributes to the previous research in three main ways. First, we contribute to the literature that investigates the causal link between wealth and health. RHWM provides a shock in wealth that is: (i) unexpected, (ii) sizable, and (iii) that affects a broad set of the population. Despite an extensive literature on the relationship between socioeconomic status (SES) and health (see Cutler, Lleras-Muney, and Vogl (2008) for an extensive summary of this literature[6]) the main difficulty is that SES can affect health and vice versa. On the one hand, lower income or wealth may lead to a decline in health through, for instance, a worsening of the individuals diet, or a reduction in access to medical care and a corresponding delay in the detection of medical conditions (Ettner (1996); Smith (1999); Currie et al. (2010)). On the other hand, people in worse health may find it difficult to go to work every day and, as such, are more likely to have low income or wealth (Wu (2003); Currie and Madrian (1999); McClellan (1998)).

The extant literature on the causal wealth-health link has used data on lottery winners (Lindahl (2005); Gardner and Oswald (2007); Apouey and Clark (2015); Brot-Goldberg et al. (2017)), inheritance (Meer et al. (2003); Kim and Ruhm (2012)), and changes in stock (McInerney et al. (2013); Schwandt (2018a)) and house prices (Fichera and Gathergood (2016)) to create settings as close to a natural experiment as possible. The main problem with studies of lottery winners is the low number of winners relative to the total population. The main concern with studies of inheritance is that an inheritance can be anticipated. An inheritance is not a random event. Households that receive a bequest are more likely to come from wealthy families and, hence, their health endowments might differ from those of households that do not inherit. Finally, the problem with studying changes in stock and house prices is that not all such changes come as unexpected shocks. In fact, the financial economics literature shows that investors are aware of return predictability and the existence of fat tails in stock returns (Bossaerts and Hillion (1999); Lettau and Ludvigson (2001)) and house prices are characterized by persistence and a high degree of predictability (Fischer and Stamos (2013); Corradin et al. (2013)).

[6] Adler et al. (1994); Backlund et al. (1999); Chandola (2000); Contoyannis et al. (2004); Cutler et al. (2010); Cutler et al. (2016); Feinstein (1993); Golberstein et al. (2016); Humphries and Van Doorslaer (2000); Lewis et al. (1998); Lleras-Muney (2005); Meara (2001); Meer et al. (2003); Wilkinson and Marmot (2003)

To address potential endogeneity and measurement error concerns with our measure of RHWM, we provide a valid instrumental variable (IV) for wealth shocks based on the interaction of interest rates and the geographical determinants of elasticity of housing supply calculated by Saiz (2010) using satellite-generated data on terrain elevation and presence of water bodies. The reasoning for the use of this interaction is as follows. When interest rates decrease, demand for housing increases. As markets can adjust prices and quantities, ceteris paribus, this increase in demand translates into higher real estate prices in areas where supply is more inelastic. This can translate into a larger underestimation of a houses true value and a larger positive wealth shock if the owners decide to sell. Although IVs based on housing-supply elasticity have previously been used in the literature to instrument local real estate prices (e.g., Himmelberg et al. (2005); Mian and Sufi (2011); Chaney et al. (2012); Cvijanović (2014)), they have never been used to analyze the impact of wealth on health status.

Our second contribution is the study of the impact of unexpected shocks in housing wealth on a broad range of health outcomes: SRH, total limitations in ADLs, limitations in mental ADLs, drug-related death rates, and alcohol and suicide related death rates. By looking at different measures of health outcomes, we can study the causes of the deaths of despair. Case and Deaton (2017) provide a first alternative explanation for the recent increase in deaths of despair. They suggest that deaths of despair respond more to prolonged economic conditions than to short-term fluctuations, and especially social dysfunctions that come with prolonged economic distress.

A second alternative explanation focuses on supply-side elements and on the fact that there might have been changes in the availability of risky drugs. In this regard, Ruhm (2018) finds that changes in the drug environment are an important aspect of the crisis. A distinguishing feature of the current epidemic of drug abuse is that many overdoses and deaths can be attributed to legal opioids that were prescribed by physicians.

In our paper, we explore another potential mechanism: unexpected shocks in housing wealth. To our knowledge, this paper is the first to document the impact of housing wealth shocks on the current US opioid crisis. To account for the two alternative explanations for the recent deaths of dispair, we control for various economic factors related to labor markets the economic environment and for several law changes in the US such as the introduction of the marijuana law, or the implementation of prescription drug monitoring programs.

Our third contribution is related to the study of the geographical variation of the effect of wealth on health outcomes and the "deaths of despair". Housing wealth is a channel through which macroeconomic shocks have different health outcomes across geographies. Ceteris paribus economic cycles have a more pronounced impact on health in MSAs where housing supply is more inelastic because unexpected shocks in housing wealth are larger in those MSAs. For example, a positive shock in demand experienced by households located in the most inelastic MSAs, such as Miami, Los Angeles-Long Beach, San Francisco, and New York, leads to a higher probability of a health improvement than a demand shock of the same magnitude experienced by those located in the top elastic MSAs, such as Cincinnati, Atlanta, San Antonio, and Oklahoma City.

The remainder of the paper is structured as follows. Section 2 describes the empirical data, which includes the description of our measure of unexpected shocks in wealth. Section 3 provides a detailed description of the empirical strategy. Section 4 presents the results. Finally, section 5 concludes.

2 Data

We use data from the Panel Study of Income Dynamics (PSID), which follows a nationally representative sample of U.S. households. The PSID contains data at the individual and family-unit levels.[7] Our dataset covers the characteristics of the head of household from 1984 to 2013.[8] Moreover, we link the PSID household-level data to health outcomes at the county-level (e.g., change in drug-induced, alcohol-induced, and suicide death rates) from the Center for Disease Control (CDC) for the analyses related to deaths of despair. Table 1 presents the summary statistics and the description of the variables used in our analysis.

[INSERT TABLE 1 HERE]

[7] Panel Study of Income Dynamics, restricted use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2017). The collection of data used in this study was partly supported by the National Institutes of Health under grant number R01 HD069609 and R01 AG040213, and the National Science Foundation under award numbers SES 1157698 and 1623684.

[8] As we focus on the SRH of the head of the household, we drop observations that indicate a change in age of more than five years from one period to the next. We also remove observations with a negative change in age.

2.1 A measure of unexpected shocks in wealth: realization of housing wealth misestimation (RHWM)

We analyze whether a shock in wealth is related to a change in health. Ideally, this shock should be unexpected in order to determine causality. As housing wealth accounts for almost two thirds of the total wealth of the median household (Iacoviello (2012)), it is the most important part of households total wealth. We create a measure of unexpected shocks in housing wealth that builds upon the fact that households tend to misestimate the value of their houses (Kish and Lansing (1954); Follain and Malpezzi (1981); Goodman Jr and Ittner (1992); Agarwal (2007); Benítez-Silva et al. (2015); Kuzmenko and Timmins (2011); Corradin et al. (2017)) and they only discover their true market value when they sell them. Therefore, households that overvalue (undervalue) their houses experience an unexpected negative (positive) shock in their housing wealth when they sell their houses. This unexpected shock in housing wealth is what we define as the realization of housing wealth misestimation ($RHWM_{it}$) for a household i at time t.

We could simply measure $RHWM_{it}$ as the difference between the house selling price and the answer to the question in PSID (i.e., "Could you tell me what the present value of this house (farm) is? I mean about what would it bring if you sold it today?") in the previous period. However, PSID does not provide information on the selling price of the house.[9] Therefore, to calculate the $RHWM_{it}$, we need to build a measure of housing wealth misestimation. To do so, we follow Corradin et al. (2017) and we compare data on reported house values from the PSID –which includes the dollar amount of home improvements– to market house values calculated as the initial buying price of the house updated by the zip code level CoreLogic Home Price Index (HPI).[10] CoreLogic HPI is a repeated-sales index calculated using the market values for house transactions in the same zip code. We define housing wealth misestimation (HWM_{it}) for a household i at time t as the difference between the reported house value and its estimated market value. Hence, HWM is zero at the time of a housing transaction.[11]

[9] If a household sells its house and buys a new one between years $t-1$ and t, we can only obtain its declared value of the previous house at time $t-1$ (before selling it) and the transaction price of the new house at time t. This declared value at time $t-1$ may be misestimated.

[10] The main assumption is that house prices evolve the same way within the zip code. Notice that the impact of house specific characteristics is already included in the initial. As in Corradin et al. (2017), we adjust the house values reported in PSID for home-improvement expenses that households report in the same survey.

[11] In Appendix B, we show an analysis of the variation of HWM between and within households.

If household i does not move in a given year t, then $RHWM_{it}$ takes a value of zero because the household is unaware of its misestimation (i.e., they only discover the true market value of the house when they sell it). Therefore, $RHWM_{it}$ is zero most of the time because most households do not move often. If household i moves in a given year t, then $RHWM_{it}$ is the difference between the market value at which the house is sold and the reported value of the house in the previous period. Therefore, $RHWM$ will be positive when the household undervalues its house (i.e., it experiences a positive unexpected shock on wealth when it sells the house) and negative when it overvalues its house (i.e., it experiences a negative unexpected shock on wealth when it sells the house.) $RHWM$ will only be different from zero for those households that move when they move. In summary, $RHWM$ represents an unexpected shock on the familys wealth. It is expressed in tens of thousands of dollars, and its mean value for our sample is 0.0047. Figure 1 presents a sketch of how our measure of $RHWM$ is created.

