changes in the state house price index (HPI) and high blood pressure, finding a negative and significant relationship.

Based on this literature, we expect that home equity serves as a predictor of health outcomes among older homeowners. We consider the association of home equity and the ability to control a costly disease as a first-step, reduced-form approach to examining the association of housing wealth and health. In addition, we expect that, in the context of health outcomes in older age, the occurrence of death cannot be ignored. Censoring a sample may introduce bias into estimates as people who are unable to control their disease may be more likely to die than those who are better able to control their disease, and home equity may act as an antecedent to this relationship, thus influencing the hazard of death. We expect that a higher level of home equity available prior to a significant health shock home equity reduces the risk of death.

2.2 Financial Consequences of a Health Shock in Older Age

The onset of a new disease in older age can be expensive despite the fact that a significant portion of healthcare costs are covered by Medicare. Prior studies of older adults document significant out of pocket (OOP) health costs associated with the onset of a new disease, (Cubanski 2014; Davidoff et al 2013; Fong 2019; Narang and Nicholas 2017). For example, in a panel data analysis of Medicare beneficiaries age 65 and older in the HRS from 2002 to 2012, Narang and Nicholas (2017) find a significant ($p<0.05$) increase in OOP expenditures following a cancer diagnosis—with average annual OOP expenditures of $4,690 compared to $3,507 for those not newly diagnosed with cancer during the sample period. In a supplemental analysis, they find similarly high annual OOP expenditures for older adults diagnosed with heart disease ($4,870), diabetes ($4,097) and lung disease ($3,970). They also document substantial variation in costs by health insurance coverage. For the 24 percent of Medicare beneficiaries without supplemental insurance, annual OOP costs following cancer diagnosis average $8,115, compared to $2,116 for the 8.5 percent of older adults on Medicaid.

In addition to direct OOP health costs, the total financial burden of a disease can be much greater. Reductions in earned income, transaction costs associated with seeking treatment, and consumption and lifestyle changes can drain financial resources (Poterba et al. 2017a, Smith 1999; 2004). Numerous studies document substantial declines to household wealth for older adults following a health shock (Coile and Milligan 2009; Dalton and LaFave 2017; Gilligan et al 2018;

Lee and Kim 2008; Pak et al. 2020; Poterba et al 2017; Smith 1999; 2005; Wallace et al. 2017). An early study of older adults using the HRS by Smith (1999) found a $17,000 decline in net wealth in the two-year period following the onset of a severe disease (cancer, heart disease, stroke, or lung disease). However, Smith (1999) does not decompose changes by type of wealth, nor does he examine outcomes beyond a two-year period.

Using data on adults age 65 and older from the 1996 to 2014 waves of the HRS, Poterba, et al. (2017) examine contemporaneous changes in total net worth in the wave in which a new disease is first diagnosed. Lung disease and stroke are associated with a statistically significant $29,000 and $25,000 reduction in total net worth, with no significant reduction associated with the onset of other diseases including diabetes, heart disease, and cancer. They further decompose changes by type of wealth, finding a significant reduction in housing wealth of $5,000 to $7,000 for stroke, heart attack, and lung disease. A limitation of their analysis is a focus on very short-term effects of a health shock on wealth, in the same period as the diagnosis. Further, they do not examine the mechanisms underlying declines in housing wealth—whether this is due to increases in borrowing, home sale, or exogenous changes to home value.

Using the 1992 to 2004 waves of the HRS, Coile and Milligan (2009) estimate a series of event study models to identify changes in ownership of particular types of assets before and after the onset of an acute (heart attack, cancer) or chronic (lung disease, diabetes) disease. For both types of health shocks, they find a significant reduction in the probability of owning a home following a health shock (relative to the wave prior to shock) that increases over time post diagnosis. By six years (3 survey waves) after the shock, study participants were about 6 percentage points less likely to own a home relative to the wave prior to the shock.

A few other studies focus specifically on the effects of a cancer diagnosis on wealth, given the severe financial burden associated with cancer treatments. Gilligan et al. (2018) study adults age 50 and older newly diagnosed with cancer using the 1998 to 2014 waves of the HRS. They estimate changes in net worth two and four years after diagnosis, relative to levels two years prior to diagnosis, finding that about 40 percent of respondents completely deplete their net worth by four years following diagnosis, with an average decline of about $50,000. However, their results are primarily descriptive. In a similar study using the 2000 to 2014 waves of the HRS, Pak et al. (2020) document a large and statistically significant 24 percent reduction in net wealth in the wave immediately following cancer diagnosis, corresponding to a decline of $125,852, with no

statistically significant reduction in wealth thereafter. They also find a re-allocation of wealth to more liquid forms, with an increase in household savings held in cash and cash equivalents.

More similar to our analysis, Gupta et al. (2018) analyze the relationship between cancer diagnosis, financial outcomes, and treatment adherence. Their data include cancer treatment and outcome data, public records property data, and mortgage data for adults with a cancer diagnosis in one state (Washington) between 1996 and 2009. They explore the relationship between the onset of a cancer diagnosis and changes in housing wealth, and the relationship between home equity extraction and adherence to cancer treatments. Their primary identifying assumption is that the timing of a new cancer diagnosis (among the sample with cancer) is unrelated to geographic variation in house price change, which they use as an instrument for home equity extraction.[2] Of those with positive equity in their homes prior to diagnosis, their findings indicate a statistically significant 17 percentage point increase in equity extraction within the five years following a cancer diagnosis. Further, they find that equity extraction, modeled as endogenous, is associated with a 23 percentage point increase in cancer treatment adherence.

Also similar to this present analysis, Moulton et al. (2020) use data from the 1998 to 2016 waves of the HRS to estimate the relationship between borrowing from home equity following a health-shock and cost-related medication non-adherence (CRN), treating borrowing as endogenous using ZIP coded lagged HPI change and an indicator for being borrowing constrained as instruments. They find that each additional $10,000 in home equity borrowed following a health shock is associated with a statistically significant 1.5 percentage point reduction in CRN—which is more than a 20 percent reduction in the probability of experiencing CRN. While this literature suggests that borrowing from home equity following a health shock may increase adherence to treatment, it does not examine the relationship with longer term health outcomes including the ability to control a disease—this being the focus of the present study.

Our study extends the analysis by Gupta et al. (2018) and Moulton et al. (2020) to analyze the relationship between home equity, mortgage borrowing, and disease specific outcomes for all older adults, not limited to those with a cancer diagnosis. Further, our use of the HRS allows us to control for a rich array of demographic and financial variables not available in previous studies.

[2] Specifically, their instrument is the average change in house prices in a ZIP code for the three years prior to cancer diagnosis. They find that a one unit increase in HPI is associated with a 15 percentage point increase in the probability of equity extraction.

Our hypothesis is that home equity *extraction* through mortgage borrowing or home sale—rather than the *stock* of home equity—is what matters for the disease outcomes of older homeowners. As a result, we expect a negative association of liquidity obtained through mortgage borrowing and home sale with the likelihood of having an uncontrolled health condition, as key mechanisms underlying the relationship between house values and health outcomes.

2.3 Prior Literature on Disease being Adequately Controlled

Medical diseases are common among older adults, with 35 percent diagnosed with a major disease including cancer, heart disease, lung disease, or stroke by age 65, rising to 65 percent by age 90 (Poterba et al. 2018). While numerous studies examine risk factors associated with being diagnosed with a disease (American Diabetes Association, 2021a; Sung et al., 2021; Vestbo et al., 2013; Virani et al., 2021), an equally important health outcome for older adults is the ability to manage and control a disease. Following prior studies, we define disease as being controlled if a person is diagnosed with a disease and their physical and blood-based indicators are within medically defined thresholds for adequate control (Mitchell et al. 2019; American Diabetes Association, 2021b; GOLD, 2020; Sung et al., 2021; Vestbo et al., 2013; Virani et al., 2021)

Biological markers help identify individuals whose illness is controlled and who therefore are considered at lower risk of morbidity and mortality from the disease (American Diabetes Association, 2021a). Biological markers also help identify individuals whose illness is not controlled and who are at higher risk of morbidities or mortality from the disease. If the biological risk markers are observed over time, it allows for the ascertainment of disease progression or lack thereof in a person and between different population groups. The focus on disease control is specific to a disease; it is distinctly different from a measure of overall health and is limited to those who have been diagnosed with a disease (American Diabetes Association, 2021a; Sung et al., 2021; Vestbo et al., 2013; Virani et al., 2021).

Despite prior research indicating that people often liquidate home equity following a health shock, no known prior literature examines the relationship between home equity or mortgage borrowing and the extent to which the disease is subsequently controlled. However, prior literature indicates that income and socioeconomic status are significantly associated with disease control. Here, we focus on studies of diabetes, lung disease, cancer and heart disease as these are the most common and costly chronic conditions for older adults and are the focus of our study.

Diabetes is characterized by high blood glucose due to insulin resistance and a relative lack of insulin secretion (American Diabetes Assocation, 2021a). The HRS does not distinguish between the onset of type 1 or type 2 diabetes; however, given we measure new onset in older age, the majority of cases will be type 2 diabetes. A robust medical literature documents that socioeconomic status is a significant predictor of glycemic (A1c) control (Hill-Briggs et al., 2020). Measures of socioeconomic status include poverty (Houle et al., 2016) as well as measures of financial hardship, such as difficulty paying bills (Walker et al., 2021). Using the Health and Retirement Study, Walker et al. (2021) find that A1c increases by about 0.1 percent among older adults for each additional measure of financial hardship.

Lung disease encapsulates a variety of conditions in which individuals have a reduced ability to engage in activities due to structural and functional decline in lung tissue (Hankinson et al., 1999). These declines lead to a reduced capacity for gas exchange and can potentially lead to hypoxia. The most common lung diseases fall under the spectrum of chronic obstructive pulmonary disease (Gonçalves et al., 2018). An established literature documents that lower socioeconomic status is associated with reduced lung function (Hegewald & Crapo, 2007). Lower income and poverty are among these socioeconomic factors (Harik-Khan et al., 2001; Prescott et al., 1999). In the multinational Burden of Obstructive Lung Disease study, a one-unit higher wealth score based on household assets (range = 0 to 10) was associated with a 0.36 percent better lung function after adjustment for age and sex (Townend et al., 2017).

