Housing Wealth, Health and Deaths of Despair

Ariadna Jou[1] Núria Mas[2] Carles Vergara-Alert[3]

Abstract

The debate on the impact of economic conditions on health has been recently amplified by the drug crisis in the US attributed by some to "deaths of despair". There is little understanding of the magnitude of the impact of economic conditions on health and the reasons why it varies across socioeconomic groups and geographical areas. We show that housing is an important unexplored driver that explains these differences. We exploit the fact that households that overvalue (undervalue) their houses experience an unexpected negative (positive) shock in their housing wealth when they sell their houses. We find that a one standard deviation positive shock in housing wealth increases the probability of an improvement in self-reported health by 1.13 percentage points and decreases the drug-related mortality rate by 0.27. We exploit the geographical variation in unexpected housing wealth shocks and find that households who live in MSAs with more inelastic housing supply experience larger changes in health outcomes.

1. INTRODUCTION

The attention on the impact of economic conditions on health has been magnified by the recent dramatic increase in suicides, drug overdoses and alcohol-related deaths from middle-aged white non-Hispanic Americans. Case and Deaton (2015) and Case and Deaton (2017) named this crisis "deaths of

[1] Department of Economics, UCLA. 8283 Bunche Hall, Mail Stop 147703, Los Angeles, CA 90095, USA. Email: ariadnajou@gmail.com.
[2] IESE Business School, University of Navarra. Pearson Avenue 21, 08034 Barcelona, Spain. Email: nmas@iese.edu. Núria Mas acknowledges financial support from the Spanish Ministry of Science and Innovation (Ref. ECO2015-71173-P) and AGAUR (Ref. 2017-SGR-1244). She is the holder of the Jaime Grego Chair of Healthcare Management.
[3] IESE Business School, University of Navarra. Pearson Avenue 21, 08034 Barcelona, Spain. Email: cvergara@iese.edu. Vergara-Alert acknowledges financial support from the Public-Private Sector Research Center at IESE, the Ministry of Economy and Competitiveness (Ref. ECO2015-63711-P), and AGAUR (Ref: 2017-SGR-1244).

despair" since they suggest that this increase has been due to difficult social and economic environments. However, there is little understanding about the magnitude of the impact of economic conditions on health and the reasons why it varies across socioeconomic groups and geographical areas. In this paper, we show that housing is an important unexplored driver that explains the effect of wealth on different measures of health such as self-reported health (SRH), drug-related mortality rates, suicide rates, alcoholic-related liver mortality rates, and limitations in activities of daily living (ADLs) 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.[4] 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.[5] 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

[4] In this paper, we study the causal relationship between SES and health. While most studies have focused on the link between income and health (Ettner, 1996; Meara, 2001; Johnson et al., 2009; Baird et al., 2011; Acemoglu et al., 2013; Chetty et al., 2016), we focus on the link between wealth and health. We do so because using income as a measure of SES presents two main problems. First, "income in a single year may not adequately measure the financial resources available (…) over the lifetime in which decisions affecting health are made" (Smith and Kingston, 1997). Second, wealth is less likely to be affected by a single episode of sickness, as it accumulates over time (Feinstein, 1993).
[5] See Kish and Lansing (1954); Follain and Malpezzi (1981); Goodman Jr. and Ittner (1992); Agarwal (2007); Benitez-Silva et al. (2008); Kuzmenko and Timmins (2011); Corradin et al. (2016).

overvalue their house by 9% or more, while 25% of the households undervalue their houses by at least 11%.[6]

Our main finding is that housing is an important channel to understand the causal effects of wealth on a broad range of health outcomes. We find that a one standard deviation positive shock in housing wealth increases (decreases) the probability of an improvement (decline) in self-reported health by 1.13 (0.96) percentage points. A shock of the same size leads to a 0.62 percentage points decrease in the probability of increasing the number of limitations in ADLs suffered by an individual. Moreover, we find that a one standard deviation positive change in housing wealth decreases the drug-related mortality rate by 0.27 (e.g., from 12.33 to 12.06 deaths per 100,000 on average). We do not find significant equivalent results for alcohol or suicide death rates.

The relationship between socioeconomic status (SES) and health has been extensively reported in the literature (Adler et al., 1994; Backlund et al., 1999; Chandola, 2000; Contoyannis et al., 2004; Cutler and Meara, 2010; Cutler et al., 2016; Feinstein, 1993; Golbstein 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). The main difficulty in such analyses 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 individual's 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).

[6] 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 Zillow's 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%) of Zillow's estimates are off by 5% (10%) or more in Phoenix, while 62.1% (44.9%) of Zillow's estimates are off by 5% (10%) or more in New York.

Our approach contributes to the previous research in three main ways. First, by using RHWM, we provide a shock in wealth that is: (i) unexpected, (ii) sizable, and (iii) that affects a broad set of the population. The extant literature on the wealth-health link has used data on lottery winners (Imbens et al., 2001; Lindahl 2005; Gardner and Oswald, 2005; Apouey and Clark, 2015), inheritance (Meer et al., 2003; Kim and Ruhm, 2012), and changes in stock (McInerney et al., 2013) 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 Ludvingson, 2001) and house prices are characterized by persistence and a high degree of predictability (Fischer and Stamos, 2013; Corradin et. al., 2014).

Second, we look at 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 contribute to the literature that explores the causes of the “deaths of despair”. Case and Deaton (2017) 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”,* however, their work does not show causality. Ruhm (2018) finds that economic hardship can explain only a small proportion of the increase in these types of deaths while drug supply factors are the main causes behind them. In our paper, we explore another potential mechanism: unexpected shocks in housing wealth.