[INSERT FIGURE 1 HERE]

2.2 Health outcomes

We use different measures of health outcomes. The first one of them is the change in self-reported health (SRH). This variable takes a value of 1 if SRH improves two years after the unexpected wealth shock, a value of -1 if it worsens, and a value of 0 if there is no change. This approach follows previous literature (see Ruhm (2018), Kim and Ruhm (2012) or Schwandt (2018b), for instance). SRH is obtained from the answer to the following question in the PSID: "Would you say your health in general is excellent, very good, good, fair or poor?". We code the answer using a 1 to 5 scale, with 5 being "excellent," 4 being "very good," 3 being "good," 2 being ''fair," and 1 being "poor." Previous research shows that SRH is a good predictor of mortality and of other health outcomes, with people who rate their health as poor being more likely to die or to have a bad health outcome (Long and Marshall (1999); Mossey and Shapiro (1982); Kaplan et al. (1988); Idler et al. (1990); McFadden et al. (2008)). We use a two-year period because of data restrictionsstarting in 1999, the PSID was undertaken every two years instead of every year. The average change in SRH for a period of two years for the sample used in our study is -0.0204. Notice that we define change in health outcome as the difference in health from two years after the unexpected wealth shock to the year of the wealth shock (i.e., when the household moves). This definition addresses a potential concern related to the fact that health shocks might trigger moving houses.

We also include also some additional measures of health outcomes: the change in the number of limitations in activities of daily living (ADLs) and the change in mental ADLs.[12] These variables aim at measuring the difficulty an individual may have in executing common daily activities. The PSID questions in this regard are of the form because of a health or physical problem, do you have any difficulty [doing an ADL]?[13] We also include three limitations in mental capacities.[14] As before, the variable takes the value of 1 if the number of limitations increases, 0 if it stays the same and -1 if it decreases. These data come from the PSID and starts in 1999.

We also look at the impact on drug-related deaths, alcohol-related deaths and nondrug suicides. We obtain this data from the Multiple Cause of Death files (Center for Disease Control), that identifies death certificates with a single underlying cause of death.[15] We follow Ruhm (2018) to classify ICD-10 codes into the 3 different groups. Thus, drug poisoning deaths include ICD-10 codes X40-X44, X60-X64, X85, Y10-Y14 and Y352. Alcohol-related deaths through liver diseases are given by ICD-10 code K70, and nondrug suicides are defined as ICD-10 codes X65-X84, Y87.0 and *U03. Our analysis includes data at the county level from the year 2000 onwards, since earlier ICD-9 categories are not exactly equivalent to ICD-10 codes (Anderson et al. (2001)). We link this county-level data to each household in the PSID sample.

The number of deaths belonging to each group is converted into mortality rates per 100,000 people using Census population data. The number of deaths belonging to each group is converted into mortality rates per 100,000 people using population census data. Moreover, since our data include years where population changes could be significant due to shocks such as hurricanes Katrina and Rita in 2005, we also realize robustness checks using population data corrected by such shocks

[12] In the PSID data there are many variables related to health outcomes. For instance, there is information about specific health conditions such as strokes, cancer, high blood pressure, and diabetes in PSID. Instead, we use the most common composite measures of health status in the health economics literature: (1) SRH, (2) total ADLs, and (3) mental ADLs. Moreover, we have long time series of the variables that we need to calculate SRH and ADLs in the PSID data.

[13] The list of activities asked at the PSID are: bathing or showering, dressing, eating, getting in or out of bed or a chair, walking, getting outside, using the toilet, preparing own meals, shopping for personal toilet items or medicines, managing own money, using the telephone, doing heavywork, doing lightwork.

[14] "Has a doctor ever told you that you have... Any emotional, nervous, or psychiatric problems?"; "...loss of memory or loss of mental ability?"; "...a learning disorder?"

[15] See https://wonder.cdc.gov/mcd.html.

from the National Cancer Institutes Surveillance Epidemiology and End Results (SEER).[16]

2.3 Control variables

Healthy is a dummy variable created from the SRH variable. It takes a value of 1 if the individuals SRH is excellent, very good, or good. It takes a value of 0 if the individuals SRH is fair or poor. This allows us to control for the health of the individuals at the moment when the house is sold.

We include house value, which is the reported house value in PSID, in order to control for the initial wealth of the individuals. It is expressed in hundreds of thousands of dollars. We also include demographic and socioeconomic variables in our empirical analyses to control for income, age, gender, race, education, and employment status. We also use the number of family members living in the household. Finally, we add year and region (west, midwest, south and northeast) fixed effects. Table 1 provides the detail description and the main statistics of these variables. Note that we are interested in exploiting the geographical variation of our panel data. For this reason, we use an IV that is based on differences in the geographical housing supply across MSAs. Therefore, we use controls at the household level whenever is possible.[17]

To control for variables that might affect the supply-side of deaths of despair, we follow Ruhm (2018) and include the following controls. First, we control for the number of hospital beds from the Area Health Resource Files database.[18] Second, we control for changes in the effects of international trade are included through two variables of exposure to Chinese import competition. This measure was first constructed by Acemoglu et al. (2016), and is offered at the Commuting Zone level. Within a Commuting Zone, all counties are assumed to have the same level of import exposure.[19] Moreover, we use a dummy variable for the size of the county developed by the USDA Economic Research Service (ERS) County Level Data Sets for year 2013.[20]

Finally, we control for two dummy variables that serve as indicators of state-level legal framework related to drug use are also included in this category. One of them looks at the existence of a prescription drug monitoring program (PDMP), an electronic database that provides information

[16] See https://seer.cancer.gov/popdata.

[17] We also show that our results are robust to the control for portfolio choice characteristics at the household level such as the ratio of housing to net wealth and stock holdings over total net wealth. Table A-1 in the Appendix reports these results.

[18] See http://www.arf.hrsa.gov.

[19] See http://www.ddorn.net/data.htm.

[20] See https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data.

about prescribing and patient behavior. The other dummy variable takes value 1 if marijuana has been legalized in a state at a certain year for medical or recreational purposes, and value 0 otherwise. Both indicators are obtained from the Prescription Drug Abuse Policy System.[21]

3 Identification Strategy and Empirical Approach

In this section we describe the identification strategy and our empirical approach. We want to test whether unexpected shocks in the wealth of individuals have an effect on their future health. Our main dependent variable is the change in SRH at the household level. As detailed in the previous section, this variable can take three values: -1 if there is a decline in SRH, 0 if SRH does not change, and +1 if SRH improves. As SRH is an interval-coded variable, our analysis is based on an ordered probit.[22]

We are interested in estimating $E(y^*|x) = x \cdot \beta$, where $a_1 \leq a_2$ are the known cell limits:

$$y = -1 \text{ if } y^* \leq a_1,$$

$$y = 0 \text{ if } a_1 \leq y^* \leq a_2, \text{ and}$$

$$y = +1 \text{ if } a_2 \leq y^*,$$

where we assume that $y^*|x \sim Normal(x\beta, \sigma^2)$ and that $\sigma^2 = Var(y^*|x)$ does not depend on x.

Our basic specification is the following:

$$\Delta H_{i,t+\tau} = \alpha + \beta RHWM_{it} + \delta H_{it} + \lambda W_{it} + \theta \Sigma X_{it} + \gamma_t + u_i + \epsilon_{ti}, \quad (1)$$

where i and t denote the head of the household and the time dimension, respectively. The dependent variable, $\Delta H_{i,t+\tau}$, is a measure of the change in health of the head of the household i from time t to time $t + \tau$.

Let $RHWM_{tj}$ denote the realization of housing-wealth misestimation in year t for head of family i. This is our variable of interest, as it captures the exogenous, unexpected shock in wealth. This

[21] See http://www.pdaps.org.

[22] An alternative approach could be to use interval regressions. Both methodologies produce coefficients of the same significance and order of magnitude, and have a similar fit in terms of log-likelihood. Although our empirical analysis is based on an ordered probit approach, we present results for both methodologies in the next section.

variable will only be different than zero when households move. Therefore, $RHWM$ will only be different from zero for those households that move at the year that they move. This identification strategy allows us to identify the impact of house wealth misestimation for households that move.

In equation (1), H denotes the level of health just before the shock and W is the level of housing wealth. X includes all relevant socio-demographic characteristics of the individuals that could have an impact on health status: age, sex, education, and race. We also include variables that could have an impact on the decision to move and, hence, on the realization of housing wealth misestimation, such as employment status and number of family members. γ_t refers to time effects, u_j denotes family fixed effects, and ϵ_{ti} is the error term.