New cancer diagnosis is defined here to include all types, including malignant tumors but excluding minor skin cancers. A rapidly growing literature on the financial toxicity of cancer has examined the significant impact of cancer on cancer patients' financial situation (de Souza et al., 2017). A smaller literature examines the role of socioeconomic status for cancer control, in particular for older adults (Friedell et al., 1998). Here, the focus is on survivorship and access to follow-up care. The ability to afford health insurance is a significant predictor of cancer control, as examination of the Affordable Care Act has shown (Zhao et al., 2020). Lower income, poverty, insurance coverage, and financial hardship situations have been identified as factors in cancer control among older adults (DiMartino et al., 2017).

Heart disease is defined here to include people diagnosed with coronary heart disease, angina, congestive heart failure, or heart attack. Heart disease has been clearly linked with socioeconomic status (Schultz et al., 2018). High blood pressure is the greatest risk factor for heart

disease (Kokubo & Matsumoto, 2017; Virani et al., 2021). Blood pressure control is important for the prevention of heart disease and a critical factor in preventing heart events in those with pre-existing heart disease including heart attacks, coronary heart disease, and congestive heart failure. Socioeconomic disparities clearly exist in hypertension (Minor et al., 2008). Income and education are key socioeconomic status measures with large multi-study consortiums showing significant associations with blood pressure, supported by meta-analyses (Brummett et al., 2019; Leng et al., 2015).

Taken together, biomarkers serve as objective measures of disease control. Their availability as part of the HRS has initiated a growing number of studies that use the biological and physical health measures in addition or complementary to the survey-based health information.

3. Data and Methods

3.1 Data and Sample Construction

The primary source of data for our analysis is the Health and Retirement Study (HRS), a long-standing and well-regarded panel survey of American adults over the age of 50 with a response rate above 80 percent. The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. Respondents are surveyed every two years, with new birth cohorts added to the existing sample every three waves. Each wave has around 20,000 respondents (for data set description, Fisher & Ryan, 2018; Sonnega et al., 2014). We use restricted HRS data from 1998 to 2016 with geographic identifiers, as well as the RAND HRS Longitudinal File 2016 (v2) which includes imputations for missing data on financial variables used in our analysis.[3]

For this analysis, we limit our sample to homeowners in the HRS who have a health shock between 2002 and 2016. Following the approach used in prior studies (Smith 1999; 2005; Poterba et al 2017a; 2017b; 2018), we define a health shock as a respondent who self-reports a new diagnosis of disease from 2002 to 2016. Of the 25,481 homeowners in the HRS during our study

[3] The RAND HRS Longitudinal File is an easy-to-use dataset based on the HRS core data. This file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

period, we limit the sample to respondents diagnosed with one of four major diseases that are common and costly: heart disease (N=3,424), diabetes (N=2,667), lung disease (N=1,455), and cancer (N=2,056). For respondents with multiple diseases diagnosed during our study period, we focus on their first newly diagnosed disease during the study period. This results in the first health shock being skewed towards earlier waves of the HRS, 18.9 percent of first health shocks in 2002, 14.6 percent in 2004, 14.4 percent in 2006, 11.7 percent in 2008, 11.7 percent in 2010, 10.5 percent in 2012, 9.6 percent in 2014, and 8.4 percent in 2016.

To define homeowners, we limit the sample to people who owned a home in the wave prior to diagnosis, who joined the HRS in 2012 or earlier (including mid-baby boomers), and who remain in the sample for at least three consecutive survey waves.[4] We also drop homeowners who defaulted on mortgage debt in 2008, 2010, 2012, 2014, or 2016 waves.[5] These restrictions result in a sample of 8,824 unique respondents. Our primary estimation sample is further restricted to 6,000 respondents age 65 and older at the time of their health shock to hold constant Medicare eligibility.

3.2 HRS Biomarker Data, Disease Control, and Self-Rated Health

The focal outcome for this study is a disease-specific indicator of a health shock being adequately controlled in the waves after the health shock. To construct this outcome, we use restricted biomarker and physical health indicators collected from HRS respondents every four years, beginning in 2006 or 2008 (Crimmins et al., 2017), with up to three periods of available data per respondent (through 2014 or 2016). Our estimation sample with biomarker data includes 2,172 respondents (3,932 respondent-wave observations) who were under age 65 at the time of diagnosis, and 4,013 respondents (6,830 respondent-wave observations) who were age 65 or older at the time of diagnosis.

There are various approaches for constructing indicators from biomarkers in the HRS. One approach is to construct an index measure across diseases, summing the number of markers that

[4] The number of lags for our explanatory variables and instruments limits our sample to observations that have complete data for all lagged periods, which is currently two lagged waves prior to the outcome year.

[5] Questions about mortgage foreclosure and delinquency are not available before the 2008 wave in the HRS. After 2008, borrowers in default on their mortgages could receive loan modifications that increase the total mortgage amount. The HRS data do not allow us to separate increases in the mortgage amount due to borrowing from increases due to modifications. Thus, we drop the small number of individuals in default on their mortgages after 2008 from the primary regression sample.

are high risk/uncontrolled (e.g., Garcia & Ailshire, 2019; Oi, 2021). Another approach is to examine the markers individually, constructing binary indicators for being uncontrolled on a specific disease (e.g., Mitchell et al., 2019). In our study, we code disease indicators separately, identifying whether or not specific biomarker indicators are within medically defined thresholds for adequate control for a particular disease (American Diabetes Association, 2021b; Armstrong, 2014; GOLD, 2020; Vestbo et al., 2013). Blood-based biomarkers include A1c (diabetes), and C-reactive protein (inflammation, e.g., cancer). Physical indicators include blood pressure (heart disease), and peak lung expiratory flow (lung disease).

Table 1 summarizes the biomarker thresholds used in our primary specifications and the proportion of respondents in the sample diagnosed with a given disease who were uncontrolled post diagnosis. Appendix A provides additional detail on each biomarker and our coding process.[6]

Table 1: Biomarker Thresholds for Disease Control and the % Uncontrolled in Sample

Disease	**Biomarker**	**Threshold**	**% Uncontrolled**	
			Diagnosis age ≥ 65	Diagnosis age < 65
Lung	Peak Expiratory Flow Rate	≤50%	33.0%	12.6%
Heart	Blood Pressure	≥140/≥90 mmHg	36.5%	27.1%
Diabetes	Hemoglobin A1c	≥7%	22.4%	27.6%
Cancer	C-Reactive Protein	≥5 mg/L	19.8%	23.7%

Note: Table provides the thresholds used in the analyses to identify disease control in the waves after the shock.

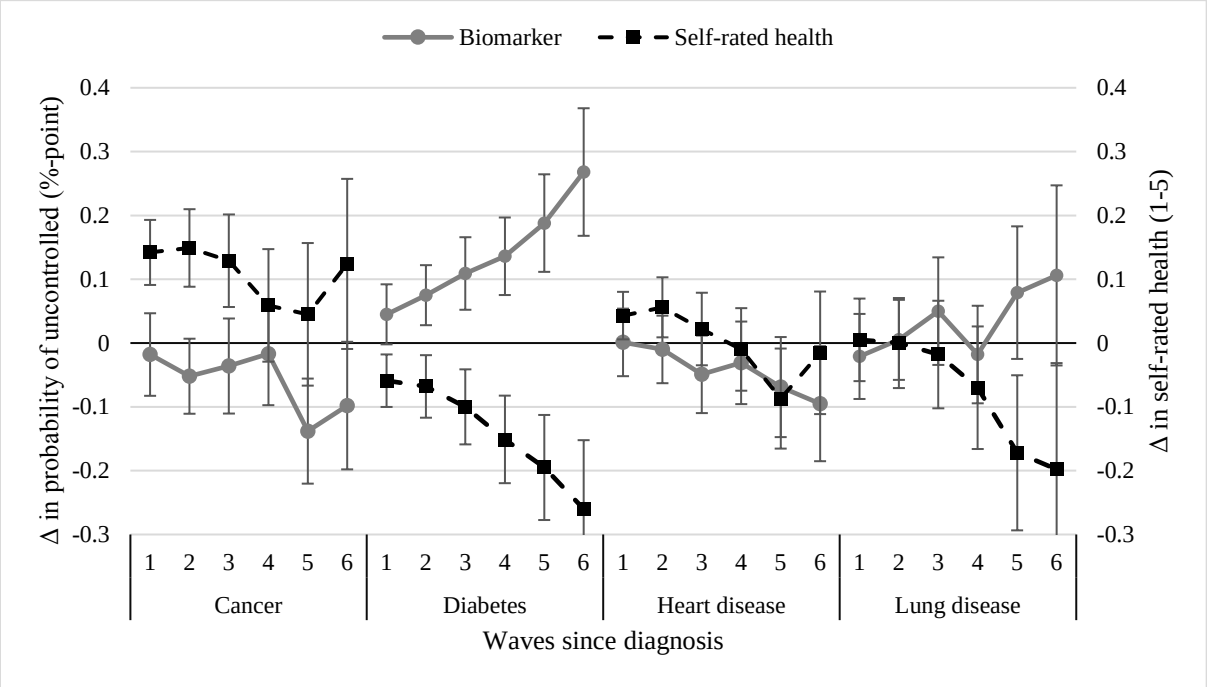
While biological markers provide objective measures of health, a large literature exists that examines measures of self-assessed, subjective health. This measure reflects a person's optimism about their health and is influenced by socio-economic and psychological factors (Layes et al., 2012). The relationship with objective measures of health varies across studies, but the measure has been consistently documented as a predictor of longevity (van Doorslaer & Gerdtham, 2003). As a result, self-assessed health provides a complementary approach to assessing health after

[6]As a sensitivity test, we re-estimate our models with alternative thresholds for a disease being uncontrolled as follows: diabetes (hemoglobin A1c ≥8%); heart disease (blood pressure ≥130/≥80 mmHg); and cancer (C-reactive protein ≥10 mg/L). The results with the alternative thresholds for heart disease and cancer are substantively similar to the results with our preferred thresholds. For diabetes, the results weaken when we use the higher level of A1c; however, only 5.1 percent of the sample with diabetes is uncontrolled using a threshold of 8 percent, versus 25.4 percent being uncontrolled with the threshold of 7 percent (the medically preferred threshold).

disease onset by accounting for non-medical factors that can influence an older adult's perception about their health.