Third, 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 house's 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; Cvijanovic, 2014), they have never been used to analyze the impact of wealth on health status. By using this IV, we conclude that 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.

2. DATA

We use data from the Panel Study of Income Dynamics (PSID), which began following a nationally representative sample of U.S. households in 1968. 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 use county-level data for the analyses related to "deaths of despair" from the Center for Disease Control (CDC). Table 1 presents the summary statistics and the description of the variables used in our analysis.

[INSERT TABLE 1 HERE]

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; Benitez-Silva et al., 2008; Kuzmenko and Timmins, 2011; Corradin et al., 2016) 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*.

---

[7] For more information, see: https://psidonline.isr.umich.edu/.

[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.

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. (2016)[10] and we compare data on reported house values from the PSID to market house values calculated as the initial buying price of the house updated by the zip code level CoreLogic Home Price Index (HPI). 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.

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.) In summary, RHWM represents an unexpected shock on the family's wealth. It is

[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. (2016), we adjust the house values reported in PSID for home-improvement expenses that households report in the same survey.

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. 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 restrictions—starting 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 -0.0212.

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.[11] 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

[11] https://wonder.cdc.gov/mcd.html

county level from the year 2000 onwards, since earlier ICD-9 categories are not exactly equivalent to ICD-10 codes (R.N. Anderson et al. 2001).

The number of deaths belonging to each group is converted into mortality rates per 100,000 people using population data from the National Cancer Institute's Surveillance Epidemiology and End Results (SEER).[12] These population estimates per county provide data for intercensal years, and correct for shocks in population such as hurricanes Katrina and Rita in 2005.

For robustness purposes, we 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.[13] 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.

2.3. Control variables

Healthy is a dummy variable created from the SRH variable. It takes a value of 1 if the individual's SRH is excellent, very good, or good. It takes a value of 0 if the individual's SRH is fair or poor. This allows us to control for the health of the individuals at the moment when the house is sold. The average value of *healthy* in our sample is 0.5783.

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

[12] https://seer.cancer.gov/popdata/

[13] The PSID asks the following types of questions: "Because of a health or physical problem, (do/does) (you/he/she) have any difficulty doing [a certain activity of daily living]"?.

and northeast) fixed effects. Table 1 provides the detail description and the main statistics of these variables.

We also include control variables at the county level in some specifications. These sociodemographic variables are obtained from five-year estimates from the American Community Survey (ACS) for the years 2005-2013, while earlier data comes from the 2000 Decennial Census. Employment and unemployment data come from the Bureau of Labor Statistics Local Area Unemployment Statistics Database[14]. We obtain family income and poverty rate data at the county level from the Bureau of the Census Small Area Income and Poverty Estimates[15]. Data on the number of hospital beds comes from the Area Health Resource Files database.[16] 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., (2015), and is offered at the Commuting Zone level. Within a Commuting Zone, all counties are assumed to have the same level of import exposure.[17] 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.[18]

Finally, 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 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 (www.pdaps.org).

[14] www.bls.gov/lau/
[15] www.census.gov/did/www/saipe/
[16] http://www.arf.hrsa.gov
[17] http://www.ddorn.net/data.htm
[18] www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/

3. IMPACT OF AN UNEXPECTED WEALTH SHOCK ON HEALTH

3.1. Empirical strategy

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.[19]

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

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

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

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

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

Our basic specification is the following:

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

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

[19] 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.

exogenous, unexpected shock in wealth. *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 is the error term.

The ordered probit estimation is then as follows:

$$P(\Delta H_{i,t+\tau} = -1 \mid RHWM_{it}, H_{it}, W_{it}, X_{it,}) = P(\Delta H_{i,t+\tau}^{*} \leq a_1 \mid RHWM_{it}, H_{it}, W_{it}, X_{it,}) = \\ = \Phi(a_1 - \beta\, RHWM_{it} + \delta\, H_{it} + \lambda\, W_{it} + \theta\, \Sigma X_{it}) \quad (2)$$

$$P(\Delta H_{i,t+\tau} = 0 \mid RHWM_{it}, H_{it}, W_{it}, X_{it,}) = P(\alpha_1 < \Delta H_{i,t+\tau}^{*} \leq a_2 \mid RHWM_{it}, H_{it}, W_{it}, X_{it,}) = \\ = \Phi(a_1 - (\beta\, RHWM_{it} + \delta\, H_{it} + \lambda\, W_{it} + \theta\, \Sigma X_{it})) \\ - \Phi((a_2 - (\beta\, RHWM_{it} + \delta\, H_{it} + \lambda\, W_{it} + \theta\, \Sigma X_{it})) \quad (3)$$

$$P(\Delta H_{i,t+\tau} = 1 \mid RHWM_{it}, H_{it}, W_{it}, X_{it,}) = P(\Delta H_{i,t+\tau}^{*} > a_2 \mid RHWM_{it}, H_{it}, W_{it}, X_{it,}) = \\ = 1 - \Phi(a_2 - (\beta\, RHWM_{it} + \delta\, H_{it} + \lambda\, W_{it} + \theta\, \Sigma X_{it})). \quad (4)$$

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.