The ordered probit estimation is then as follows:

$$\begin{aligned} P(\Delta H_{i,t} = -1|RHWM_{it}, H_{it}, W_{it,}X_{it}) &= P(\Delta H^*_{i,t+\tau} \leq a_1|RHWM_{it}, H_{it}, W_{it,}X_{it}) = \\ &= \Phi(a_1\beta RHWM_{it} + \delta H_{it} + \lambda W_{it} + \theta\Sigma X_{it}) \end{aligned} \tag{2}$$

$$\begin{aligned} P(\Delta H_{i,t+\tau} = 0|RHWM_{it}, H_{it}, W_{it,}X_{it}) &= P(\alpha_1 < \Delta H^*_{i,t+\tau} \leq a_2|RHWM_{it}, H_{it}, W_{it,}X_{it}) = \\ &= \Phi(a_1\beta RHWM_{it} + \delta H_{it} + \lambda W_{it} + \theta\Sigma X_{it}) - \Phi(a_2\beta RHWM_{it} + \delta H_{it} + \lambda W_{it} + \theta\Sigma X_{it}) \end{aligned} \tag{3}$$

$$\begin{aligned} P(\Delta H_{i,t} = +1|RHWM_{it}, H_{it}, W_{it,}X_{it}) &= P(\Delta H^*_{i,t+\tau} > a_2|RHWM_{it}, H_{it}, W_{it,}X_{it}) = \\ &= 1 - \Phi(a_2\beta RHWM_{it} + \delta H_{it} + \lambda W_{it} + \theta\Sigma X_{it}) \end{aligned} \tag{4}$$

In some specifications, our dependent variable is quantitative (e.g., changes in drug related rates, and changes in alcohol or suicide related rates) rather than qualitative. In such cases, we use a standard panel OLS specification.

4 Empirical Results

4.1 Impact of an unexpected wealth shock on health: Baseline results

This section shows the baseline results of our study. First, Table 2 presents the estimates of the effect of levels and changes in housing wealth on the change in several health outcomes. Results shows that there is a positive relationship between housing wealth and health. However, establishing a causal link requires the identification of an unexpected housing wealth shock. In the reminder of this section, we address the causal link between housing wealth and health.

[INSERT TABLE 2 HERE]

Table 3 presents the baseline estimates of the effect of an unexpected housing wealth shock (i.e., RHWM) on the change in several health outcomes using different control variables in various specifications. Columns [1] and [2] in panel A show the ordered probit estimates on changes in SRH. The first column controls only for the main effects, i.e., initial house value, year and division fixed-effects. In column 2, we add a broad set of demographics.[23] Specifications [3] and [4] present the results of a RHWM shock on the change of the number of limitations in ADLs as well as on the number of mental impairments. Finally, the rest of expressions present the effects of the unexpected shock in housing wealth on the change of deaths of despair measured as drug-related deaths rates and alcohol and suicide death rates.

[INSERT TABLE 3 HERE]

In specifications [1] and [2] the coefficient for RHWM is positive and statistically significant, indicating that a positive housing wealth shock leads to a significant change in self-reported health. Panel B in Table 3 shows that the corresponding marginal effect of a positive shock in housing wealth (i.e., an increment in RHWM) on the probability of a health improvement is 0.0042. In other words, if households experienced a one standard deviation positive shock in housing wealth, their probability of improving their health in the next period increases by 1.00 percentage points (=0.0042*0.5597/0.2347, where 0.2347 is the average probability of an improvement in health for our sample). In addition, the marginal effect of positive shock in housing wealth on the probability of a decline in health is -0.00485. In other words, if households experienced a one standard deviation positive shock in housing wealth, their probability of declining health in the next period decreases by 1.06 percentage points(=-0.00485*0.5597/0.2552, where 0.2552 is the average probability of a decline in health for our sample). The magnitude of these results is consistent to the previous literature that explores the effects of wealth shocks on health outcomes (Fichera and Gathergood

[23] Our results are robust to the use of interval regressions.

(2016), Meer et al. (2003), Lindahl (2005), McInerney et al. (2013)). In specifications from [3] to [8], negative coefficients indicate a health improvement (i.e., fewer limitations of ADLs or lower death rates). In column [3], the impact of the RHWM in total ADLs is not statistically significant from zero, but the effect of an unexpected positive shock in house wealth has a strong negative impact on the number of mental conditions (column [4]). One explanation for the fact that total ADLs is not significant while mental health are, might be that the effects on total ADLs take longer to materialize than mental conditions because they imply much more severe impairments. Previous literature has also found significant negative effect of worsening economic conditions on mental health (Ruhm (2005); Ruhm (2015); Dávalos and French (2011); Dávalos et al. (2012); Golberstein et al. (2016)). Panel B in Table 3 shows that the corresponding marginal effect of a positive shock in housing wealth (i.e., an increment in RHWM) on the probability of decreasing the number of mental ADLs (i.e., improving their health) is 0.0008. In other words, if households experienced a one standard deviation positive shock in housing wealth, their probability of improving their health in the next period increases by 1.10 percentage points (=0.0008*0.5597/0.0406, where 0.0406 is the average probability decreasing the number of mental health complications for our sample). In addition, the marginal effect of positive shock in housing wealth on the probability of a worsening mental health is -0.00203. In other words, if households experienced a one standard deviation positive shock in housing wealth, their probability of declining mental health in the next period decreases by 2.3 percentage points(=-0.00203*0.5597/0.0491, where 0.0491 is the average probability of a decline in health for our sample).

Columns from [5] to [8] present the effects of the RHMW on deaths of despair. In columns [5] and [7] we use the same control variables as in expressions [2], [3] and [4]. The coefficient for RHWM is negative and statistically significant, indicating that positive housing wealth shocks decrease death rates. Our results show that an unexpected shock in housing wealth is negatively correlated with drug-related deaths. However, we do not find any significant effect on alcohol and suicide related death rates. In particular, a one standard deviation change in housing wealth leads to a 4.3 percent decrease in the drug-related death rate (i.e., 0.041/0.961, where 0.961 is the average change in drug-related death rate.) The effects on alcohol and suicide related deaths are not statistically significant. Columns [6] and [8] include additional controls to take into account elements that the previous literature has suggested could play a role on the recent rise of deaths of despair. Following Ruhm (2018), we control for various economic factors related to labor market outcomes -such as employment status and the change in manufacturing jobs- and international trade shocks. We also control for changes in the drug environment such as the introduction of Prescription Drug Monitoring Programs (PDMP) or marijuana laws. The implementation of these last programs and laws only start presenting some variation across states later on the sample. Therefore, we lose some observations in these latest specifications. The results are robust to the inclusion of these additional controls. A one standard deviation increase in RHWM, reduces the change in drug-related death rates by 5 percent (i.e., from 0.961 to 0.911). Specifications [6] to [8] use rates per 100,000 inhabitants according to the US Census population. Appendix table A3 presents the coefficients for all the covariates for the same specifications. Alternatively, the Surveillance, Epidemiology, and End Results (SEER) Program provides population data designed to adjust for population shifts such as those resulting from the hurricanes Katrina and Rita. In the Appendix, we show that our results are robust to the use of SEER population data instead of US Census data. In the Appendix (table A4) we also show the results for a four-years effect of *RHWM* on health outcomes. The coefficients are consistent to our baseline results but less significant for some specifications.

Finally, for a causal interpretation of the results, housing wealth shocks must be independent of any unobserved heterogeneity in health changes. One could be concerned about the fact that housing market shocks could be correlated with other macroeconomic environment shocks affecting wealth, such as stock market value changes or changes in the employment status. For this reason, we run a robustness check where we also control for the proportion of total wealth held in stocks and the proportion of total wealth in housing in addition to our standard control variables. Results are robust and are presented in the Appendix.

4.2 RHWM as an unexpected shock in housing wealth

There could be three types of concerns regarding the unexpectedness of the RHWM shock. The first type of concern refers to the possibility that people who move have different health status from those who do not sell. Maybe those who are sick decide to change houses to adapt to their healthcare needs. To address this concern we perform two analyses: first, we control for the health of the head of the household in all our specifications. Second, we present a two sample t-test of the health status –measured as self-reported health and as limitations in ADLs– of two groups of people, those who move and those who do not move. The goal of this test is to check that there is not a significant difference between the health status of heads of household who move prior to moving and the health status of those who do not move. Table 4 panel A presents the results and it shows that there are not significant differences in health status between the two groups.

The second question refers to the possibility that households that move and sell their house at a large discount are different for those that move and sell at a high price. For example, those who lose their jobs might be forced to move and sell their house at a large discount and, therefore, have a negative wealth shock. To address this issue, we have performed t-tests to study whether there are significant differences among socioeconomic and demographic characteristics between households that experience a positive or negative wealth shock when moving. We find that there are no such differences in variables that could trigger housing moves such as employment, number of family members, and marital status.[24]

The third type of concern refers to the fact that households that significantly overestimate their houses may not sell them because they are loss averse. This concern is already addressed in the type of data that we use because households included in PSID report what they believe is the value of their houses.[25] Nevertheless, we test whether households only realize their house wealth misestimation when they sell their house, in other words, whether RHWM is actually an unexpected shock.

The economic intuition behind this test goes as follows. If misestimation is truly something that homeowners only realize when they sell their house, then the effects of housing wealth misestimation (HWM) on health should not be significant prior to selling the house. This should hold for two groups of people: (i) those who never sell the house and (ii) those who decide to sell it before selling and realizing their misestimation. The first column of Table 4 panel B includes all households that never realized their house wealth misestimation. Therefore, we include all the observations related to households that never moved and the observations of households that moved up to the period before moving. Column [1] shows that there is no effect on SRH if the household does not realize its

[24]The p-values for the t-tests on employment status, number of family members, and marital status are 0.28, 0.78, and 0.61.