The HRS uses a simple question inquiring about a person's health status on a five-point Likert scale ranging from poor, fair, good, very good and excellent (Question C001). The question is used in several national survey efforts, such as the Survey of Health, Aging, and Retirement in Europe (SHARE), the Household, Income, and Labor Dynamics in Australia Survey (HILDA), and the German Socio-Economic Panel (SOEP).[7]

Figure 1: Trends in the probability of biomarker uncontrolled and self-rated health following a new diagnosis by type of diagnosis



Source: 2006-2016 HRS survey waves. Restricted to respondents with a health shock between 2002 and 2016 who owned a home in the wave prior to the shock. Samples combine homeowners shocked before and on or after age 65 (N = 8.435 total person-waves across all diseases). Samples are unbalanced panels.
Note: All models control for age and age-squared and calendar year of the shock, and include random effects. Linear probability models are used for estimation.

We use the five-point scale for self-rated health as an alternative outcome in our study. Figure 1 compares trends in our biomarker-based indicator for being uncontrolled with self-rated health after the diagnosis. Note that all trends are relative to the omitted wave immediately after

[7] Besides retaining the 5-item coding, studies have used a binary coding of the measure based on combining "poor" and "fair" responses (Coe & Zamarro, 2011) or focus on the lowest, "poor" response (Dave et al., 2008; Eibich, 2015)

the person was diagnosed with a disease. All trends adjust for age, age-squared, and calendar year of diagnosis, and include individual random effects. For three of the four diseases, the two measures follow opposite trajectories as expected post-diagnosis (an increase in being uncontrolled is associated with a decline in self-rated health), with the shape of the trends being idiosyncratic for the disease type. Heart disease is the exception as respondents are slightly less likely to be uncontrolled on biomarkers at wave five, yet they also report slightly worse self-reported health at wave five. These conflicting trends in disease progression confirm that biomarkers and self-reported health measure two distinct underlying constructs.

3.3 Empirical Specifications

We begin with a descriptive analysis of trends in health expenditures, income, financial wealth, home equity, and non-housing debt for individuals in the HRS with a health shock, beginning with the survey wave prior to the health shock through 2016, or when the individual exits the sample. Unique to our study, we further separate changes in home equity due to mortgage borrowing from changes due to home sale. We estimate a series of event study models to analyze trends, where "time 0" is the HRS survey wave when the person reports first being diagnosed with a disease and the omitted baseline period is the survey wave immediately prior to being diagnosed with the disease. We estimate trends separately by age at the time of diagnosis (under or over age 65). All of the event study models control for age, age-squared, and calendar year of diagnosis, and include individual random effects. We also compare average stocks of home equity and loan-to-value ratios in the wave immediately prior to the shock, and rates of new mortgage borrowing in the wave immediately after the shock, by HRS birth cohort, holding the age of diagnosis constant.

We then move to a series of causal analyses. Our first specification models the reduced form relationship of time invariant home equity in the wave prior to a disease diagnosis (E_i) and whether or not a disease is adequately controlled in the waves of or after the diagnosis (Y_{it}).[8] A disease that is not adequately controlled is coded "1", or "0" otherwise. We control for time invariant health levels that are predetermined as of the wave prior to diagnosis including

[8] This specification tests whether the amount of home equity held prior to diagnosis of a disease is associated with whether the disease is controlled in all waves following the diagnosis. It does not allow the association to differ depending on how many waves after the diagnosis have occurred. In supplemental analyses, we re-estimated equation (1) including interactions between home equity held prior to the diagnosis and the wave since diagnosis dummy variables, this allowing the association between home equity and disease outcomes to vary over time. None of the interaction terms were significant.

comorbidities, self-reported health, smoking, functional and cognitive limitations, mental health, and presence and types of health insurance (H_i), as well as income and liquid wealth (A_i). X_i is a set of time invariant demographic control variables measured as of the wave prior to the diagnosis, including race/ethnicity, sex, education, marital status, household size, number of living children, region and urban-rural residence, as well as age and age-squared at the time of diagnosis and the calendar year of the diagnosis. W_{it} is a set of time varying control variables including dummies for the wave since the diagnosis and calendar year dummies, μ_i is a person-specific effect that captures unobserved individual factors, and η_{it} is a transitory shock. We include a vector of indictors for disease type (D_i) that take the value of "1" for the new disease that is associated with the health shock at time 0. We estimate Equation (1) using a linear probability model with individual random effects.[9] We estimate the model separately by age at the time of disease onset (<65 or ≥65).

$$Y_{it} = \beta_0 + \beta_1 E_i + \beta_2 H_i + \beta_3 A_i + \beta_4 X_i + \beta_5 W_{it} + \beta_6 D_i + \mu_i + \eta_{it} \quad (1)$$

Our second specification includes the lagged amount of home equity extracted through borrowing (B_{it-1}), modeled as an endogenous choice. Time varying financial controls include lagged income and liquid wealth (A_{it-2}), as well as non-financial, time varying controls (X_{it-2}) including changes in marital status, death of a spouse, region and urban-rural residence, household size, number of living children, presence and type of health insurance, and spouse health levels including comorbidities, self-reported health, and physical limitations. We lag the time-varying control variables two waves, as they are also included in the first stage regression predicting the amount borrowed at t-1. W_{it} is a set of indicators for the number of waves since the disease diagnosis, μ_i is a person-specific effect that captures unobserved individual factors, and η_{it} is a transitory shock. We estimate our models with random effects and include vectors of time invariant variables measuring respondent health levels in the wave prior to disease diagnosis (H_i), (A_i), and (X_i), as well as disease type (D_i) following the specification in Equation (1). Results from a Hausman test comparing Equation (2) with fixed versus random effects were not significant, indicating that the latter is consistent with the former and random effects are statistically more efficient and thus preferred (chi2 = 35.610, p = 0.746). Nevertheless, as a robustness test, we

[9] In supplemental analyses not shown, we re-estimated equation (1) using a probit regression model and found substantively similar results (available by request).

present results from a fixed effects specification that controls for all possible unobserved time-invariant confounders. We estimate Equation (2) separately by age of disease onset (<65 or ≥65).

$$Y_{it} = \beta_0 + \beta_1 B_{it-1} + \beta_2 A_{it-2} + \beta_3 X_{it-2} + \beta_4 W_{it} + \mu_i + \eta_{it} \quad (2)$$

This specification tests whether the amount of borrowing in a wave after the diagnosis affects disease control in the following wave. Thus, only the short-term effect is estimated. The specification assumes there are no longer run effects of borrowing (e.g., four or more years after the new loan occurs). We estimate Equation (2) using a two-stage least squares panel model, with the first stage estimating the amount of home equity extracted and the second stage estimating whether or not the disease is adequately controlled. One instrument for home equity extraction is the lagged local area two-year percent change in ZIP code house prices as measured by the FHFA House Price Index (ΔHPI), from t-2 to t-1 (FHFA, 2020). Change in house prices is a commonly used instrument for endogenous changes in home equity and mortgage borrowing in the literature (Costa-Font et al. 2019; Fichera & Gathergood 2016; Gupta et al. 2018; Hamoudi & Dowd 2013). We also include as an instrument the level of house prices in the ZIP code at t-2 drawn from the Zillow Home Value Index (ZHVI). Our identifying assumption is that geographic variation in ΔHPI and house price levels at a given point in time are unrelated to health outcomes (conditional on all controls) except through their effect on extracting home equity. Our third instrument is an indicator of being borrowing constrained at t-2, which we measure as having a loan-to-value (LTV) ratio of 80 percent or higher from HRS survey data as it is more difficult to be approved for additional borrowing with LTVs above 80 percent.[10]

In our primary specifications for Equation (2), home equity extracted (B_{it-1}) is limited to the amount extracted through borrowing on a mortgage. In an alternative specification, we replace B_{it-1} with the amount of home equity extracted through home sale as of t-1. Unfortunately, our instruments fail the weak instrument test in the first stage when extraction is defined as home sale (Kleibergen-Papp rk LM statistic = 5.556, p = 0.135). We subsequently estimate our models

[10] We test alternative instruments, including an indicator of monthly housing costs to monthly income being greater than 30 percent, as well as an indicator of the count of bank branches in a respondent's ZIP code. We find that these indicators do not significantly predict mortgage borrowing and thus are not good instruments. We also consider alternative thresholds for being constrained by LTV, including 90 percent LTV. LTV thresholds above 90 percent are statistically associated with lower levels of mortgage borrowing, however the 80 percent threshold has the strongest relationship with future borrowing and thus is the threshold we use for our primary specifications.

replacing B_{it-1} with a combined indicator of the total amount of equity extracted through borrowing and home sale as of t-1. Instrument tests for this model meet generally accepted thresholds.

In robustness checks we test whether the relationships for home equity held prior to the shock (Equation 1) or equity extraction (Equation 2) and post-diagnosis disease outcomes varies by (a) whether the primary source of income in the wave prior to the shock was Social Security (for those diagnosed after age 65);[11] (b) whether the homeowner held any mortgage debt in the wave prior to diagnosis; and (c) whether the homeowner was borrowing constrained in the wave prior to diagnosis (measured by an LTV ratio of 80 percent or higher or a mortgage payment-to-income ratio of 20 percent or higher in the wave before the diagnosis).

Our primary outcome is an indicator for whether or not the disease is adequately controlled as measured using biomarker data. As a complimentary analysis, we estimate our specifications (Equations 1 and 2) with a commonly used indicator of overall self-reported health measured on a scale of 1 to 5, where 1 is "poor" and "5" is excellent. This is a different construct from disease control, as it is not disease specific and is perceptual. Self-reported health has one additional analytical advantage: unlike biomarker data that begins in 2006 and is observed only every other wave, self-reported health is measured every wave for each respondent, thereby increasing the number of observations.

One of the limitations of our empirical approach is to censor people when they die. This censoring may introduce bias into our estimates as people who are unable to control their disease may be more likely to die than those who are better able to control their disease, and home equity may act as an antecedent to this relationship, thus influencing the hazard of death. As a supplemental specification to Equation (1), we estimate the reduced form relationship between home equity prior to diagnosis on post-diagnosis all-cause mortality. We do this with a Cox proportional hazards model, estimating the risk of dying (h) at age t, where the onset of risk is defined as the age of diagnosis, as shown in Equation (3). Survivors are censored as of the last available interview wave. We include the same set of time invariant variables included in Equation (1), measured as of the wave prior to diagnosis.