3.2. Impact of an unexpected wealth shock on health: baseline results

Table 2 presents the estimates of the effect of a housing wealth shock (i.e., RHWM) on the change in several health outcomes using different control variables in each specification. Columns [1] and [2] in Panel A show the ordered probit estimates on SRH. For robustness, we also report the interval regression results in column [3].[20] Columns [4]-[7] show the OLS estimates on changes in

[20] As previously discussed, an ordered probit model is a more appropriate framework because the change in SRH is an interval-coded variable (columns [1] and [2]). However, we include the results from the equivalent interval regression model for robustness (column [3]).

health outcomes related to "deaths of despair". Panel B exhibits the estimated marginal effects on the change in SRH for specification [2] in Panel A.

[INSERT TABLE 2 HERE]

In specifications [1]-[3] the coefficient for RHWM is positive and statistically significant, indicating that a positive housing wealth shock leads to a significant positive change in SRH. As expected, older individuals are less likely to improve their health in the next period. Moreover, more educated, employed, and married individuals are more likely to experience an improvement in their health.

Panel B in Table 2 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 0.0041. 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 1.13 percentage points (=0.0041*0.5685/0.2057, where 0.2057 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 -0.0047. 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 1.11 percentage points (=-0.0047*0.5685/0.2430, where 0.2430 is the average probability of a decline in health for our sample).

In specifications [4]-[5] the coefficient for RHWM is negative and statistically significant, indicating that positive housing wealth shocks decrease drug related death rates. Column [4] presents an equivalent specification to the one in [2], but using data aggregated at the county level and an OLS estimation since changes in death rates is a quantitative variable. Our results show that a one standard deviation change in housing wealth leads to a 0.27 decrease in drug-related deaths (i.e. they go from an average of 12.33 per 100,000 to 12.06

per 100,000, which represents a 2.15% reduction in drug related death rates). Ruhm (2018) suggest that there are important supply factors such as the legal drug environment, health supply or globalization exposure, which could also help explain the drug epidemic in the US. The regression in column [5] follows Ruhm (2018) and controls for these variables. We find that the impact of a housing wealth positive shock on drug death rates continues being significant and negative.

Columns [6] and [7] present a similar exercise but looking at the effect of changes in housing wealth on changes in suicide or alcohol-related deaths. Here the results have been found to be not significant. This is consistent with the existing literature, which has found non-conclusive effects of the economy on alcohol consumption (Dávlos et al., 2012; Ruhm and Black, 2002; Ruhm, 1995)

4. ROBUSTNESS CHECKS

4.1. RHWM as an unexpected shock in housing wealth

There could be some concerns about 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.[21] 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: those who never sell the house

[21] 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?".

and those who decide to sell it before selling and realizing their mistake. The first column of Table 3 shows that there is no effect on health if the household does not realize its house wealth misestimation (i.e., in any period before selling the house). We obtain the same result for the subgroup of households that never move (column [2]) and for households that sell their house before selling (column [3]).

[INSERT TABLE 3 HERE]

4.2. Other measures of health: ADLs

Table 4 presents the estimates of the effect of a housing wealth shock (i.e., changes in RHWM) on the change in the number of total limitations of ADLs (Column [1]) and the change in the number of mental ADLs (column [2]). Several control variables related to sociodemographic and housing conditions are again used in the two specifications. Panel B shows the estimated marginal effects on the change in mental ADLs for specification [2] in Panel A.

[INSERT TABLE 4 HERE]

In specification [1] the coefficient for RHWM is not statistically significant, whereas it is negative and significant in specification [2]. The corresponding marginal effect of a positive shock in housing wealth on the probability of improved Mental ADLs (i.e., a decrease in Mental ADLs scores) is 0.0021. Specifically, if an individual experienced a one standard deviation positive shock in housing wealth, her probability of improving Mental ADLs in the next period increases by 5.5 percentage points (=0.0021*0.5685/0.0217, where 0.0217 is the average probability of an improvement in mental ADLs for our sample). Furthermore, the marginal effect of a positive shock in housing wealth on the probability of a decline in Mental ADLs is -0.0006. That is to say, if an individual experienced a one standard deviation positive shock in housing wealth, her probability of a deterioration in mental ADLs in the next period decreases by 0.17 percentage points (=-0.0006*0.5685/0.1925, where 0.1925 is the average probability of a decline in mental ADLs scores for our sample).

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, we control for variables such as initial health, housing wealth, the number of family members in the house and employment status, and we implement an IV strategy.

Our IV—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—has not previously been used in the health economics literature. The economic intuition behind 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. 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.[22]

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

[22] http://www.federalreserve.gov/.

bubbles. Mian and Sufi (2011) use the same instrument for house prices to analyze household leverage. Chaney et al. (2012) and Cvijanovic (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 A. Second, both the amount of developable land and the interest rates are exogenous to changes in health status.[23]

[INSERT TABLE 5 HERE]

Table 5 Panel B presents the estimates of the effect of a shock on wealth (i.e., RHWM) on the change in SRH using the IV described above and different control variables in each specification. Panel C presents the estimated marginal effects on the change in SRH for specification [2] in Panel B.[24]

In all of the specifications, the coefficient for the instrumented RHWM is positive and statistically significant, indicating 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 0.0060. In other words, if households experience a one standard deviation shock in their housing wealth, the probability of an improvement in their health

[23] Davidoff (2015) 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.

[24] 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).

in the next period increases by 1.66% (=0.0060*0.5685/0.2057, where 0.2057 is the average 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 -0.0055. 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 1.28% (=-0.0055*0.5685/0.2438, where 0.2438 is the average probability of a decline in health for our sample).

The IV described above 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.

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 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 the limitations in activities of daily living (ADLs). 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 President´s 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. As a result, further efforts should be devoted to the study of housing-related policies, such as affordable housing plans, and their impact on health outcomes.