[25]Even if they do not sell, they would report a lower value of their house if they found that it was worth less because the question in PSID states "Could you tell me what the present value of this house (farm) is? I mean about what would it bring if you sold it today?"

house wealth misestimation in any period before selling the house. We obtain the same result for the two subgroups: first, observations of households that never moved (column [2]) and observations of households that moved until the period before moving (column [3]). In summary, these results suggest that RHWM is an unexpected shock in housing wealth.

[INSERT TABLE 4 HERE]

4.3 Instrumental variable results

There could be some unobserved variables that affect both health status and realized housing wealth misestimation (e.g., when a family members dies, an individual might be more likely to move to a smaller house and might also feel more depressed.) To address reverse-causality concerns, all the analyses in the paper control for variables such as initial health, housing wealth, the number of family members in the house and employment status. Moreover, we run an extra analysis and we implement an IV strategy for robustness.

Our instrumental variable is the interaction between local supply elasticity in the housing market and the interest rates for the market yield on US Treasury securities at 10-year constant maturity. Therefore, our instrument is time-varying.[26] To our knowledge, this is the first time that this instrument is used in the health economics literature. The economic intuition behind this interaction goes as follows. When interest rates decrease, demand for housing increases. As markets can adjust prices and quantities, ceteris paribus, this increase in demand translates into higher real estate prices in areas where supply is more inelastic. As there is persistence in housing-wealth perceptions (Kuzmenko and Timmins (2011)), misestimations will be greater in more inelastic supply areas where house prices vary the most. We use the elasticity of supply of housing as estimated in Saiz (2010), who employs satellite-generated data on the slope of the terrain, and the presence of rivers, lakes, and other water bodies to estimate the amount of developable land at the MSA level. We use data on yields of US Treasury securities at 10-year constant maturity from the Federal Reserve website.[27] [28]

[26]Changes in the elasticity of supply at the MSA level are large in the cross-section but small in the time-series since we consider time lags of 2 years for changes in health outcomes in our panel. Recent studies that consider changes in the house price elasticity do not find relevant changes over short periods of time (e.g., Kirchhain et al. (2018)). Furthermore, there are no available time-varying measures of land elasticity at the MSA or city level that cover our period of study (1986-2015). For instance, Kirchhain et al. (2018) cover the time period 2014-2016.

[27]See http://www.federalreserve.gov/.

[28]When limiting the specification to only those who move, results are consistent since RHWM will only be different

This instrument has been extensively used in the finance and real estate economics literature to address endogeneity issues related to real estate prices. Himmelberg et al. (2005) instrument local house prices using the interaction of local housing-supply elasticity and long-term interest rates to study housing bubbles. Mian and Sufi (2011) use the same instrument for house prices to analyze household leverage. Chaney et al. (2012) and Cvijanović (2014) use this instrument for commercial real estate prices in their study of firms investments and leverage, respectively. However, this is the first time that the interaction between the local supply elasticity of individual housing markets and long-term interest rates is used as an instrumental variable for an unexpected shock in wealth.

This is a good instrument for our empirical strategy for two reasons. First, the IV is highly correlated with RHWM. In other words, this IV has a strong first stage. The results of the first-stage regression are presented in Table 5 Panel B. The instrument is strongly statistically significant and, as expected, has a negative sign. Second, both the amount of developable land and the interest rates are exogenous to changes in health status.[29]

[INSERT TABLE 5 HERE]

Table 5 Panel A presents the estimates of the effect of a shock on wealth (i.e., RHWM) using the IV described above on the change in SRH, change on the number of mental impairments and change on drug and alcohol and suicide-related death rates. We also use different control variables in each specification. Panel C presents the estimated marginal effects on the change in SRH for specification [1] in Panel A.[30]

In specification [1] in Table 5 panel A, the coefficient for the instrumented RHWM is positive and statistically significant. This indicates that a positive wealth shock leads to a significant positive change in SRH. The corresponding marginal effect of a positive shock in housing wealth on the probability of a health improvement is 0.0057. In other words, if households experience a one standard deviation shock in their housing wealth, the probability of an improvement in their health in the next period increases by 1.36% (=0.0057*0.5597/0.2347, where 0.2347 is the average

from zero for those households that move when they move.

[29]Davidoff (2016) criticizes the use of housing-supply constraints as IVs for house prices in studies in which the dependent variable has an economic component, such as consumption growth, leverage, or investments, because some demand factors that could affect both house prices and the dependent variable of interest might have been omitted. This is not the case in our study, as the dependent variable is change in health status.

[30]We estimate this model using maximum likelihood. The estimation is performed using the CMP user-provided package in STATA. See https://ideas.repec.org/c/boc/bocode/s456882.html and Roodman (2009). This approach has been used extensively in the literature (e.g., Einav et al. (2012); Cullinan and Gillespie (2016)).

probability of an improvement in health for our sample). In addition, the marginal effect of a positive shock in household wealth on the probability of a decline in health is -0.0065. Therefore, if households experience a one standard deviation shock in their housing wealth, the probability of a decline in their health in the next period decreases by 1.43% (=-0.0065*0.5597/0.2552, where 0.2552 is the average probability of a decline in health for our sample).

The measures reported in specifications from [2] to [4] in Table 5 panel A correspond to a worsening of health conditions. Therefore, the coefficient for the instrumented RHWM is negative, as expected. The effect is only statistically significant for the case of a change in drug-related death rates (specification [3]). As before, a shock on RHWM has not a significant effect on alcohol and suicide related deaths (specification [4]). Moreover, we lose significance on its effect on the change in the number of mental health problems (specification [5]) when using an IV. Our results show that a one standard deviation increase in housing wealth leads to a 6.995 decrease in changes in drug-related death rates.

4.4 Differential effects across geographical areas

In this section we study how the effect of housing wealth on health varies across geographical areas. Figure 2 shows an exploratory analysis of the effect of a sharp growth (and decrease) of house prices in health outcomes related to "deaths of despair" for the U.S. MSAs with more than 100,000 inhabitants. The top (bottom) left figure shows the relationship between changes in house prices and changes in the drug-related (alcohol and suicide) death rates for the recent period of sharp increase in house prices 2003-2007. The top (and bottom) right figure exhibits the same figure for the recent period of sharp decrease in house prices 2007-2010. All figures show a negative relationship between growth in house prices and growth of death rates related to "deaths of despair".

[INSERT FIGURE 2 HERE]

The instrumental variable approach that we developed in the previous section implies that, ceteris paribus, the RHWM is, on average, larger in those areas where housing supply is constrained. Hence, an increase in demand should translate into a higher positive change in health in areas where housing supply is more inelastic. For instance, a demand shock experienced by households located in the most inelastic MSAs, such as Miami, Los Angeles-Long Beach, San Francisco, and New York, leads to a higher probability of a health improvement than a demand shock of the same magnitude experienced by those located in the top elastic MSAs, such as Cincinnati, Atlanta, San Antonio, and Oklahoma City.

We study the differential effects of unexpected housing wealth shocks on health across different geographies. We want to understand if the economic cycles have a differential effect across different geographical areas. To do so, we classify the households in our sample in the ones that live in a housing supply inelastic area and the ones that live in an elastic area. We define a dummy variable $Inelastic_{P33}$ that takes the value of 1 of the household lives in an area located in the top 33% of housing inelastic cities according to the measure in Saiz (2010) and zero otherwise.[31] We also separate the sample in periods of housing boom and periods of housing bust. Housing boom (bust) includes the years with growth in house prices at least one standard deviation above (below) their historical mean.

Table 6 reports the results of this analysis. All the specifications in this table control for demographic and economic characteristics. The coefficients for $Inelastic_{P33}$ are statistically significant for changes in SRH and changes in drug-related death rates. Table 6 shows that for the boom periods (i.e., when households are more likely to experience positive housing wealth shocks), the improvement on health outcomes is larger on MSAs with a more inelastic housing supply market. During recessions (i.e., when households are more likely to experience negative housing wealth shocks), health is likely to worsen more in these areas with inelastic housing supply.

[INSERT TABLE 6 HERE]

5 Conclusions

Several studies have documented the positive effect of changes in wealth on health. To analyze this causal relation, the extant literature has used either shocks in wealth that affect only a small part of the population (e.g., lottery winners) or shocks that can be expected, at least to some extant (e.g., an inheritance). In contrast, we develop a new measure of unexpected wealth shocks: realizations

[31] This choice of 33% divides our sample in about half, that is, 50% of the households in our sample live in the top 33% inelastic MSAs. Our results are robust to the choice of 33% as the threshold between elastic and inelastic cities. In the Appendix, we also report these results using a continuous measure of elasticity. These results are also robust, but less significant.

of housing wealth misestimations (RHWM). Our results show that a positive, unexpected shock in wealth increases the probability of an improvement in self-reported health, a decrease in the drug-related mortality rate, and a reduction in mental health problems. The opposite effect also holds, such that a negative shock on wealth increases the probability of a decline in health.

Our results provide important policy implications to the set of initiatives provided by the Presidents Commission on Combating Drug Addiction and the Opioid Crisis. If the economy is the main cause of this crisis, one should look for measures to stimulate worst-off communities. But, if the crisis is mostly drug supply-driven, then one should implement measures such as the promotion of opioid prescription guidelines, physicians education, and a stricter control of illegal drug supply. However, we are probably facing a multidimensional challenge. In this paper, we show that there is an additional driver that should be taken into account: housing wealth. Our results also emphasize the different effects that booms and crisis can have in areas where the housing supply is more inelastic. Further efforts should be devoted to the study of housing-related policies, such as affordable housing plans, and their impact on health outcomes.