[11] We measure Social Security as the primary source of income if income from Social Security Supplemental Security, Disability, and Retirement constitutes 90% or more of total household income. This indicator is time invariant, measured as of the wave prior to the health shock.

$$h(t) = h_0(t)* exp\ (\beta_1 E_i + \beta_2 H_i + \beta_3 A_i + \beta_4 X_i + \beta_5 D_i) \quad (3)$$

3.4 Variable Construction and Sample Characteristics

Appendix B reports summary statistics for the estimation sample in Equation (1) and Equation (2).[12] Home equity is calculated as the difference between respondents' estimate of the home value and their outstanding mortgage balance on all primary and secondary residences. All dollar values are adjusted for inflation to 2016 dollars using the Consumer Price Index for All Urban Consumers-All Items. The sample means home equity at baseline is $211,400 for those diagnosed on or after age 65 and $161,100 for those diagnosed before age 65 with diabetes, heart disease, lung disease, or cancer.

New mortgage borrowing is calculated as the amount of the increase in the self-reported mortgage balance on primary and secondary residences (combined) between two waves (Moulton et al. 2020). Negative values, which represent mortgage repayments, are set to 0. The new mortgage borrowing measure combines four types of mortgage debt into one measure, including first mortgages, home equity lines of credit (HELOCs), second mortgages, and other mortgages on the primary and secondary residences.[13] We do not use the imputed RAND mortgage debt data; those with RAND imputed values are set to missing. Using imputed values for mortgage amounts can yield false indications of increased borrowing from one wave to another. In addition, we set borrowing amounts to 0 in the wave that a respondent moves, purchases a second home, or splits from a household. These assumptions eliminate erroneous instances of borrowing due to a purchase of a new home or change in marital status. We also create a binary measure of new mortgage borrowing, which is coded as 1 in the wave of mortgage borrowing and 0 other waves. Outliers are set to missing, including households with home equity greater than $1,500,000 in years t or t-1 (48 cases) and households that borrow more than $500,000 from year t to t-1 or t-1 to t-2 (7 cases). In our estimation samples, 18.2 percent of homeowners under age 65 at the time of the shock and 11.0 percent of homeowners age 65 and older at the time of the health shock borrow from home equity over a two-year period (from one wave to the next), with an average borrowed amount of $52,800 and $41,700. The sample mean amount borrowed (including $0 for

[12] Summary statistics are generated for the sample used to estimate reduced form Equation (1) which includes biomarkers measured in the wave of the new diagnosis.

[13] We re-estimated equation (2) with a borrowing amount variable limited to primary residences and on the portion of the sample who do not own second homes. We find substantively similar results in both cases.

ranges from 0 to 20 (Hamoudi & Dowd 2014) and a measure of self-reported memory, with 1 being poor memory and 5 being excellent memory (Insel, Morrow, and Figueredo 2006). These cognitive and memory variables are measured in the wave prior to the new diagnosis.[15] To account for unobserved local economic shocks that may be correlated with both mortgage borrowing and health outcomes, we control for the lagged average annual county unemployment rates and the change in these rates between t-2 and t-1 (Bureau of Labor Statistics 2019).

Key sample characteristics, among the sample diagnosed on or after age 65, show that the average age of diagnosis is 72.7, 50.7 percent of respondents are male, 89 percent of respondents are White, 8.4 percent of respondents are Black, 5.5 percent are Hispanic (of any race), and 2.6 percent are another race. In terms of education, 18.3 percent of the older diagnosed sample have less than a high school degree, 38.6 percent have a high school degree or GED, 21.7 percent have some college, and 21.3 percent have a college or higher degree. In terms of baseline health levels, average self-rated health in the wave prior to the diagnosis is in the "good" range (mean = 3.346), 9.8 percent of the sample were smokers in wave prior to the diagnosis, and the average number of comorbidities prior to the diagnosis was 0.389.

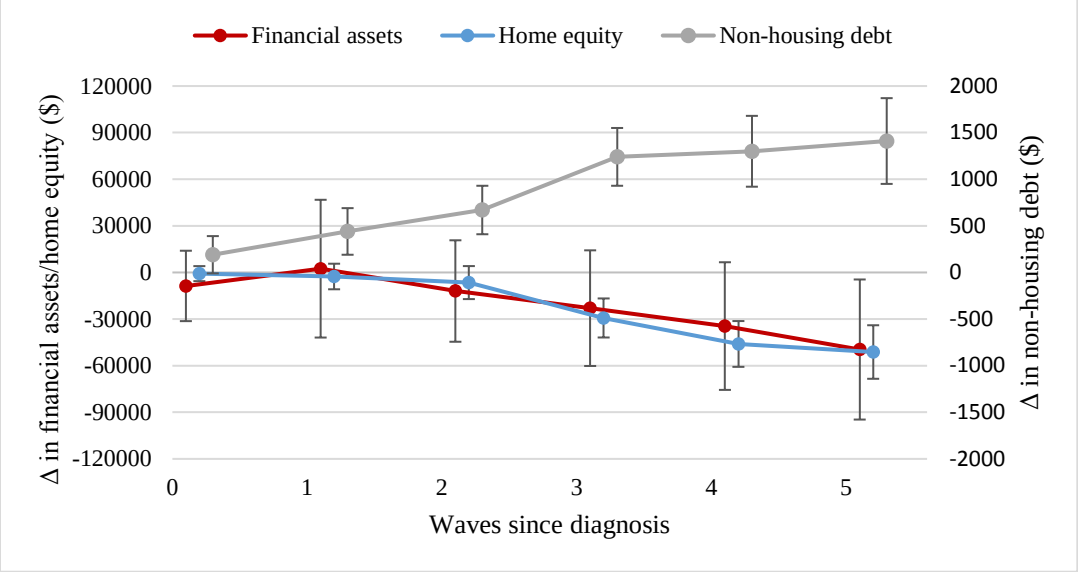
4. Results

4.1 Descriptive Trends: Financial Variables Following Health Shock

We begin by examining trends in financial variables in the waves following a new diagnosis. All trends adjust for age, age-squared, and the year of the new diagnosis. The omitted period is the wave prior to the shock. Figure 2 charts mean health care expenditures and household earnings for homeowners with a new diagnosis before age 65. Relative to the wave prior to the shock, prescription drugs and total out-of-pocket health care expenditures increase by an average of $890 and $1,500 respectively ($p < 0.05$). At the same time, annual individual earnings decrease by an average of $4,500 relative to the wave prior to the health shock ($p < 0.05$). Figure 3 charts these same financial variables for homeowners with a new diagnosis after age 65. These older homeowners who experience a health shock exhibit similar increases in average prescription drug

[15] We include a dummy variable that equals one if the respondent is missing data on the memory variable in the wave prior to the diagnosis. In our sample, 3.1% of homeowners diagnosed on or after age 65, and 3.9% of homeowners diagnosed before age 65, are missing data on this variable.

Figure 5: Trends in assets, debts, and home equity following a diagnosis on or after 65



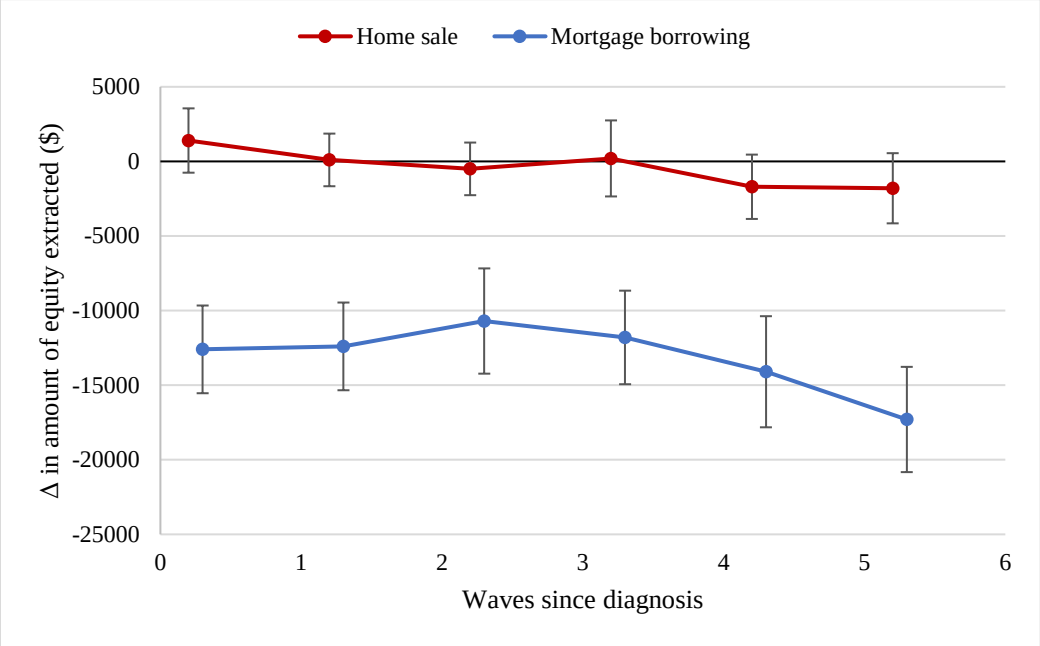
Source: 2000-2016 HRS survey waves. Restricted to respondents with a health shock between 2000 and 2016 who were age 65 or older in the wave of the shock and owned a home prior to the shock (N = 20.538 person-waves). Note: All models control for age and age-squared and calendar year of the shock and include random effects. Linear probability models used for estimation. Dots are staggered along the x-axis to enhance interpretability.

Next, we present trends in new mortgage borrowing and home sales for the samples diagnosed before age 65 (Figure 6) and on or after age 65 (Figure 7). The amount of new mortgage borrowing declines in the waves following the health shock for those diagnosed before age 65 ($p < 0.001$) relative to the wave prior to the diagnosis; there are no significant changes in the amount of new mortgage borrowing following a new diagnosis for the sample of homeowners diagnosed on or after age 65. Turning to home sales, there are no significant changes in the amount of equity extracted through home sales following the new diagnosis for the under-age 65 sample. For homeowners diagnosed on or after age 65, the average amount of equity extracted through a home sale is $3,800 higher in the wave of the shock than the prior wave ($p < 0.05$).