REFERENCES

Acemoglu, D., Finkelstein, A., and Notowidigdo, M. J. (2013). Income and health spending: Evidence from oil price shocks. *Review of Economics and Statistics*, 95(4), 1079-1095.

Acemoglu, D., Autor, D., Dorn, D., Hanson, G.H., and Price, B. (2015) "Import Competition and the Great US Employment Sag of the 2000s." *Journal of Labor Economics* 34 (1): 141–198.

Adler, N., T. Boyce, M.A. Chesney, S. Cohen, S. Folkman, R.L. Kahn, and S. L. Syme (1994) "Socioeconomic status and health the challenges of the gradient." *American Psychologist* 49: 15-24.

Agarwal, S. (2007) "The impact of homeowners' housing wealth misestimation on consumption and saving decisions." *Real Estate Economics* 35 (2): 135-154.

Apouey, B., and A.E. Clark (2015) "Winning big but feeling no better? The effect of lottery prizes on physical and mental health." *Health Economics* 24: 516–538.

Backlund, E., P. Sorlie, and N. Johnson (1999) "A comparison of the relationship of education and income with mortality: the national longitudinal mortality study." *Social Science and Medicine* 49: 1371-1384.

Baird, Sarah, Jed Friedman, and Norbert Schady (2011) "Aggregate income shocks and infant mortality in the developing world." *Review of Economics and Statistics* 93.3: 847-856.

Benitez-Silva, H., S. Eren, F. Heiland, and S. Jimenez-Martin (2008) "How well do individuals predict the selling prices of their homes?" *Levy Economics Institute Working Paper.*

Bossaerts, P., and Hillion, P. (1999) "Implementing Statistical Criteria to Select Return Forecasting Models: What Do We Learn?" *Review of Financial Studies* 12 (2): 405-428.

Case, A., and Deaton, A. (2015) "Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century." *Proceedings of the National Academy of Sciences*, 1-6.

Case, A., and Deaton, A. (2017) "Mortality and morbidity in the 21st century." *Brookings Papers on Economic Activity*.

Chandola, T. (2000) "Social class differences in mortality using the new UK National Statistics Socio-Economic classification." *Social Science and Medicine* 50: 641-649.

Chaney, T., D. Sraer, and D. Thesmar (2012) “The collateral channel: How real estate shocks affect corporate investment." *American Economic Review* 102: 2381-2409.

Chetty, R., M. Stepner, S. Abraham, S. Lin, B. Scuderi, N. Turner, A. Bergeron, and D. Cutler (2016) “The Association Between Income and Life Expectancy in the United States, 2001-2014.” *JAMA, 315(16), p.1750.*

Contoyannis, P., A.M. Jones, and N. Rice (2004) “The dynamics of health in the British Household Panel Survey.” *Journal of Applied Econometrics* 19: 473-503.

Corallo, A. N., R. Croxford, D.C. Goodman, E.L. Bryan, D. Srivastava, and T.A. Stukel (2014). A systematic review of medical practice variation in OECD countries. *Health Policy*, 114(1), 5-14.

Corradin, S., J. Fillat, and C. Vergara-Alert (2014) “Optimal portfolio choice with predictability in house prices and transaction costs.” *Review of Financial Studies* 27 (3): 823-880.

Corradin, S., J. Fillat, and C. Vergara-Alert (2016) “Portfolio choice with house value misperception.” *ECB Working Paper*.

Cullinan, J., and P. Gillespie (2016) “Does overweight and obesity impact on self-rated health? Evidence using instrumental variables ordered probit models.” *Health Economics* 25: 1341-1348.

Currie, J., S. DellaVigna, S., E. Moretti, E., and V. Pathania (2010) “The effect of fast food restaurants on obesity and weight gain.” *American Economic Journal: Economic Policy*, 2(3), 32-63.

Currie, J., and B. Madrian (1999) “Health, health insurance and the labor market” in Ashenfelter O., and D. Cards (Eds.), *Handbook of Labor Economics* vol. 3. North Holland, Amsterdam: 3309-3415.

Cutler, D., Huang, W., and A. Lleras-Muney (2016) “Economic conditions and mortality: evidence from 200 years of data.” *NBER Working paper 22690.*

Cvijanovic, D. (2014) “Real estate prices and firm capital structure." *Review of Financial Studies* 27 (9): 2690-2735.

Dávlos, M.E., H. Fang, and M.T. French (2012). “Easing the pain of an economic downturn: macroeconomic conditions and excessive alcohol consumption”. *Health Economics* 21 (11), 1318–1335.

Einav L., A. Finkelstein, I. Pascu, and M.R. Cullen (2012) “How general are risk preferences? Choice under uncertainty in different domains.” *American Economic Review* 21 (1): 415-448.

Ettner, S. (1996) “New evidence on the relationship between income and health.” *Journal of Health Economics* 15: 67-85.

Ettner, S. (1997) “Measuring the human cost of a weak economy: does unemployment lead to alcohol abuse?” *Social Science and Medicine* 44(2): 251-260.

Feinstein J. (1993) “The relationship between socio-economic status and health: a review of the literature.” *The Millbank Quarterly* 71(2): 279-322.

Fichera E., and J. Gathergood (2016) “Do wealth shocks affect health? New evidence from the housing boom.” *Health Economics*. 25(Suppl. 2): 57-69.

Fischer, M., and M. Stamos (2013) “Optimal life cycle portfolio choice with housing market cycles.” *Review of Financial Studies* 26: 2311-52.