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Table 1: **Descriptive Statistics.**

Panel A. Head of household level data

	Description	Mean	SE	Observations	Min	Max
Health outcomes						
Change in SRH	Measure of change in self-reported health (SRH) for a two year period. If SRH increases it takes value 1, if it decreases value -1, and if it remains the same, value 0. SRH takes the value 5 if the individual rated his health as excellent, 4 if very good, 3 if good, 2 if fair and 1 if poor.	-0.0204	0.700	93,807	-1	1
Change in total ADLs	Change in the total number of limitations of activities of daily living (ADLs).	0.8653	0.3658	165,861	-1	1
Change in mental ADLs	Change in the number of limitations of activities of daily living (ADLs) classified as mental.	0.0085	0.299	36,170	-1	1
Measure of wealth shock						
Realization of housing wealth misestimation (RHWM)	Shock in housing wealth when the household sells its current house. It is estimated as the difference between the market house value at which the house in sold and the self-reported house value in the survey before selling the house. It is expressed in tens of thousands of US dollars.	0.00431	0.560	153,112	-41.24	49.19
Health, wealth and sociodemographic controls						
Healthy	Health control variable. It takes value 1 if the individual's Self-Reported Health is good, very good or excellent. It takes value zero otherwise.	0.580	0.494	103,248	0	1
House value	Reported house value in hundreds of thousands of dollars.	1.364	1.403	51,514	1.00e-05	35
Family income	Total family income in hundreds of thousands of dollars.	0.467	0.600	105,765	-0.993	55
Age	Age of the head of the household in years.	41.18	13.13	106,157	16	100
Male	Gender of the head of the household. It takes the value of 1 if male and 0 if woman.	0.685	0.465	106,168	0	1
Non-white	Race of the head of the household. It takes value 1 if the individual is nonwhite and 0 if the individual is white.	0.456	0.498	105,989	0	1
High school	Level of studies of the head of the household. It takes the value 0 if the individual has a level of studies below high school, and 1 if high school or a higher level of education is completed.	0.775	0.418	115,324	0	1
Employed	Dummy variable equal 1 if the head of household is employed and 0 otherwise.	0.788	0.409	106,137	0	1
Married	Dummy variable that takes the value 1 if the head of the household is married and 0 if not.	0.506	0.500	123,760	0	1
Family members	Number of members in the household.	3.388	1.716	106,949	0	14
Year	Year of the data collection.	1,996	8.561	123,760	1,984	2,013
Division	US Census division of the household. It takes value 1 if the household is located in the Pacific, 2 in Mountain, 3 in West North Center, 4 in East North Center, 5 in Middle Atlantic, 6 in New England, 7 in West South Center, 8 in East South Center, and 9 in South Atlantic.	5.349	2.656	150,194	1	9
Housing supply elasticity and interest rates						
Supply elasticity (SE) of the house market	Housing supply elasticity as estimated in Saiz (2010).	1.658	0.904	84,915	0.600	5.450
10-year interest rate (IR)	Yield of the U.S. Treasury bond at the 10-year maturity.	6.567	2.457	123,760	2.350	12.46
SE*IR	Interaction between housing supply elasticity and the 10-year interest rates.	10.84	7.529	69,925	1.410	49.84

Table 1: **Descriptive Statistics (cont.)**

Panel B. County level data

	Description	Mean	Std. Dev.	Observations	Min	Max
Health outcomes						
Change in drug-induced death rate	Change in deaths by unintentional drug poisoning per 100,000 people, as cataloged by ICD-10 codes X40 to X44.	0.9614	3.8169	20,591	-12.5298	18.7494
Change in alcohol and suicide-induced death rate	Change on alcohol and suicide-induced causes of death per 100,000 people, as cataloged by ICD-10 codes X45, X65, Y15 and others.	0.3419	2.1328	14.946	-8.8995	11.8846
Number of hospital beds	Number of hospital beds in the county.	2.767664	2.369005	20,852	8	23,094
Change in manufacturing employers	Change in percentage of manufacturing employers in working age population	-3.036349	3.251128	25,378	-23.4701	6.5501
Change in import exposure	Change in import exposure per worker	3.652997	3.584937	25,378	1.57e-06	49.0050
Legal environment controls						
PDMP operational	Takes the value of 1 from the first year in which Prescription Drug Monitoring Program (PDMP) was implemented onwards.	0.6094	0.4879	28,323	0	1
First marijuana law	Takes the value of 1 from the first year in which the marijuana law was implemented in its state onwards.	0.6749	0.4684	28,332	0	1

Table 2: **Effects of change in house wealth on health outcomes.** This table reports estimates of the effect of housing wealth in terms of Log(House Wealth) and Δ(Log(House Wealth)) on health outcomes. Specifications [1] and [2] show the effect of the logarithm of housing wealth on self-reported health. Column [3] and [4] report the effects of the change on the log of housing wealth on the change in SRH. In specifications [5] and [6], our dependent variable is mental ADLs and change in mental ADLs respectively. Specifications [7]-[8] and [9]-[10] show the effect of house wealth on drug death rates and alcohol death rates, respectively. t-statistics are reported in parentheses. All specifications include age, gender and socioceonomic controls, as well as division fixed effects and year fixed effects.

	SRH		Δ(SRH)		Mental ADLs	Δ(Mental ADLS)	Drug death rates		Alcohol or suicide death rates	
	OLS	Ord. probit	OLS	Ord. probit	OLS	OLS	OLS	OLS	OLS	OLS
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Log House Wealth	0.04478***	0.1552***			-0.01093**		-0.7223***		-0.3107***	
	(7.8511)	(7.4532)			(-2.2175)		(-4.8444)		(-4.2954)	
Δ(Log House Wealth)			0.03052*	0.05160*		-0.02765***		0.02173		-0.1777
			(1.6425)	(1.6416)		(-2.9352)		(0.1328)		(-1.6172)
Healthy	1.4586***	16.280***	-0.07422***	-0.1248***	-0.03983***	3.188e-04	-0.002004	0.06402	-0.1164**	-0.1189*
	(202.41)	(134.25)	(-9.5247)	(-9.4453)	(-7.8108)	(0.07697)	(-0.02051)	(0.6940)	(-2.3155)	(-1.8596)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,425	45,425	31,643	31,643	18,702	14,020	11,021	6,869	8,636	4,855