Figures 8 and 9 compare median home equity and average loan-to-value ratios in the wave prior to a new diagnosis by birth cohort and age of the shock. The diamonds in the graphs mark the age range when the median-aged cohort member experienced the 2008 housing crisis. Moving from left to right on the X-axis, there is a general trend across cohorts of higher median home equity as homeowners are diagnosed at older ages. Moreover, there are few notable differences in median home equity across cohorts diagnosed at similar ages. The exception is the

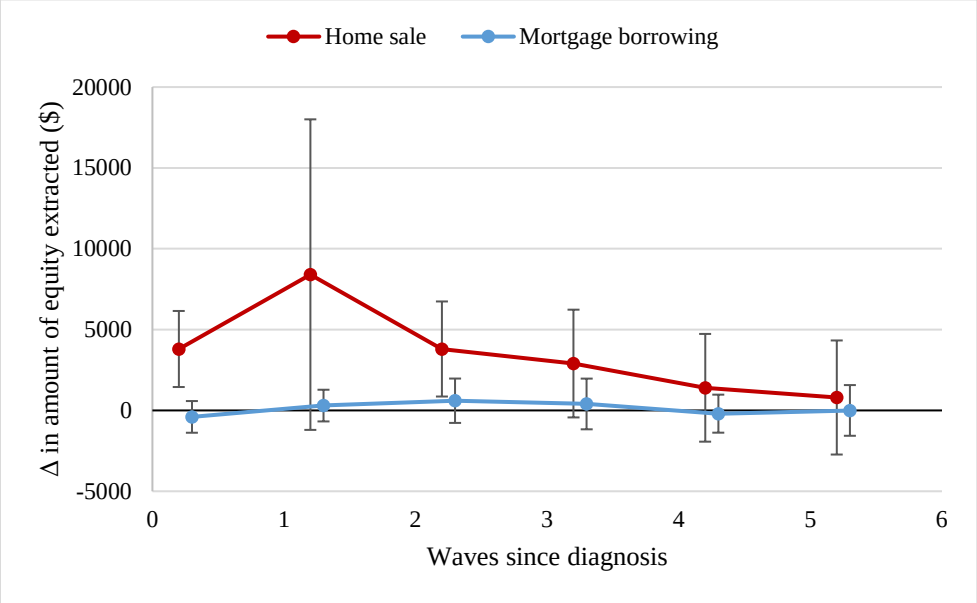
Mid-Baby Boomers cohort that has notably lower median home equity than earlier cohorts diagnosed at similar ages.

Figure 6: Trends in home equity extraction amount following a diagnosis before age 65



Source: 2000-2016 HRS survey waves. Restricted to respondents with a health shock between 2000 and 2016 who were age 64 or younger in the wave of the shock and owned a home prior to the shock (N = 11,043 person-waves). Note: All models control for age and age-squared and calendar year of the shock and include random effects. Linear probability models used for estimation. Dots are staggered along the x-axis to enhance interpretability.

Figure 7: Trends in home equity extraction amount following a diagnosis on or after 65

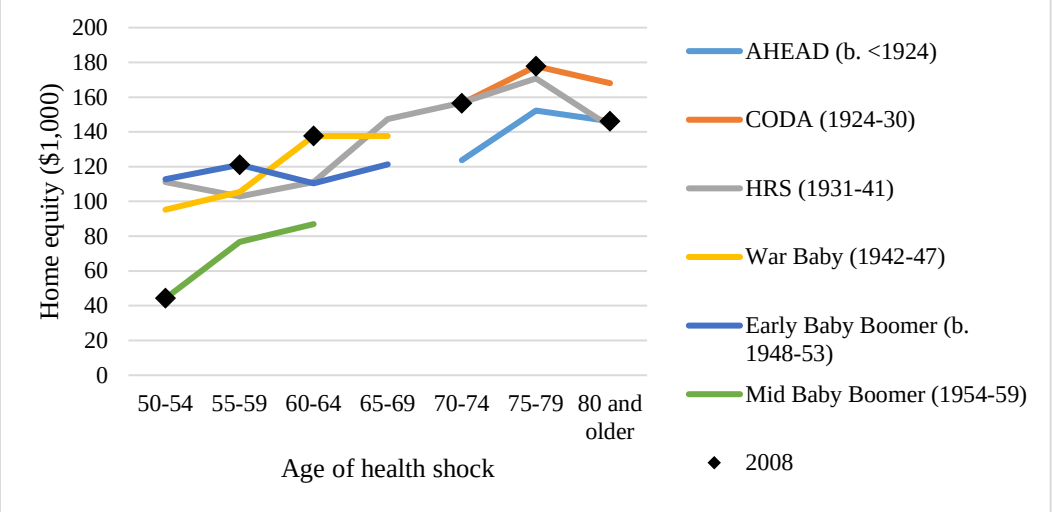


Source: 2000-2016 HRS survey waves. Restricted to respondents with a health shock between 2000 and 2016 who were age 65 or older in the wave of the shock and owned a home prior to the shock (N = 20.538 person-waves). Note: All models control for age and age-squared and calendar year of the shock, and include random effects. Linear probability models used for estimation. Dots are staggered along the x-axis to enhance interpretability.

Further, average LTV ratios are generally higher among younger cohorts of homeowners diagnosed at similar ages. For example, compared to members of the War Baby cohort that were newly diagnosed between age 60 to 64 (21.9%), Early-Baby Boomers diagnosed between age 60 and 64 have average LTVs that are about 10 percentage-points higher (30.1%), and Mid-Baby Boomers diagnosed between age 60 and 64 have average LTVs that are 25 percentage-points higher (45.4%). The higher LTV ratios suggest that younger cohorts of homeowners with a new diagnosis of disease may face greater constraints when trying to access home equity as they enter retirement than older cohorts with these costly diseases.

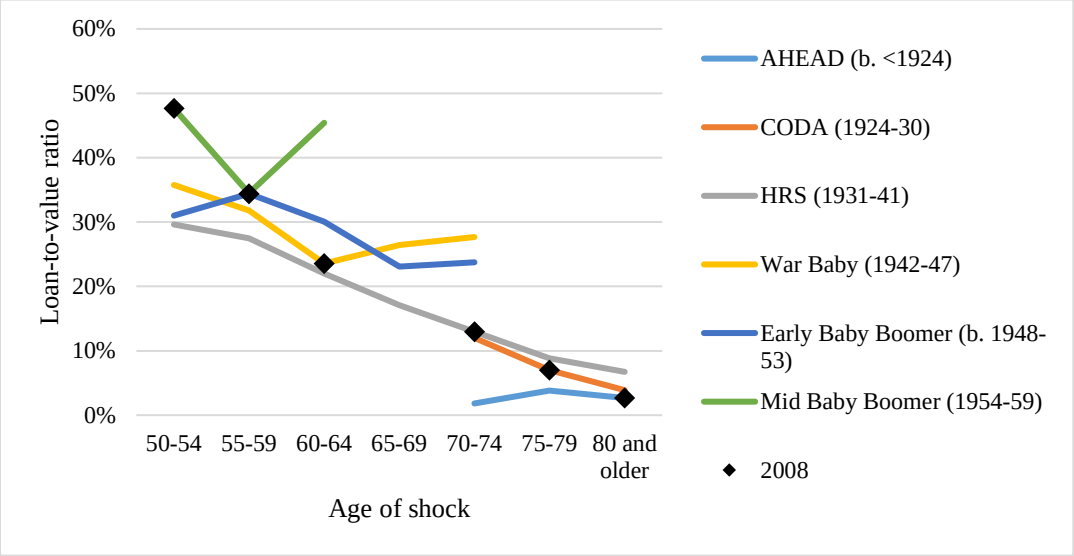
We conclude our descriptive analysis by examining trends in borrowing incidence in the wave immediately following a new diagnosis by birth cohort and age at the time of diagnosis (Figure 10). Moving left to right on the X-axis, for most cohorts, there is a declining trend in new mortgage borrowing as homeowners receive a new diagnosis at older ages. Early Baby Boomers are an exception to this pattern, as borrowing rates among this cohort are higher for those diagnosed at age 60 to 64 compared to those diagnosed before age 60. There is little evidence that new mortgage borrowing after the onset of a disease is higher for more recent cohorts of older homeowners.

Figure 8: Median home equity prior to diagnosis by diagnosis age and cohort



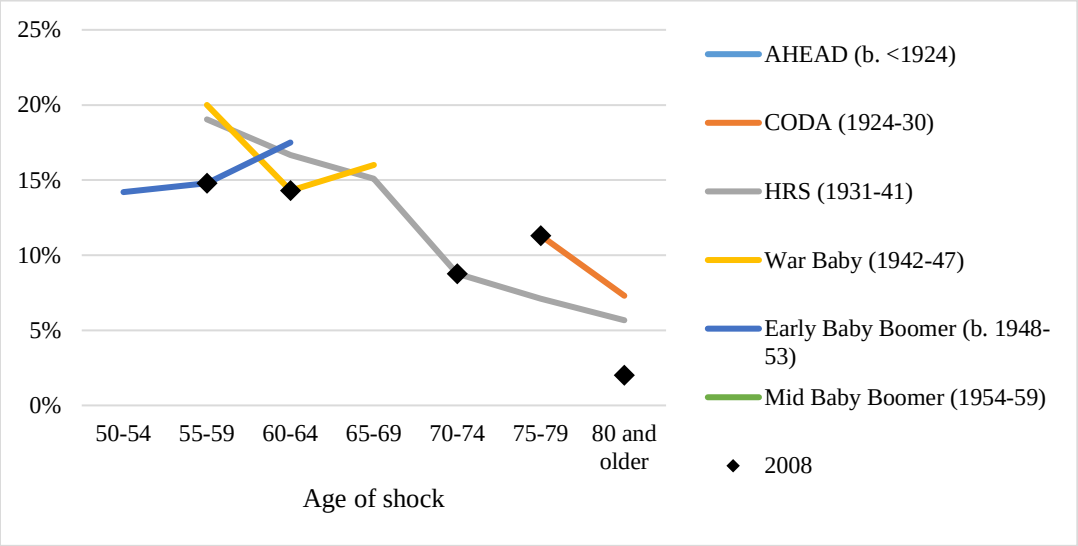
Source: 2006-2016 HRS survey waves. Restricted to respondents with a health shock between 2002 and 2016 who owned a home prior to the shock (N = 7,975).

Figure 9: Average home loan-to-value prior to diagnosis by diagnosis age and cohort



Source: 2006-2016 HRS survey waves. Restricted to respondents with a health shock between 2002 and 2016 who owned a home prior to the shock (N = 7,975).