Follain, J.R., and S. Malpezzi (1981) “Are occupants accurate appraisers?” *Review of Public Data Use* 9 (1): 47-55.

Gardner, J., and Oswald, A. (2005) Erratum to “How is mortality affected by money, marriage, and stress?” [J. Health Econ. 23 (2004) 1181–1207]. Journal of Health Economics, 24(3), p.629.

Golberstein, E., Gonzales, G., and Meara, E. (2016) “Economic conditions and children's mental health.” *NBER Working paper 22459.*

Goodman Jr., J.L., and J.B. Ittner (1992) “The accuracy of home owners’ estimates of house value.” *Journal of Housing Economics* 2 (4): 339-357.

Himmelberg, C., C. Mayer, and T. Sinai (2005) “Assessing high house prices: Bubbles, fundamentals and misperceptions.” *Journal of Economic Perspectives* 19 (4): 67-92.

Humphries, K., and E. van Doorslaer (2000) “Income related health inequality in Canada.” *Social Science and Medicine* 50: 663-671.

Hurst, E., and A. Lusardi (2004) “Liquidity constraints, household wealth and entrepreneurship.” *Journal of Political Economy*, vol. 112(2): 319-346.

Iacoviello, M. (2012), “Housing wealth and consumption.” *International Encyclopedia of Housing and Home*, 673-678, Elsevier.

Idler, E., S. Kasl, and J. Lemke (1990) “Self-evaluated health and mortality among the elderly in New Haven, Connecticut, and Iowa and Washington counties, Iowa, 1982–1986.” *American Journal of Epidemiology*, 131(1): 91-103.

Imbens, G., D. Rubin, and B. Sacerdote (2001) "Estimating the effect of unearned income on labor earnings, savings and consumption: evidence from a survey of lottery players." *American Economic Review* 91: 778-794.

Kaplan, G., V. Barell, and A. Lusky (1988) "Subjective state of health and survival in elderly adults." *Journal of Gerontology,* 43(4): S114-S120.

Kim, B., and C.J. Ruhm (2012) "Inheritances, health and death." *Health Economics* 21: 127-144.

Kish, L., and J.B. Lansing (1954) "Response errors in estimating the value of homes." *Journal of the American Statistical Association* 49 (267): 520-538.

Kuzmenko, T., and C. Timmins (2011) "Persistence in housing wealth perceptions: Evidence from the Census data." Working paper.

Johnson, D., C. Propper, and M. Shields (2009) "Comparing subjective and objective measures of health: Evidence from hypertension for the income/health gradient." *Journal of Health Economics* 28: 540-552.

Lettau, M., and S. Ludvingson, (2001) "Consumption, aggregate wealth, and expected stock returns." *The Journal of Finance* 56 (3): 815-849.

Lewis, G., P. Bebbington, T. Brugha, M. Farrell, B. Gill, R. Jenkins, and H. Meltzer (1998) "Socioeconomic status, standard of living and neurotic disorder." Lancet 352: 605-609.

Lindahl, M. (2005) "Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income." *Journal of Human Resources* 40: 144-168.

Lleras-Muney, A. (2005). The relationship between education and adult mortality in the United States. *The Review of Economic Studies*, 72(1), 189-221.

Long, M., and B. Marshall (1999) "Case Management and the Cost of Care in the Last Month of Life: Evidence from One Managed Care Setting". *Health Care Management Review*, 24(4): 45-53.

McClellan, M. (1998) "Health events, health insurance and labor supply: Evidence from the health and retirement survey." In: D. Wise (Ed) Frontiers in the Economics of Aging; University of Chicago Press, Chicago: 301-346.

McFadden, E., R. Luben, S. Bingham, N. Wareham, A.L. Kinmonth, and K.T. Khaw (2009) "Does the association between self-related health and mortality vary by social class?" *Social Science and Medicine* 68: 2075-280.

McInerney, M., J.M. Mellor, and L.H. Nicholas (2013) “Recession depression: Mental health effects of the 2008 stock market crash.” *Journal of Health Economics* 32: 1090-1104.

Meara, E. (2001) “Why is health related to socioeconomic status? The case of pregnancy and low-birth weight.” NBER Working Paper 8231

Meer, J., D. Miller, and H. Rosen (2003) “Exploring the health-wealth nexus.” *Journal of Health Economics* 22: 713-730.

Mian, A., and A. Sufi (2011) “House prices, home equity-based borrowing, and the US household leverage crisis.” *American Economic Review* 101 (5): 2132-56.

Mossey, J., and E. Shapiro (1982) “Self-rated health: a predictor of mortality among the elderly.” *American Journal of Public Health*, 72(8), pp.800-808.

Roodman, D. (2009) “Fitting fully observed recursive mixed-process models with cmp.” *Stata Journal* 11: 159-206.

Ruhm, C.J., and W.E. Black (2002) “Does drinking really decrease in bad times?” *Journal of Health Economics* 21(4): 659–678.

Ruhm, C.J. (1995) “Alcohol Policies and Highway Vehicle Fatalities.” *Journal of Health Economics* 15 (4): 435-454.

Ruhm, C.J. (2018) “Deaths of despair or Drug Problems?” NBER Working Paper No. 24188.

Saiz, A. (2010) “The geographic determinants of housing supply.” *Quarterly Journal of Economics* 125 (3): 1253-96.

Skinner, J. (2012). Causes and consequences of regional variations in health care. *Handbook of health economics*, 2, 45-93.