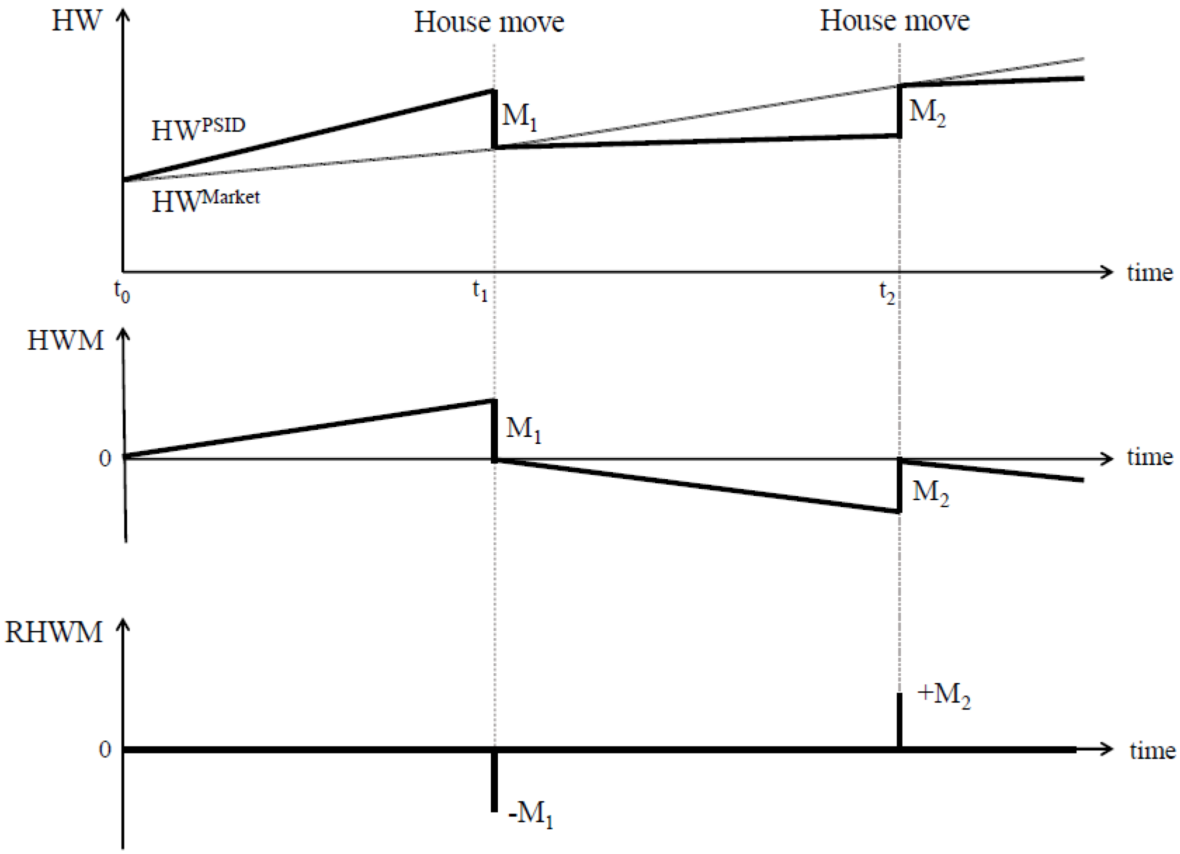

Figure 1: **Sketch of the misperception mechanism.** This figure details the definition of $RHWM$ from the house wealth reported in PSID, HW^{PSID}, and the house wealth in market value, HW^{Market}. The figure on the top plots a sketch of a path for a households reported housing wealth from PSID, HW^{PSID}, and a sketch of the path for the housing wealth in market value, HW^{Market}, of the same house. In this sketch, the household moves to a different house at times t_1 and t_2. In these specific times, the household realizes the market value of its house and, therefore, its housing wealth misestimation (e.g., M_1 and M_2 is the housing wealth misestimation at times t_1, and t_2, respectively). The plot in the middle exhibits the resulting path of house wealth misestimation, HWM, for the top figure. Notice that the household in this sketch is overvaluing its housing wealth from time t_0 to t_1 (i.e., its HW^{PSID} is above its HW^{Market}), hence HWM is positive during this period. At time t_1, the household realizes its overvaluation of size M_1 and experiences a negative housing wealth shock of size M_1. The household is undervaluing its housing wealth from time t_1 to t_2 (i.e., its HW^{PSID} is below its HW^{Market}), hence HWM is negative during this period. At time t_2, the household realizes its undervaluation of size M_2 and experiences a positive housing wealth shock of size M_1. The figure in the bottom plots realized housing wealth misestimation, $RHWM$, which takes always the value of zero, except at times t_1 and t_2 when it takes the values of $-M_1$ and M_2, respectively.

Table 3: **Baseline. Effects of shocks in wealth on changes in health.** This table reports estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in health outcomes. All specifications include age control, year fixed effects and division fixed effects. Specifications [1] and [2] show the estimates of an ordered probit model for self-reported health, Δ(SRH). Specification [1] only includes as control variables House value. Specification [2] adds health level (SRH), as well as all the demographic controls, which include family income, race (Non-white), education (High school or more), employment (Employed), marital status (Married), and Family members. Specifications [5] and [6] report the estimates for change in drug death rates. Specifications [7] and [8] report the estimates for the change in alcohol or suicide death rates. t-statistics are reported in parentheses. All the specifications include year and division fixed effects and all errors are clustered at the family level.

Panel A. Baseline regressions for the different health outcomes.

	Δ(SRH)		Δ(Total ADLs)	Δ(Mental ADLs)	Δ(Drug death rates)		Δ(Alcohol or suicide death rates)	
	Ord. probit	Ord. probit	Ord. probit	Ord. probit	OLS	OLS	OLS	OLS
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
RHWM	0.0102*	0.01720**	0.00048	-0.02450**	-0.07416***	-0.08943***	0.00666	-0.01110
	(1.81)	(2.39)	(0.06)	(-2.07)	(-2.69)	(-2.60)	(0.36)	(-0.47)
Healthy	-1.147***	-1.1741***	-0.2311***	-1.7867***	0.08683	0.07252	-0.1340**	-0.1538**
	(-6.67)	(-46.35)	(-9.89)	(-9.02)	(1.08)	(0.66)	(-2.43)	(-1.98)
House value		0.0477***	-0.0033	-0.0503***	0.0051	0.0137	-0.0222	-0.0078
		(7.41)	(-0.39)	(-5.14)	(0.22)	(0.46)	(-1.34)	(-0.34)
PDMP Operational						0.2712		0.3598***
						(1.62)		(2.72)
First marihuana law						1.1720***		-0.0071
						(6.17)		(-0.05)
Hospital beds rate						-0.0436		0.0591
						(-1.07)		(1.57)
Δ manufact. employers						0.0514		0.0143
						(1.06)		(0.39)
Δ import exposure						-0.0434		-0.0768**
						(-1.00)		(-2.47)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,506	35,427	12,069	15,294	8,879	4,979	6,300	3,535

Panel B. Marginal effects. Ordered probit specifications [2] and [4].

	[2]			[4]		
	Decrease	No change	Increase	Decrease	No change	Increase
RHWM	-0.00485**	0.00062**	0.00423**	0.00085**	0.00118**	-0.00203**
	(-1.90)	(-1.75)	(1.75)	(2.08)	(2.06)	(-2.08)

Table 4: **RHWM as an unexpected shock in housing wealth.** Panel A reports the results of two sample t-tests of the differences of health variables for households that moved and did not move. Health variables are self-reported health (SRH) and Total ADLS. It displays the mean of the health outcomes for movers and non-movers, as well as the t-test for different age ranges. Standard deviations are reported in parentheses. Panel B reports the estimates of the determinants of house wealth misestimation, HWM, and moving, using in all the cases ordered probit regressions. All specifications include age and gender controls, socieconomic controls, year fixed effects and division fixed effects. In model [1], we only take into account individuals who did not move during the previous two-year period. Model [2] takes into account individuals who never moved, and model [3] individuals who sometime moved but not during the previous period. Errors are clustered at the family level in all the specifications.

Panel A. Two sample t-test of health status by movers and non-movers.

	SRH			Total ADLs		
	Moved	Did not move	t-test	Moved	Did not move	t-test
Age 25-40	0.6350	0.6095	5.3913***	0.1578	0.2038	-2.5376***
	(0.4814)	(0.4879)		(0.8492)	(0.9474)	
Age 41-55	0.5617	0.4604	13.8784***	0.2744	0.3673	-3.7124***
	(0.4962)	(0.4985)		(1.1068)	(1.2523)	
Age >55	0.4639	0.3734	6.4427***	0.5947	1.0671	-7.1878***
	(0.4987)	(0.4839)		(1.5890)	(2.4071)	

Panel B. Two sample t-test.

	Households that did not move during the previous period [1]	Households that never moved [2]	Households that had moved until the period before moving [3]
HWM	-0.05238	-0.00049	0.00037
	(-0.10)	(-0.52)	(0.63)
Healthy	-1.2549***	-1.4034***	-1.1634***
	(-20.36)	(-11.65)	(-16.27)
House Value	0.06359***	0.07754**	0.04900*
	(2.85)	(2.18)	(1.69)
Controls	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes
Observations	8,351	2,692	5,659

Table 5: **Effects of shocks in wealth on changes in health. Instrumental variables.** This table reports the ordered probit estimates of the second stage (Panel A) and the first stage (Panel B) of the instrumental variable model. Panel C exhibits the marginal effects of the ordered probit IV specification in column [1]. The dependent variable is the change in SRH (column [1]), change in mental ADLs (column [2]), change in drug death rates (column [3]), and change in alcohol or suicide death rates (column [4]). The variable RHWM has been instrumented by the interaction between housing supply elasticity (SE) and the interest rate at 10 years (IR). Errors are clustered at the family level in all the specifications.

Panel A. Second stage regressions.

	Δ(SRH)	Δ(Mental ADLs)	Δ(Drug death rates)	Δ(Alcohol or suicide death rates)
	Ord. probit	Ord. probit	OLS	OLS
	[1]	[2]	[3]	[4]
RHWM	0.02165*	0.00892	-6.99570***	-0.07796
	(1.76)	(0.67)	(-4.24)	(-0.17)
Controls	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes
Observations	38,256	29,991	7,597	5,627

Panel B. First stage regressions.

	Δ(SRH)	Δ(Mental ADLs)	Δ(Drug death rates)	Δ(Alcohol or suicide death rates)
	[1]	[2]	[3]	[4]
SE*IR	-0.00304***	-0.00303***	-0.01594***	-0.01252***
	(-2.98)	(-2.97)	(-4.45)	(-3.08)
Controls	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes
Observations	38,256	29,991	7,597	5,627

Panel C. Marginal effects. Ordered probit IV specification [1] in Panels A and B.