Figure 10: Percent taking out mortgage in wave after diagnosis by diagnosis age and cohort



Source: 2006-2016 HRS survey waves. Restricted to respondents with a health shock between 2002 and 2016 who owned a home prior to the shock (N = 7,975).

4.2 Reduced Form Regression: Home Equity Prior to Health Shock and Disease Control

In this section we present results from our reduced form regressions of disease outcomes on home equity held prior to the onset of the disease (Equation 1). Table 2 presents results from the main

analytic sample of HRS respondents diagnosed with one of the four diseases on or after age 65 (Column 1), and results for homeowners diagnosed with one of the four diseases before age 65 (Column 2). The full regression results for the main analytic sample (age 65+) are available in Appendix C. The coefficients from the linear probability model can be interpreted similarly to marginal effects as the percentage-point change in the probability of the disease being uncontrolled corresponding to a one-unit change in the independent variable. The main model in Column 1 shows that home equity held in the wave prior to the health shock is not statistically significantly associated with the probability of the disease being uncontrolled following the diagnosis (b = -0.003, p = 0.443).[16] As shown in Column 2, home equity held prior to the health shock is also not significantly associated with subsequent disease control status among homeowners diagnosed before age 65 (b = 0.001, p = 0.835). However, our primary assumption is that home equity *extraction* through mortgage borrowing or home sale—rather than the *stock* of home equity—is what matters for the disease outcomes of older homeowners.

Table 2: Random effects linear probability models predicting disease outcomes on time-invariant home equity held prior to the diagnosis

Outcome variable	Biomarker uncontrolled (0/1)	Biomarker uncontrolled (0/1)	Self-rated health (1-5)
Age at diagnosis	Age ≥ 65	Age < 65	Age ≥ 65
	Beta (robust S.E.)	Beta (robust S.E.)	Beta (robust S.E.)
Home equity prior to diagnosis ($100k)	-0.003 (0.003)	0.001 (0.006)	0.020** (0.007)
Control variables			
Socioeconomic characteristics	Yes	Yes	Yes
Health characteristics	Yes	Yes	Yes
Demographic characteristics	Yes	Yes	Yes
Year and wave since/of diagnosis	Yes	Yes	Yes
N (person-waves) =	5,056	2,806	12,677

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
Notes: All control variables are measured in the wave prior to the diagnosis. Socioeconomic characteristics include annual household income, net financial assets, net other assets, and non-housing debt. Health characteristics include the type of diagnosis, self-rated health, smoking status, comorbidities, self-rated memory, cognitive status, CES-Depression scale, problems with activities of daily living, and the presence and type of health insurance. Demographic characteristics include race/ethnicity, sex, immigration status, education, age and age-squared at time of diagnosis, marital status, number of living children and household size, rural-urban residence, region of residence, and the county unemployment rate.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

[16] Appendix D re-estimates the reduced form model on subsamples by the type of disease diagnosis among homeowners diagnosed on or after age 65. Home equity has a negative coefficient for cancer and lung disease patients. In contrast, home equity has a positive sign for heart and diabetes patients. However, for none of these sub-samples is home equity held prior to the diagnosis significantly associated with disease outcomes.

We explore differences in the relationship between home equity held prior to the shock and post-diagnosis disease outcomes for people for whom Social Security benefits comprise 90 percent or more of their income; homeowners with mortgage debt in the wave prior to diagnosis; and a homeowner with high LTV or mortgage payment-to-income ratios in the wave before the diagnosis. We test for differences using interactions and sub-sample analyses. We find no significant differences by any of these criteria—home equity at baseline remains insignificant at conventional levels.[17]

Several control variables are significantly associated with the probability of the disease being uncontrolled following the diagnosis in the main model (see Appendix C). Rural residence (relative to suburban), residence in the Mid-Atlantic (relative to Pacific) region, having Medicare/VA coverage (relative to no health insurance), lower levels of education, lower levels of self-rated health and smoking and higher levels of self-rated memory in the wave prior to the shock are all positively associated with the disease being uncontrolled ($p < 0.05$). In addition, all disease type dummies are positive and significant, with heart disease patients having the lowest likelihood of disease control ($b = 0.281$, $p < 0.001$).[18] Notably, household income, financial assets, and non-housing debts at baseline are not significantly associated with disease outcomes. We find a marginally significant positive relationship between net other assets, including other savings, non-housing real estate, transportation, and business values, in the wave prior to the shock and the probability of the disease being uncontrolled ($b = 0.003$, $p = 0.079$). That few of the financial

[17] There are several differences in the coefficients of the other variables in the model between the Social Security subsamples. Household income was positively associated with being uncontrolled for the subsample who relied on Social Security for 90% or more of their income but was not significant for the subsample who was less reliant on Social Security. Net other debt was positively associated with being uncontrolled and having never been married (relative to currently married) and suburban residence (relative to rural) were negatively associated with being uncontrolled, for the subsample who relied on Social Security for 89% or less of their income. Being separated, divorced, or widowed (relative to currently married) is positively associated with being uncontrolled for the sample that received 90% or more of its income from Social Security. Having health insurance in the wave prior to the shock was positively associated with being uncontrolled only for the subsample who received 89% or less of their income from social security. In addition, self-rated health and memory at baseline were more strongly associated with being uncontrolled for the sample who received 90% or more of their income from Social Security, while smoking status in the wave prior to the shock was more strongly associated with being uncontrolled for the sample who received 89% or less of their income from Social Security. Disease type was significantly associated with the probability of the disease being uncontrolled for both subsamples, with a new heart disease diagnosis being associated with the highest risk of being uncontrolled.

[18] People may be diagnosed with more than one disease at the same point in time and thus all disease indicators are included in the model. Individuals diagnosed with more than one disease are considered uncontrolled if biomarkers on any of their new diseases exceed the thresholds in Table 1.

variables are significant may reflect a high degree of collinearity between financial security and education, disease type, baseline health levels, and other factors in the model, possibly leading the latter factors to serve as stronger proxies for permanent financial security than the financial variables themselves.

As a complementary analysis, we re-estimated the reduced-form regression of home equity held prior to the shock on post-diagnosis self-rated health levels for the main sample of homeowners diagnosed on or after age 65 (Column 3). We find that a $100,000 dollar increase in pre-diagnosis home equity is associated with a 0.02 scale-point increase in self-rated health ($p = 0.005$).[19] To put this effect in context, the average homeowner in our sample has an average post-diagnosis self-rated health score of 2.992. Ceteris paribus, a one standard-deviation increase in pre-diagnosis home equity ($211,700) increases this homeowner's self-rated health by 1.3 percent to a score of 3.032. Home equity held prior to the health shock thus has a small, positive effect on self-reported health following the diagnosis, net of all other factors in the model.

4.3 Home Equity Prior to Health Shock and Hazard of Death

The second set of empirical analyses examines the relationship between home equity held prior to a health shock on the hazard of death, estimated using a Cox proportional hazard model where "failure time" is modeled as the age at death and the onset of risk is defined as the age of the new diagnosis. Survivors are censored in the last available interview wave following the diagnosis of diabetes, heart disease, lung disease or cancer. The hazard model includes the same set of time-invariant covariates as the reduced form regression presented in Section 4.2. Table 3 presents the hazard ratio of pre-shock home equity on the probability of post-diagnosis death estimated on the sample of homeowners age 65 and older at the time of diagnosis. Home equity significantly reduces the hazard of death, with each additional $100,000 in pre-shock home equity reducing the risk of death by 2.7 percent ($p = 0.02$). To illustrate this effect, we explore differences in the cumulative mortality rate for cancer patients by age 79 depending on their place in the home equity distribution. Comparing the failure functions, 29.6% of cancer patients in the bottom 25th

[19] If baseline self-rated health is included in the model as a predictor, the coefficient on home equity is reduced to 0.014 but remains statistically significant ($p < 0.026$).

percentile of home equity prior to the diagnosis had died by age 79. In comparison, only 17.3% of cancer patients in the top 25th percentile of home equity prior to the diagnosis had died by age 79.

Table 3: Cox proportional hazard model of all-cause mortality on time-invariant home equity held prior to diagnosis

Age at diagnosis	Age ≥ 65 Hazard ratio (S.E.)
Home equity prior to diagnosis ($100k)	0.973* (0.012)
Control variables	
Socioeconomic characteristics	Yes
Health characteristics	Yes
Demographic characteristics	Yes
Wave of diagnosis	Yes
N unique respondents =	5,223

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
Note: Onset of risk defined as age at diagnosis. All control variables are measured in the wave prior to the diagnosis. Socioeconomic characteristics include annual household income, net financial assets, net other assets, and non-housing debt. Health characteristics include the type of diagnosis, self-rated health, smoking status, comorbidities, self-rated memory, cognitive status, CES-Depression scale, problems with activities of daily living, and the presence and type of health insurance. Demographic characteristics include race/ethnicity, sex, immigration status, education, age and age-squared at time of diagnosis, marital status, number of living children and household size, rural-urban residence, region of residence, and the county unemployment rate.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

4.4 Endogenous Regression: Home Equity Extraction and Disease Control

We now turn to our preferred model of post-diagnosis disease control. This model focuses on time-varying home equity extraction, treated as endogenous. Table 4 presents results for the main sample of homeowners diagnosed with a disease at age 65 or older (Columns 1-3), as well as for homeowners diagnosed before age 65 (Column 4). Similar to the reduced form regressions above, the results of these two-stage least square linear probability models can be interpreted directly as marginal effects. The full results of the first and second stages of the main regression model (homeowners age 65 and older at the time of the health shock) is available in Appendix E.

Table 4: Random effects linear probability models predicting disease outcomes on time-varying post-diagnosis endogenous home equity extraction

Outcome variable	Biomarker uncontrolled (0/1)				Self-rated health (1-5)
Age at diagnosis		Age ≥ 65		Age < 65	Age ≥ 65
	Beta (robust S.E.)	Beta (robust S.E.)	Beta (robust S.E.)	Beta (robust S.E.)	Beta (robust S.E.)