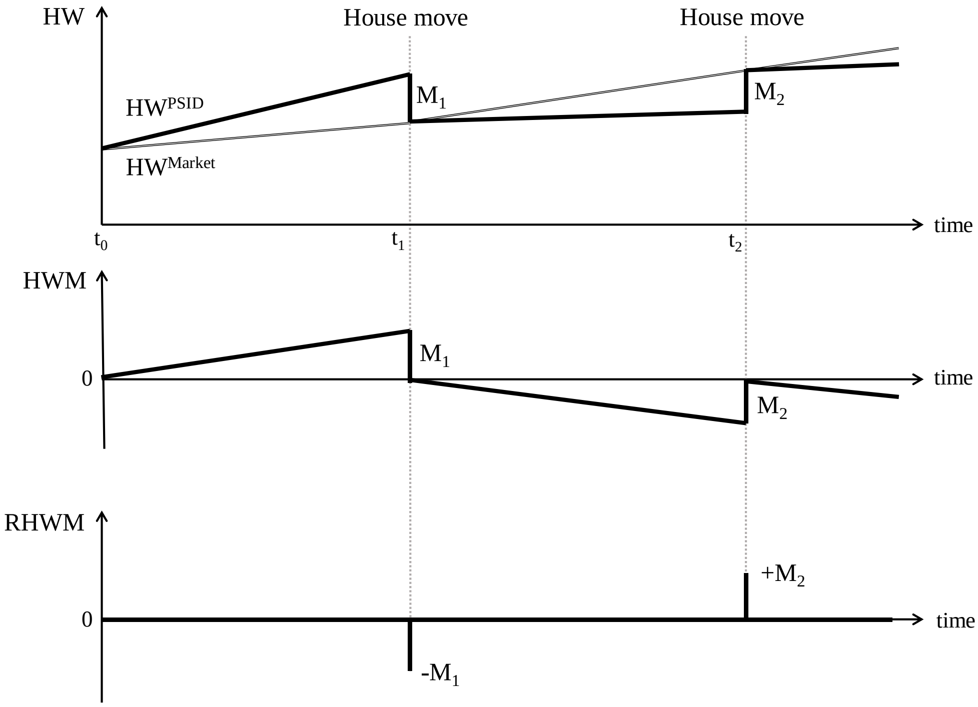
Smith, J., and R. Kingston (1997) “Socioeconomic status and health in late life” in Martin L.G. and B.J. Soldo (Eds) Racial and Ethical differences in the health of older Americans, National Academy Press, Washington DC.

Smith, J. (1999) “Healthy bodies and thick wallets: the dual relation between health and economic status.” *Journal of Economic Perspectives* 13: 145-166.

Wilkinson, R., and M. Marmot eds. (2003) “Social determinants of health: the solid facts.” World Health Organization.

Wu, S. (2003) “The effects of health events on the economic status of married couples.” *Journal of Human Resources* 38(1): 219-23.

Figure 1. Sketch of the definition of RHWM from the house wealth reported in PSID, HW^{PSID}, and the house wealth in market value, HW^{Market}



Note: The figure on the top plots a sketch of a path for a household's 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 1. Descriptive statistics

Panel A. Summary statistics for PSID. Head of household level data

	Description	Mean	Std. Dev.	Observations
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.	-0.0212	0.6992	89,464
Change in total ADLs	Measure of change in the total number of limitations of activities of daily living (ADLs).	0.7426	0.4734	86,794
Change in mental ADLs	Measure of change in the number of limitations of activities of daily living (ADLs) related to mental wellbeing.	0.5868	0.5257	86,794
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.	0.0047	0.5685	148,017
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.	0.5783	0.4938	98,916
House value	Reported house value in hundreds of thousands of dollars.	1.3915	1.4209	49,577
Family income	Total family income in hundreds of thousands of dollars.	0.4769	0.6095	101,300
Age	Age of the head of the household in years.	41.37	13.16	101,692
Male	Gender of the head of the household. It takes the value of 1 if male and 0 if woman.	0.6838	0.4650	101,703
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.	0.4558	0.4980	101,524
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 the individual completed high school or a higher level of education.	0.7766	0.4165	109,684
Employed	Dummy variable equal 1 if the head of household is employed and 0 otherwise.	0.7889	0.4081	101,672
Married	Dummy variable that takes the value 1 if the head of the household is married and 0 if not.	0.5060	0.4999	118,103
Family members	Number of members in the household.	3.3718	1.7147	102,484
Year	Year of the data collection.	1996.6	8.335	118,103
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.	5.3471	2.6556	145,204
Elasticity and interest rates				
SE*IR	Interaction between housing supply elasticity (SE) as estimated in Saiz (2010) and the 10-year interest rate (IR) yield of the U.S. Treasury bond at 10-year maturity.	1.6581	0.9038	81,721

Table 1. Descriptive statistics (cont.)