	Decrease	No change	Increase
RHWM	-0.00648*	0.00079	0.00568*
	(-1.75)	(1.32)	(1.75)

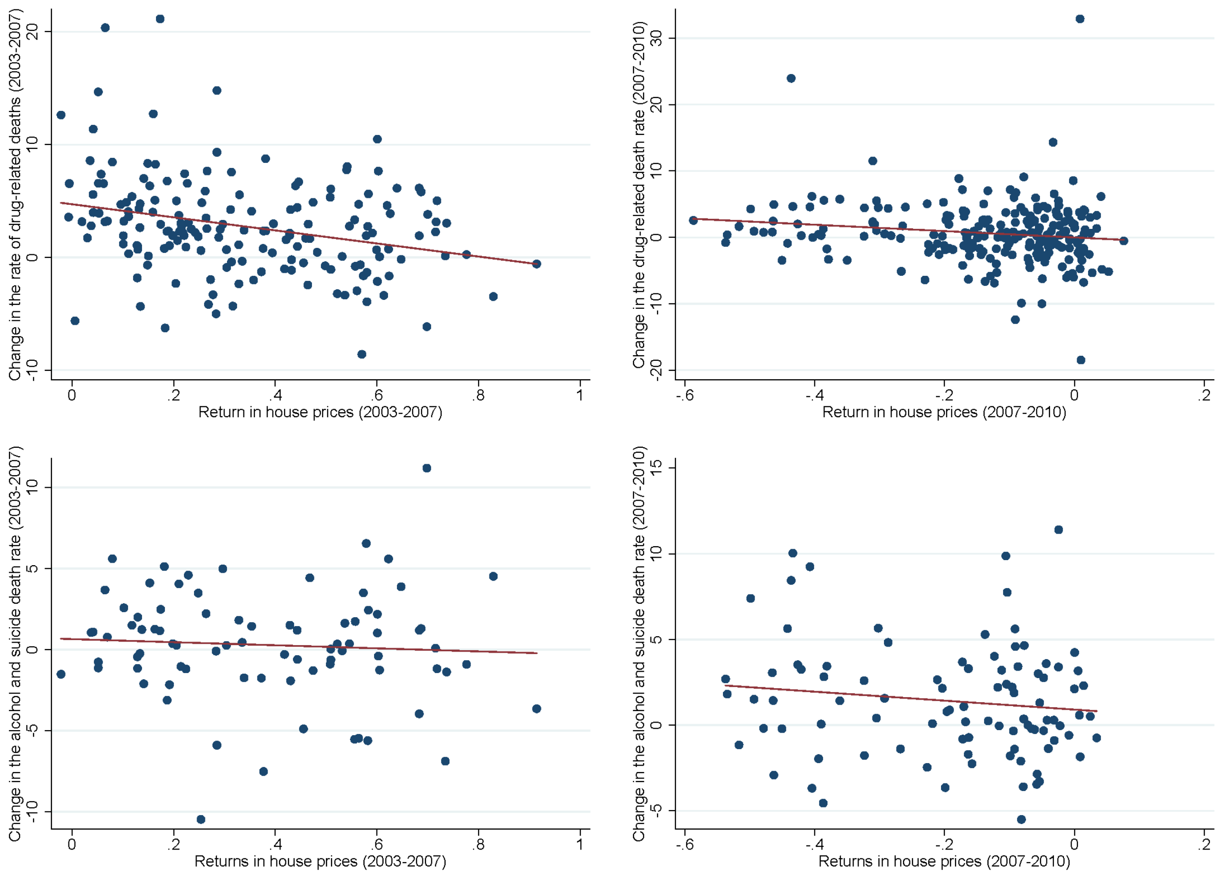

Figure 2: **Changes in house prices and changes in health outcomes.** The top two figures report the effect of returns in house prices in the change in the rate of drug-related deaths. The bottom two figures report the effect of returns in house prices in the change in the alcohol and suicide of drug-related deaths. Every dot represents an MSA with more than 100,000 inhabitants. The two figures in the left show the effects for the recent period of sharp increase in house prices 2003-2007. The two figures in the right exhibit the effect for the recent period of sharp decrease in house prices 2007-2010.

Table 6: **Effects of housing supply constraints and the housing market cycles.** This table reports the effects of housing supply constraints during periods of sharp increasing house prices (booms) and periods of sharp decreasing house prices (busts). Errors are clustered at the family level in all the specifications.

	Increasing house prices			Decreasing house prices		
	Δ(SRH)	Δ(Mental ADLs)	Δ(Drug death rates)	Δ(SRH)	Δ(Mental ADLs)	Δ(Drug death rates)
	Ord. probit	Ord. probit	OLS	Ord. probit	Ord. probit	OLS
	[1]	[2]	[3]	[4]	[5]	[6]
Inelastic_{P33}	0.1567**	-0.0558	-1.8050***	-0.0844*	0.0197	0.4940***
	(2.02)	(-0.53)	(-9.83)	(-1.73)	(0.27)	(3.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,252	1,193	2,148	2,763	2,631	2,349

Appendix A

This appendix presents several robustness checks and full table versions of our main specifications in the paper. First, we show that our results are robust when we control for asset allocation controls. Table A-1 exhibits the estimates of the effect of RHWM on the change in the different health outcomes when controlling for the ratio of housing wealth over total net wealth and stock holdings over total new wealth in addition to the baseline demographic controls. Overall, this table shows that our results are robust to the inclusion of this controls.

Table A-1: **Robustness control for asset allocation.** This table reports estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in health outcomes when controlling for the ratio of housing wealth over total net wealth and stock holdings over total new wealth. All specifications include year fixed effects and division fixed effects. Specifications [1]-[3] show the estimates for self-reported health, Δ(SRH). Specification [1] is equivalent to the baseline ordered probit specification. Specifications [2] and [3] show the second and first stage IV regressions. Specification [4] shows the estimates for mental ADLs, Δ(Mental ADLs). Specifications [5] and [6] report the estimates for change in drug death rates and change in alcohol or suicide death rates, respectively. t-statistics are reported in parentheses. All the specifications include year and division fixed effects and all errors are clustered at the family level.

	Δ(SRH)	Δ(SRH)	RHWM	Δ(Mental ADLs)	Δ(Drug death rates)	Δ(Alcohol or suicide death rates)
	Ord. probit	IV (2nd stage)	IV (1st stage)	Ord. probit	OLS	OLS
	[1]	[2]	[3]	[4]	[5]	[6]
RHWM	0.02531***	0.02499*		-0.008965	-0.07399**	0.04086
	(2.87)	(1.84)		(-0.88)	(-2.06)	(1.47)
SE*IR			-0.006145***			
			(-3.2487)			
Healthy	-1.0082***	-1.0082***	-0.02141	-1.6479***	0.1379	-0.1235*
	(-44.66)	(-44.66)	(-1.05)	(-12.54)	(1.39)	(-1.66)
House value	0.03838***	0.03838***	0.007474	-0.03982***	0.05782*	0.07472***
	(5.36)	(5.36)	(0.37)	(-4.06)	(1.87)	(3.23)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Asset allocation controls	Yes	Yes	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,098	15,219	15,219	11,150	5,163	3,633

Second, we show that our results are robust when using SEER-adjusted population data instead of U.S. Census data.

Table A-2: **Robustness check using population SEER data.** This table reports estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in health outcomes when controlling for SEER-adjusted population data. Specifications [1]-[2] report the estimates for change in drug death rates and [3]-[4] report the change in alcohol or suicide death rates. Robust standard errors are reported in parentheses. All the specifications include year and division fixed effects and all errors are clustered at the family level.

	Δ(Drug death rates)	Δ(Drug death rates)	Δ (Alcohol or suicide death rates)	Δ (Alcohol or suicide death rates)
	[1]	[2]	[3]	[4]
RHWM	-0.0771***	-0.0935***	0.00657	-0.0112
	(0.0277)	(0.0346)	(0.0187)	(0.0237)
Healthy	0.0919	0.0740	-0.134**	-0.154**
	(0.0807)	(0.111)	(0.0550)	(0.0779)
House Value	0.00313	0.0124	-0.0224	-0.00792
	(0.0235)	(0.0297)	(0.0166)	(0.0228)
PDMP Operational		0.297*		0.364***
		(0.168)		(0.132)
First marihuana law		1.177***		-0.00518
		(0.190)		(0.132)
Hospital beds rate		-0.0414		0.0588
		(0.0409)		(0.0375)
Δ manufact. employers		0.0452		0.0136
		(0.0485)		(0.0371)
Δ import exposure		-0.0475		-0.0776**
		(0.0434)		(0.0311)
Demographic Controls	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes
Observations	8,868	4,973	6,300	3,535

Third, we show the full Table 3 including the coefficients of all the covariates.

Table A-3: **Full Table 3 including all the covariates coefficients.** This table presents the exact same specifications as in table 3, but including the coefficients for the whole set of covariates.