Mortgage borrowing ($100k), t-1 – t-2	-0.925* (0.457)			0.239 (0.281)	0.571+ (0.337)
Equity extracted through sale ($100k), t-1 – t-2		-0.523 (0.447)			
Combined equity extracted through borrowing and sale ($100k), t-1 – t-2			-0.558+ (0.299)		
Control variables					
Socioeconomic characteristics	Yes	Yes	Yes	Yes	Yes
Health characteristics	Yes	Yes	Yes	Yes	Yes
Demographic characteristics	Yes	Yes	Yes	Yes	Yes
Year and wave since/of diagnosis	Yes	Yes	Yes	Yes	Yes
Instrumental variables					
Change in zip code FHFA house price inflation (%), t-1 – t-2	0.038* (0.017)	0.083 (0.052)	0.111* (0.047)	0.066+ (0.035)	0.011 (0.008)
Loan-to-value ≥ 80% (0/1), t-2	-0.099*** (0.023)	-0.011* (0.005)	-0.072*** (0.018)	-0.116*** (0.022)	-0.154*** (0.019)
Zillow zip code house value index ($100k), t-2	0.002 (0.003)	0.002 (0.003)	0.003 (0.004)	0.013 (0.008)	0.008+ (0.005)
N (person-waves) =	4,120	4,049	4,120	2,342	10,359
First-stage instrument tests					
Cragg-Donald F statistic	9.259	12.212	10.912	6.492	34.531
Under-identification test	13.283**	5.676	14.677***	28.763***	40.224***
Hansen-J statistic	1.339	3.679	1.878	1.732	0.839

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
Notes: Unless otherwise stated, all controls are time-varying and lagged two waves (t-2). Socioeconomic characteristics include annual household income, net financial assets, net other assets, and non-housing debt. Respondent health characteristics include the type of diagnosis, self-rated health, smoking status, comorbidities, self-rated memory, cognitive status, CES-Depression scale, and problems with activities of daily living, all time-invariant and measured prior to the diagnosis. Spouse health characteristics include disease indicators, self-rated health, comorbidities, problems with activities of daily living, and spouse death. Demographic characteristics include race/ethnicity, sex, immigration status, education, age and age-squared, marital status, number of living children and household size, rural-urban residence, region of residence, and the county unemployment rate.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

In Column 1, we find a significant, negative effect of new mortgage borrowing after the diagnosis on the probability of the disease being uncontrolled (b = -0.925, p =0.043).[20] Specifically, we estimate that each additional $10,000 in new mortgage borrowing reduces the likelihood of the disease being uncontrolled by 9.3 percentage-points. Thus, we estimate that new mortgage borrowing has a large, positive, and economically significant effect on post-diagnosis disease outcomes.

[20] Results from the model in Column 1 re-estimated on each of the disease subsamples are available in Appendix F. The coefficient on new mortgage is in the expected negative direction for three of the four disease subsamples. The exception is heart disease patients, for whom new mortgage borrowing has a positive coefficient. However, in no case are any of the coefficients of new mortgage borrowing significant at conventional levels. These null results may reflect insufficient power of our instruments to predict new mortgage borrowing for these relatively small subsamples.

In terms of the first-stage results of Column 1, we find that our instruments meet generally accepted criteria for valid identification. The Kleigbergen-Paap rk LM statistic is significant, indicating that our two-stage model is not under identified ($p < 0.01$). Results of the Hansen-J test are not significant, which suggests that our model is not overidentified. Finally, two out of the three first-stage instruments—HPI change and having an LTV ratio of 80 percent or higher—are significantly associated with new mortgage borrowing and in the expected direction.

Columns 2 and 3 re-estimate the model in Column 1 but replace new mortgage borrowing with measures of the amount of equity extracted through home sale and a combined indicator of the total amount of equity extracted through new borrowing and home sale. As expected, Column 2 finds that the coefficient on equity extracted through a home sale has a negative sign, however, this coefficient is not significant at conventional levels ($b = -0.523$, $p = 0.242$). Inspection of the first-stage shows that this result may reflect the insufficient power of our instruments to predict home sales.[21] Column 3 replaces the measure of equity extracted through home sale with a combined measure of total extraction through mortgage borrowing and home sale. This model finds a negative and marginally significant association between total home equity extraction and the likelihood of being uncontrolled following the diagnosis ($b = -0.558$, $p = 0.062$). Standard first-stage instrument tests for this equation meet accepted thresholds for valid identification.

Column 4 shows the results for the endogenous borrowing model estimated on the sample of homeowners age 64 or younger at the time of the diagnosis. Mortgage borrowing is not statistically significantly associated with disease control for this subsample of individuals. In a series of robustness tests for the sample diagnosed at age 65 or older, we estimate subsample regressions for people for whom Social Security benefits comprise 90 percent or more of their income; homeowners with mortgage debt in the wave prior to diagnosis; and homeowner with high LTV or mortgage payment-to-income ratios in the wave before the diagnosis. Unfortunately, the models are not well-identified in the first stage, and thus we cannot reliably interpret the results of the second stage predicting disease control.

In complimentary analyses, we re-estimate the endogenous mortgage borrowing model replacing the biomarker outcome with the indicator of post-diagnosis self-rated health (Column 5). This model shows that new mortgage borrowing following a new diagnosis has a marginally

[21] We tried replacing the continuous measure of extraction through home sale with a dummy for home sale and found that we were similarly underidentified.

significant and positive impact on self-rated health. Specifically, each additional $100,000 in mortgage borrowing is associated with a 0.56 scale-point increase in self-rated health (p = 0.093). Moreover, instrument tests for the first-stage of the model meet standard thresholds. In a supplementary analysis, we find that the coefficient on new mortgage borrowing is unchanged when pre-diagnosis self-rated health is included as a control variable in the first and second-stages.

Table 5: Alternative specifications of time-varying post-diagnosis endogenous home equity extraction random effects linear probability models

Outcome variable	Biomarker uncontrolled (0/1)	Biomarker uncontrolled (0/1)
Age at diagnosis	Age ≥ 65	Age ≥ 65
	Beta (robust S.E.)	Beta (robust S.E)
Mortgage borrowing ($100k), t-1 – 1-2	-0.441+ (0.264)	-0.945+ (0.525)
Control variables		
Socioeconomic characteristics	Yes	Yes
Health characteristics	Yes	Yes
Demographic characteristics	Yes	Yes
Year and wave since/of diagnosis	Yes	Yes
Individual fixed-effects	Yes	No
Wave of diagnosis included in model	No	Yes
Instrumental variables		
Change in zip code FHFA house price inflation (%), t-1 – t-2	0.081* (0.034)	0.041* (0.016)
Loan-to-value ≥ 80% (0/1), t-2	-0.244*** (0.067)	-0.046** (0.017)
Zillow zip code house value index ($100k), t-2	0.013 (0.012)	0.007 (0.005)
N (obs.) =	2,578	5,266
First stage instrument tests		
Cragg-Donald F statistic	13.725	5.929
Under-identification test	15.093**	13.338**
Hansen-J statistics	0.231	0.226

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
Notes: Unless otherwise stated, all controls are time-varying and lagged two waves (t-2). Socioeconomic characteristics include annual household income, net financial assets, net other assets, and non-housing debt. Respondent health characteristics include the type of diagnosis, self-rated health, smoking status, comorbidities, self-rated memory, cognitive status, CES-Depression scale, and problems with activities of daily living, all time-invariant and measured prior to the diagnosis. Spouse health characteristics include disease indicators, self-rated health, comorbidities, problems with activities of daily living, and spouse death. Demographic characteristics include race/ethnicity, sex, immigration status, education, age and age-squared, marital status, number of living children and household size, rural-urban residence, region of residence, and the county unemployment rate.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

Table 5 presents results from alternative specifications of the endogenous mortgage borrowing model, estimated on the sample of homeowners who were 65 or older at the time of

diagnosis. Column 1 replaces the individual random effects with individual fixed effects, thus effectively controlling for all time-invariant unobserved confounders. This model reveals that new mortgage borrowing retains a negative sign, but the size of the coefficient is reduced from -0.925 to -0.441, and the statistical significance is now marginal (p = 0.095). Given the insignificant result of the Hausman test and the fact that our biomarker outcome measures are limited to a maximum of three observations per person, the random effects specification is preferred. As a final sensitivity test, we re-estimate the endogenous mortgage borrowing model with individual random effects and begin measuring the outcome as of the wave of diagnosis rather than the wave after diagnosis (Column 2). The coefficient is similar, but the confidence interval is larger (b = -0.945, p = 0.072). It makes sense that the standard error of the estimate is larger when the wave of diagnosis is included in the regression. People are diagnosed with the disease at different points in time within the two years prior to the wave of diagnosis, and borrowing also occurs at different points in time; thus not all borrowing as of the wave of diagnosis would follow the onset of the disease.

5. Discussion

Health shocks pose a significant risk to economic security in retirement, however, the financial behaviors that effectively help older adults manage the progress of costly diseases are little understood. One of the largest financial resources held by older adults is the equity in their homes—yet it is illiquid and can only be used to pay for health costs if converted to a more liquid form through borrowing or home sale. While prior studies find a reduced form relationship between housing wealth and health outcomes (Angrisani and Lee 2016; Costa-Font et al. 2018; Fichera & Gathergood 2016; Hamoudi and Dowd 2013; 2014), ours is the first study to document a significant relationship between liquidating housing wealth following a health shock and the ability to better manage disease in older age.

In our reduced form model specifications, we observe no significant relationship between home equity levels prior to diagnosis and biomarker indicators for the disease being uncontrolled post diagnosis. The second set of empirical analyses is based on the assumption that home equity *extraction* through mortgage borrowing or home sale—rather than the *stock* of home equity—is what matters for the disease outcomes of older homeowners. Here, we model equity extraction as endogenous. We find that there is a substantial effect of accessing home equity through mortgage borrowing on the likelihood of controlling disease following a health shock. The impact of $10,000

of new mortgage borrowing is a statistically significant reduction in the probability of the disease being uncontrolled by a relatively large amount, 9.3 percentage points, measured two years after diagnosis by a set of biomarkers that are disease specific.

Our findings differ when we estimate our models with a common measure of health; specifically, a self-rated health index. For adults age 65 and older, we find a very small, positive relationship between home equity levels prior to being diagnosed with a disease and self-reported health after the onset of a disease. In our second set of empirical specifications, the estimated increase in self-rated health from home equity extraction is relatively small and is not statistically significant at standard levels. Self-rated health is a measure that combines psychological self-perceptions with medical information known by an older adult, while the biomarkers are quantitative measures backed by substantial medical information regarding the correspondence of their levels with the degree of control of a disease. We also find a small but significant relationship between home equity held prior to a health shock and the hazard of all-cause mortality.