Panel B. Summary statistics for the county level data

	Description	Mean	Std. Dev.	Observations
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.	1.0543	4.4280	2,595
Change in alcohol-induced and suicide death rates	Change on alcohol-induced causes of death per 100,000 people, as cataloged by ICD-10 codes X45, X65, Y15 and others, plus the change in suicide deaths by drug poisoning per 100,000 people, as cataloged by ICD-10 codes.	0.5052	2.7154	781
Measure of wealth shock				
Realization of housing wealth misestimation at the county level ($RHWM_C$)	Average at the county level of the shock in housing wealth when the household sells its current house, RHWM.	0.0038	0.9784	1,684
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.	0.5884	0.2610	1,884
House value	Reported house value in hundreds of thousands of dollars.	1.8403	1.2476	1,733
Unemployment rate	Percentage of unemployed adults in the county.	6.6525	3.2514	25,733
Family Income	Average family income in hundreds of dollars at the county level.	40,253.0	11,027.5	25,134
Non-white population	Percentage of non-white population in the county.	0.1700	0.1618	13,885
High school	Percentage of people who graduated from high school and/or enrolled in further studies in the county.	83.8638	7.5686	14,346
Middle age	Percentage of people aged between 45 and 64 years old in the county.	26.8747	3.9278	14,346
Elderly	Percentage of people aged 65 years old or over in the county.	14.7532	4.3314	14,346
Ownership rate	Percentage of people that own the house they live in.	0.7194	0.0821	14,346
RUCC_1	Dummy variable that equals 1 for metropolitan counties with population over a million in 2013.	0.1554	0.3623	26,262
RUCC_2	Dummy variable that equals 1 for metropolitan counties with population between 250,000-999,999 in 2013.	0.1247	0.3305	26,262
RUCC_3	Dummy variable that equals 1 for metropolitan counties with population below 250,000 in 2013.	0.1143	0.3182	26,262
RUCC_5	Dummy variable that equals 1 for urban areas with population between 2,500-20,000 people in 2013.	0.0281	0.1654	26,262
Number of hospital beds	Number of hospital beds in the county.	2.7677	2.3690	20,852
Δ Manufacturing employers	Change in percentage of manufacturing employers in working age population.	-3.0363	3.2511	25,378
Δ Import exposure	Change in import exposure per worker.	3.6530	3.5849	25,378
Legal environment controls				
PDMP operational	Dummy variable that equals 1 from the year the state first implemented a Prescription Drug Monitoring Program. It takes 0 for the period when it has not been implemented yet.	0.6049	0.4879	1,391
First marijuana law	Dummy variable that equals 1 from the year the state first passed a law regulating the distribution of medical or recreational marijuana. It takes value 0 otherwise.	0.1950	0.3948	1,391

Table 2. Effects of shocks in wealth on changes in health

Panel A. Estimates on changes in self-reported health (SRH) and changes in measures of distress

	Δ(SRH)			Δ(Drug death rates)		Δ(Alcohol or suicide death rates)	
	Ordered probit	Ordered probit	Interval regression	OLS	OLS	OLS	OLS
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
RHWM	0.0142 *	0.0168 **	0.0194 **	-0.2751 **	-0.2797 **	-0.0003	0.0113
	(0.0074)	(0.0072)	(0.0084)	-0.1184	(0.1200)	(0.0793)	(0.0863)
Healthy	-12,019 ***	-12,078 ***	-13,961 ***	-0.7776 *	-0.8247	0.5630	0.7469 *
	(0.0222)	(0.0234)	(0.0204)	(0.5445)	(0.6306)	(0.4324)	(0.4264)
House value		0.0486 ***	0.0562 ***	0.0507	0.0438	0.0586	0.0795
		(0.0065)	(0.0077)	(0.0801)	(0.0819)	(0.0833)	(0.0962)
Poverty (%)				-0.0632	-0.0581	-0.1264 ***	-0.1289 **
				(0.0578)	(0.0701)	(0.0491)	(0.0564)
PDMP Operational					-0.2252		0.2376
					(0.3069)		(0.3481)
First marihuana law					0.6919		-1.0035 *
					(0.7291)		(0.5936)
Hospital beds rate mean					0.0065		-0.0091
					(0.0965)		(0.0879)
Δ Manufacturing employers					0.1028 **		0.0469
					(0.0490)		(0.0537)
Δ Import exposure					0.0230		0.0327
					(0.0670)		(0.0627)
Age control	yes	yes	yes	yes	yes	yes	yes
Gender control	yes	yes	yes	-	-	-	-
Socioecon. controls	-	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Division fixed effects	yes	yes	yes	yes	yes	yes	yes
Observations	44,282	38,664	38,664	664	658	337	332
R^2				0.08	0.09	0.06	0.08

Note: This table reports estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in health outcomes. Specifications [1], [2], and [3] show the estimates for the health outcome change in self-reported health, D(SRH). Specifications [1] and [2] use an ordered probit model and [3] uses an interval regression. Specification [1] only includes as control variables the health status, age, and gender of the head of the household. Specification [2] adds 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. Specification [3] reports the estimates of the interval regression with all the demographic and wealth controls. Specifications [4] and [5] report the estimates for the health outcome change in drug death rates. Specifications [6] and [7] report the estimates for the health outcome change in drug death rates. Specifications [4]-[7] control for urban-rural categories. Standard errors are reported in parentheses.

Table 2. Effects of shocks in wealth on changes in health (cont.)

Panel B. Marginal effects. Ordered probit specification [2] in panel A

	Self-reported health		
	Decrease	No change	Increase
RHWM	-0.0047 **	0.0006 **	0.0041 **
	(0.0020)	(0.0003)	(0.0018)
Healthy	0.3400 ***	-0.0449 ***	-0.2951 ***
	(0.0060)	(0.0033)	(0.0047)
House value	-0.0137 ***	0.0018 ***	0.0119 ***
	(0.0018)	(0.0003)	(0.0016)
Age control	yes	yes	yes
Gender control	yes	yes	yes
Socioecon. controls	yes	yes	yes
Observations	38,664	38,664	38,664

Note: Errors are clustered at the family level. Standard errors are reported in parentheses.