	Δ(SRH)	Δ(SRH)	Δ(Total ADLs)	Δ(Mental ADLs)	Δ(Drug death rates)		Δ(Alcohol or suicide death rates)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
RHWM	0.0102*	0.0172**	0.000476	-0.0245**	-0.0742***	-0.0894***	0.00667	-0.0111
	(0.00562)	(0.00719)	(0.00867)	(0.0118)	(0.0276)	(0.0344)	(0.0186)	(0.0237)
Healthy	-1.147***	-1.174***			0.0868	0.0725	-0.134**	-0.154**
	(0.0172)	(0.0253)			(0.0808)	(0.111)	(0.0550)	(0.0778)
HVnew		0.0477***	-0.231***	-1.787***	0.00514	0.0137	-0.0222	-0.00776
		(0.00643)	(0.0234)	(0.198)	(0.0235)	(0.0297)	(0.0166)	(0.0228)
PDMP Operational						0.271		0.360***
						(0.168)		(0.132)
First marihuana law						1.172***		-0.00714
						(0.190)		(0.132)
Hospital beds rate mean						-0.0436		0.0591
						(0.0409)		(0.0375)
Δ manufacturing employers						0.0513		0.0143
						(0.0485)		(0.0371)
Δ import exposure						-0.0434		-0.0768**
						(0.0433)		(0.0311)
Age	-0.00560***	-0.00572***	0.00742***	-0.00772***	-0.00336	-0.000718	0.000436	0.00181
	(0.000505)	(0.000744)	(0.00127)	(0.00158)	(0.00363)	(0.00482)	(0.00250)	(0.00343)
Family Income	0.0803***	0.0359***	-0.0195	-0.00328	-6.32e-07	-1.18e-08	2.51e-07	5.85e-07
	(0.0167)	(0.0122)	(0.0137)	(0.0209)	(4.71e-07)	(6.29e-07)	(3.30e-07)	(4.89e-07)
Male	0.0249	-0.0424	0.105*	-0.102	-0.0327	-0.335	0.0542	0.0423
	(0.0219)	(0.0356)	(0.0582)	(0.0688)	(0.159)	(0.213)	(0.107)	(0.148)
Marital Status	-0.00150	0.0478	-0.0362	0.0954	0.0119	0.171	0.0334	0.0120
	(0.0219)	(0.0334)	(0.0549)	(0.0651)	(0.152)	(0.203)	(0.102)	(0.141)
Family Members	-0.0152***	-0.00956*	-0.00128	-0.00463	-0.0100	-0.00257	-0.00516	-0.0167
	(0.00363)	(0.00519)	(0.0100)	(0.0130)	(0.0297)	(0.0449)	(0.0197)	(0.0304)
Employed	0.127***	0.165***	-0.0902*	-0.397***	-0.109	-0.207	-0.0161	-0.0653
	(0.0153)	(0.0237)	(0.0478)	(0.0591)	(0.118)	(0.155)	(0.0807)	(0.111)
High School	0.130***	0.144***	-0.111**	-0.0632	-0.271*	-0.418**	-0.157	-0.382**
	(0.0151)	(0.0244)	(0.0503)	(0.0566)	(0.139)	(0.204)	(0.0984)	(0.149)
Nonwhite	-0.136***	-0.0858***	-0.0824**	-0.200***	-0.259***	-0.320**	-0.0643	-0.00184
	(0.0147)	(0.0209)	(0.0324)	(0.0441)	(0.0967)	(0.141)	(0.0669)	(0.0996)
Observations	62,449	35,427	12,069	15,294	8,879	4,979	6,300	3,535

Note: This table reports estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in health outcomes. All Specifications. include age control, year fixed effects and division fixed effects. Specifications [1] , [2] and [3], [4] show the estimates for the health outcome change in self-reported health (SRH), total ADLS and Mental ADLS using an ordered probit model. Specification [1] only includes as control variables the health status, age, and gender of the head of the household. Specifications [2], [3] and [4] add the house value as control, as well as all the demographic controls, which include family income, race (i.e., non-white dummy), education (i.e., dummy high school or more), employment (i.e., dummy employed), marital status (i.e., dummy married), and family members. These two ordered probit specifications include errors clustered at the family level. Specifications [5] and [6] report the estimates for the health outcome change in drug death rates. Specifications [7] and [78 report the estimates for the health outcome change in drug death rates. Specifications [5]-[8] control for urban-rural categories. Standard errors are reported in parentheses.

Fourth, the following table shows results with the choice of a four-year lag to explore longer run effects as opposed to the two-year changes that we use in our main analyses.

Table A-4: **The effects of RHWM on four-year health outcomes.** This table presents estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in health outcomes after four years from the housing wealth shock. In a longer run the effects of RHWM on the different health outcomes is smaller, and it become not statistically significant for some specifications.

	Δ(SRH)	Δ(SRH)	Δ(Total ADLs)	Δ(Mental ADLs)	Δ(Drug death rates)		Δ(Alcohol or suicide death rates)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
RHWM	0.00836	0.0154**	0.00332	-0.0181**	-0.0452	-0.0305	-0.00197	-0.0292
	(0.00556)	(0.00709)	(0.00979)	(0.00854)	(0.0320)	(0.0390)	(0.0227)	(0.0287)
Healthy	-1.370***	-1.409***	-0.488***	-2.637***	-0.0544	-0.0697	-0.00246	0.0277
	(0.0181)	(0.0262)	(0.0717)	(0.249)	(0.103)	(0.127)	(0.0664)	(0.0856)
HVnew		0.0489***	-0.0366***	-0.0636***	-0.0149	-0.0229	-0.0655***	-0.0372
		(0.00791)	(0.0118)	(0.0133)	(0.0299)	(0.0341)	(0.0197)	(0.0252)
PDMP Operational						1.104***		1.165***
						(0.191)		(0.146)
First marihuana law						0.171		-0.939***
						(0.214)		(0.142)
Hospital beds rate mean						-0.338***		0.0460
						(0.0469)		(0.0394)
Δ manufacturing employers						0.105*		-0.228***
						(0.0565)		(0.0397)
Δ import exposure						-0.0175		-0.162***
						(0.0501)		(0.0337)
Observations	53,582	30,369	7,227	13,284	7,438	4,909	5,379	3,522

Note: This table reports estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in health outcomes after 4 years. All Specifications. include age control, year fixed effects and division fixed effects. Specifications [1] , [2] and [3], [4] show the estimates for the health outcome change in self-reported health (SRH), total ADLS and Mental ADLS using an ordered probit model. Specification [1] only includes as control variables the health status, age, and gender of the head of the household. Specifications [2], [3] and [4] add the house value as control, as well as all the demographic controls, which include family income, race (i.e., non-white dummy), education (i.e., dummy high school or more), employment (i.e., dummy employed), marital status (i.e., dummy married), and family members. These two ordered probit specifications include errors clustered at the family level. Specifications [5] and [6] report the estimates for the health outcome change in drug death rates. Specifications [7] and [78 report the estimates for the health outcome change in drug death rates. Specifications [5]-[8] control for urban-rural categories. Standard errors are reported in parentheses.

Fifth, we run a robustness check of the effect of the housing market cycles on changes in health using the continuous measure in Saiz (2010).

Table A-5: **Effects of housing supply constraints and the housing market cycles using the continuous measure of housing supply elasticity in Saiz (2010).** This table reports the effects of housing supply constraints during periods of sharp increasing house prices (booms) and periods of sharp decreasing house prices (busts). Errors are clustered at the family level in all the specifications. This table presents the equivalent results than Table 6 when using the continuous measure of housing supply elasticity in Saiz (2010). The estimates are robust to our main specifications, but less statistically significant.

	Increasing house prices			Decreasing house prices		
	Δ(SRH)	Δ(Mental ADLS)	Δ(Drug death rates)	Δ(SRH)	Δ(Mental ADLS)	Δ(Drug death rates)
	Ord. Probit	Ord. Probit	OLS	Ord. Probit	Ord. Probit	OLS
	[1]	[2]	[3]	[4]	[5]	[6]
Inelasticity, negative elasticity	0.1011	-0.05761	-0.9320***	-0.04488	0.06287	0.03484
	(-1.1267)	(-0.9107)	(-9.1846)	(-1.5734)	(1.5530)	(0.4430)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year and division FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,252	1,193	2,148	2,763	2,631	2,349

Appendix B

In this Appendix, we discuss the results of the analysis of the variance in household misestimation explained by household (family) fixed effects and by year fixed effects. Our goal is to understand how much of the variation in house wealth misestimation comes from *within* versus *between* households. First, B-1 shows that the standard deviation of misestimation is much larger by individual household ID than by year.

Additionally, B-2 shows the R-squares of different OLS specifications using (or not) covariates, individual FE, and year FE. These results show that the proportion of the variance in misestimation explained when using individual household fixed effects is more than 20 times larger than when using only year fixed effects. This result remains true when we add the covariates.

Finally, we perform an ANOVA analysis of house value misestimation. B-3 shows that the variation across family IDs is substantial. F indicates that the variation between is 5.98 times the variation within household ID. Therefore, we include fixed effects in all our specifications in order to take into account these large variation among families (i.e., the *between* effect).

Table B-1: **Analysis of the variation in house value misestimation. Summary statistic average of misestimation (by household ID and year).** This table reports the summary statistics of the variable house wealth misestimation (HWM) in aggregate terms, by household ID, and by year.

	Mean	St.Dv.	Obs.
House Wealth Misestimation (HWM)	0.768	21.965	58,701
Average HWM by ID	0.462	11.089	116,413
Average HWM by Year	0.623	2.168	123,760

Table B-2: **Analysis of the variation in house value misestimation. Analysis of within and between R-squared using our simple OLS approach (no panel).** This table shows the results of the analysis of the variation in House Wealth Misestimation (HWM) using an OLS approach. The dependent variable in all the specifications is HWM. Specifications [1]-[3] do not include covariates, whils [4]-[6] do include them. Specifications [2]-[3] and [5]-[6] include household individual fixed effects (FE). Specifications [1], [3], [4], and [6].

	[1]	[2]	[3]	[4]	[5]	[6]
R-squared	0.012	0.374	0.386	0.017	0.394	0.405
Covariates	No	No	No	Yes	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	No	Yes	Yes	No	Yes
Observations	58,701	58,701	58,701	53,196	53,196	53,196

Table B-3: **Analysis of the variation in house value misestimation. ANOVA.** This table shows the results of the one-way ANOVA test using individual household ID. It compares the variance between and within individual households. Let F denote the variation *between* the sample mean squares, MS, of the model divided by the variation *within* the sample MS.

Source	Partial SS	df	MS	F	Prob.>F
Model	10,602,331	5,338	1,986.20	5.98	0
Residual	17,717,600	53,362	332.02		
Total	28,319,931	58,700	482.45		
Observations	58,701				
R-squared	0.374				