Table 3. RHWM as an unexpected shock in housing wealth

Estimates of ordered probit specifications using as dependent Variable is Change in Self-Reported Health

	Households that did not move during the previous period [1]	Households that never moved [2]	Households that had moved but not in the previous period [3]
Housing wealth misestimation	-0.0004	-0.0008	0.0000
	(0.0005)	(0.0009)	(0.0006)
Healthy	-1.2888***	-1.4179***	-1.2160***
	(0.0634)	(0.1222)	(0.0745)
House value	0.0814***	0.0951***	0.0633*
	(0.0255)	(0.0396)	(0.0339)
Age control	yes	yes	yes
Gender control	yes	yes	yes
Socioecon. controls	yes	yes	yes
Year fixed effects	yes	yes	yes
Division fixed effects	yes	yes	yes
Observations	8,053	2,518	5,535
Log Likelihood	-7,368.70	-2,243.04	-5,097.68

Note: This table reports the estimates of the determinants of house value misestimation and moving, using in all the cases ordered probit regressions. 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. In all the models errors are clustered at the family level.

Table 4. Other measures of health outcomes: Changes in ADLs

Panel A. Estimates on changes in ADLs

	Δ(Total ADLs) Ordered probit [1]		Δ(Mental ADLs) Ordered probit [2]	
RHWM	0.0004		-0.0151	**
	(0.0086)		(0.0076)	
Total ADLs	-0.02311	***	-11648	***
	(0.0234)		(0.0869)	
House value	-0.0033		-0.0315	***
	0.0084		(0.0083)	
Age control	yes		yes	
Gender control	yes		yes	
Socioecon. controls	yes		yes	
Year fixed effects	yes		yes	
Division fixed effects	yes		yes	
Observations	12,069		18,240	
Log Likelihood	-6,188.24		-6,268.76	

Note: This table reports ordered probit estimates of the effect of Realization of Housing Wealth Misestimation (RHWM) on the change in self- reported health in (1) (2) and (3), and the estimates of the interval regression in (4). Specification (1) only includes as control variables the health status, age, and gender of the head of the household. Specification (2) adds the house value as control, and specification (3) includes all the demographic controls. These three ordered probit specifications include errors clustered at the family level. Specification (4) reports the estimates of the interval regression with all the demographic and wealth controls. Standard errors are reported in parentheses.

Panel B. Marginal Effects. Ordered probit specification [2] in panel A

	Δ (Mental ADLs)					
	Decrease		No change		Increase	
RHWM	0.0006	**	0.0016	**	-0.0021	**
	(0.0002)		(0.0008)		(0.0011)	
Healthy	0.0447	***	0.1248	***	-0.1695	***
	(0.0031)		(0.0098)		(0.0125)	
House value	0.0012	***	0.0033	***	-0.0046	***
	(0.0003)		(0.0008)		(0.0012)	
Age control	yes		yes		yes	
Gender control	yes		yes		yes	
Socioecon. controls	yes		yes		yes	

Note: Errors are clustered at the family level. Standard errors are reported in parentheses.

Table 5. Instrumental variables for RHWM

Panel A. First stage of the linear Instrumental Variable regression

	[1]		[2]	
SE*IR	-0.0524	***	-0.0543	***
Healthy	0.0063		0.0054	
House Value	-0.0247	**	-0.0210	
Age control	yes		yes	
Gender control	yes		yes	
Socioecon. controls	-		yes	
Year fixed effects	yes		yes	
Division fixed effects	no		no	
Observations	43,132		41,537	
Log Likelihood	72,317.76		69,971.78	

Note: This table reports linear estimates of Realized Housing Wealth Misestimation, in the first stage of the instrumental variable model. As instrument, the interaction between supply elasticity (SE) of the house market and interest rates (IR) at 10 years is used. In all three models errors clustered at the family level.

Panel B. Order Probit Instrumental Variable Regression. Second Stage

	[1]		[2]	
RHWM	0.0216	*	0.0204	*
Healthy	-0.9736	***	-1.0037	***
House Value	0.0692	***	0.0460	***
Age control	yes		yes	
Gender control	yes		yes	
Socioecon. controls	-		yes	
Year fixed effects	yes		yes	
Division fixed effects	yes		yes	
Observations	43,132		41,537	
Log Likelihood	72,317.76		69,971.78	

Note: the table reports the ordered probit estimates of the second stage of the instrumental variable model. The dependent variable is the change in SRH, and the variable RHWM has been instrumented by the interaction between supply elasticity of the house market and the interest rate at 10 years. In all the three models the errors are clustered at the family level.

Table 5. Instrumental variables for RHWM (cont.)

Panel C. Estimated marginal effects on the change of Self-Reported Health
IV Ordered Probit Regression. Panel B, column [2]

	Self Reported Health					
	Decrease		No change		Increase	
RHWM	-0.0055	*	-0.0005		0.0060	*
Healthy	0.2378	***	0.0774	***	-0.3152	***
House value	-0.0124	***	-0.0011		0.0134	***
Family income	-0.0107	***	-0.0009		0.0116	***
Age	0.0013	***	0.0001		-0.0014	***
Male	0.0167	**	0.0021		-0.0188	**
Nonwhite	0.0166	***	0.0010		-0.0176	***
Hisghschoolmore	-0.0351	***	-0.0002		0.0353	***
Employed	-0.0456	***	0.0006		0.0450	***
Married	-0.0180	**	-0.0009		0.0190	**
Family Members	0.0018		0.0002		-0.0020	
Observations	41,537		41,537		41,537	

Note: Errors clustered at the family level