It is important to point out the limitations of our study. The biomarker data are only available for a maximum of three survey waves and are measured only every four years. Indicators of whether a disease is controlled may change more quickly and thus some variations in our focal outcome will not be observed. A second limitation is that we only measure the short-term impact of borrowing on disease control. Studying long-term impacts will be facilitated as more biomarker data become available. A third limitation is that we aggregate our measure of control across four quite different diseases. The relatively small sample sizes that occur when limiting the focus to a specific disease makes empirical analysis difficult.

Despite these limitations, this study makes several novel contributions to research and policy. Most importantly, our findings indicate that it is not the *stock* of home equity that matters for disease outcomes of older homeowners—but it is the *extraction* of home equity, particularly through borrowing, that is associated with disease outcomes. This finding has important implications for policy and the role of home equity as a resource to enable economic security for older adults. Borrowing through a mortgage is not accessible to all older adults. In an analysis of 2.5 million mortgage applications by adults age 62 and older reported in 2018 under the Home Mortgage Disclosure Act (HMDA), Mayer and Moulton (2020) found that one in four applicants was denied a mortgage by a lender. An additional quarter of applicants withdrew their applications. The primary reason for denial was an inability to afford the monthly mortgage payment, followed

by having a poor credit history. Future policy and market innovations can consider ways to safely increase access to home equity for this population of older adults.

The federally insured Home Equity Conversion Mortgage (HECM) may be one alternative, as it allows older adults to borrow from the equity in their homes without required repayment until they exit the home (Moulton and Haurin 2019). However, the HECM requires owners to have substantial equity in their homes (typically, loan to value ratios below 60 percent) and to have the liquidity to pay for ongoing property related expenses (Lambie-Hanson and Moulton 2020; Mayer and Moulton 2020). Home sale is another option to extract equity—however, many older adults' express strong attachment to their homes and communities (Fannie Mae 2016) and the replacement costs of housing to remain in the same community may cost prohibitive. Future innovations could include small dollar reverse mortgages (Moulton and Haurin 2019) or other innovations that allow older adults to draw from home equity following a health shock safely and affordably.

Aside from implications for the economic security of older adults, the findings here suggest a relationship between housing markets and the longevity projections of Social Security beneficiary cohorts. In times of strong house price growth borrowing constraints are relaxed, potentially allowing a larger share of older adults to access home equity following a health shock, thereby improving their ability to manage a disease and extending life expectancy. Prior research (Bhutta and Keys 2016; Mian and Sufi 2011) indicates that strong house price growth is more likely to affect the equity extraction behaviors of homeowners who were previously borrowing constrained (e.g., with high levels of mortgage debt relative to the value of their homes). As a higher proportion of seniors are entering retirement with mortgage debt and holding higher levels of debt (Brown et al. 2019; Haurin et al. 2019; Lusardi et al 2017; 2020), house price dynamics may play a more important role in the economic security of newer cohorts of Social Security beneficiaries than in the past.

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Appendices

Appendix A: Measures of adequate control

Disease	Measurement thresholds
Adequately Controlled: Lung Disease	Measure: Peak lung expiratory flow Threshold: ≤50% Note: Predicted values for general population by gender, race, age, sex, height prediction table are taken from the UpToDate.com. For those who are categorized as another race/ethnicity besides non-Hispanic Black, Hispanic, or non-Hispanic White by the HRS survey instrument (i.e., American Indian/Alaska Native, Asian and Pacific Islander, and multiracial individuals), the predicted values are for the majority racial and ethnic group in the respondent's Census Tract of residence. Lung disease encapsulates a variety of conditions in which individuals have a reduced ability to engage in activities due to structural and functional decline in lung tissue. These declines lead to a reduced capacity for gas exchange and can potentially lead to hypoxia. The most common lung diseases fall under the spectrum of chronic obstructive pulmonary disease (COPD). The functional diagnosis of COPD relies on a post-bronchodilator forced expiratory volume in one second (FEV1) over the forced vital capacity (FVC) of less than 0.70 (1). The Global Initiative for Chronic Obstructive Lung Disease (GOLD) has further defined four stages of chronic obstructive lung disease. These range from mild (Stage 1), moderate (Stage 2), severe (Stage 3), to very severe (Stage 4) airflow limitations which are largely based on functional lung tests. These stages are based on FEV1 values relative to average individuals of similar age, weight, height, race/ethnicity, and sex. An FEV1 greater than or equal to 80% of predicted is considered Stage 1, between 50% and 80% is considered Stage 2, between 30% and 50% is considered Stage 3, and less than 30% is considered Stage 4. Another test of lung function is Peak Expiratory Flow (PEF). The instrument used to assess PEF is widely available and cheap compared to the clinical standard of spirometry which is used to assess FEV1. There is a moderate correlation between predicted FEV1 and PEF1 among men (0.768, $p< 0.001$) and women (0.725, $p<0.001$) (2). Given that PEF it is the measure of lung function available in the HRS and the ability to expel air from the lungs correlates well with subjective well-being related to lung disease induced constraints of daily activities of living, we use this measure to assess lung function among participants. 1. Gonçalves I, Guimarães MJ, van Zeller M, Menezes F, Moita J, Simão P. Clinical and molecular markers in COPD. *Pulmonology* 2018;24(4):250–259. 2. Aggarwal AN, Gupta D, Jindal SK. The Relationship Between FEV1 and Peak Expiratory Flow in Patients With Airways Obstruction Is Poor. *Chest* 2006;130(5):1454–1461.
Adequately Controlled:	Measure: C-Reactive Protein Threshold: ≥5 mg/L

Cancer	An elevated systemic inflammatory response (SIR) among individuals with operable cancer is associated with lower survival rates (3). Serum C-reactive protein (CRP) levels are reflective of general inflammation in the body. CRP is synthesized in the liver in response to the secretion of interleukin-6 by several immune cells. CRP binds to the surface of cells that are undergoing or have undergone apoptosis or necrosis. This causes further recruitment of the immune system to clear these cells. A maximum CRP (mCRP) of greater than 5 mg/L is generally considered to reflect higher than normal levels of inflammation. Among 7716 individuals that attended the Taussig Cancer Institute between 2006 and 2012 with solid tumor diagnosis, the risk of death was 46% higher among those with an mCRP greater than 10 mg/L versus less than 10 mg/L (4). Another study assessing the impact of CRP following patients with metastatic renal cell carcinoma before, during, and after treatment found that a CRP level greater than 5 mg/L also a significant negative impact on survival. Among patients with a pretreatment CRP less than 5 mg/L, pretreatment CRP greater than 5 mg/L than dropped below 5 mg/L during treatment, and those with greater than 5 mg/L before and during treatment had 2-year survival rates of 69%, 55%, and 4%, respectively (5). Thus, higher levels of CRP are associated with worse survival. 3. Dolan RD, Lim J, McSorley ST, Horgan PG, McMillan DC. The role of the systemic inflammatory response in predicting outcomes in patients with operable cancer: Systematic review and meta-analysis. *Sci. Rep.* 2017;7(1):16717. 4. Shrotriya S, Walsh D, Nowacki AS, Lorton C, Aktas A, Hullihen B, Benanni-Baiti N, Hauser K, Ayvaz S, Estfan B. Serum C-reactive protein is an important and powerful prognostic biomarker in most adult solid tumors. *PLOS ONE* 2018;13(8):e0202555. 5. Saito K, Tatokoro M, Fujii Y, Iimura Y, Koga F, Kawakami S, Kihara K. Impact of C-Reactive Protein Kinetics on Survival of Patients with Metastatic Renal Cell Carcinoma. *Eur. Urol.* 2009;55(5):1145–1154.
Adequately Controlled: Diabetes	Measure: Hemoglobin A1c Threshold: ≤7.0% Hemoglobin-A1c (A1c) is a measure that assesses the 3-month average blood sugar level in an individual. Specifically, it is the percentage of hemoglobin, the oxygen carrying protein in red blood cells, is glycated. An A1c greater than or equal to 6.5% leads to the diagnosis of diabetes mellitus. The 2021 American Diabetes Association Standards of Medical Care has set an A1c goal for non-pregnant adults without significant hypoglycemia to <7%. Strong evidence suggests that A1c levels less than 7% reduce the broad array of microvascular complications in type 2 diabetes (6). 6. American Diabetes Association. 6. Glycemic Targets: Standards of Medical Care in Diabetes—2021. *Diabetes Care* 2021;44(Supplement 1): S73–S84.
Adequately Controlled:	Measure: Blood pressure Threshold: ≥140/ ≥90 mmHg

Heart Disease	High blood pressure (BP) is the greatest risk factor for heart disease (CVD) and the population-attributable fractions of prehypertension and hypertension for CVD is between 30% and 60% based on large national prospective cohort studies (7). BP control is not only important for primary prevention of CVD, but it is also a critical factor in the preventing heart events in those with pre-existing heart disease including myocardial infarctions, coronary heart disease, and congestive heart failure among others. The Eighth Joint National Committee (JNC 8) on hypertension control recommends that among that blood pressure should be treated to a goal of less than 140 mmHg and 90 mmHg for systolic and diastolic, respectively (8). These guidelines are based on the preponderance of evidence that suggests that this target substantially reduces the risk of heart events. 7. Kokubo Y, Matsumoto C. Hypertension Is a Risk Factor for Several Types of Heart Disease: Review of Prospective Studies. In: Islam MdS, ed. *Hypertension: from basic research to clinical practice*. Advances in Experimental Medicine and Biology. Cham: Springer International Publishing; 2017:419–426. 8. James PA, Oparil S, Carter BL, Cushman WC, Dennison-Himmelfarb C, Handler J, Lackland DT, LeFevre ML, MacKenzie TD, Ogedegbe O, Smith SC, Svetkey LP, Taler SJ, Townsend RR, Wright JT, Narva AS, Ortiz E. 2014 Evidence-Based Guideline for the Management of High Blood Pressure in Adults: Report from the Panel Members Appointed to the Eighth Joint National Committee (JNC 8). *JAMA* 2014;311(5):507.

Appendix B: Summary statistics for estimation samples by age of diagnosis

Age at time of diagnosis	Age ≥ 65		Age < 65	
	Mean	S.D.	Mean	S.D.
Uncontrolled, t	0.278	0.448	0.238	0.426
Self-rated health, t	2.925	1.002	2.891	0.987
Housing characteristics				
Any mortgage borrowing (0/1), t-1 – t-2	0.110	0.313	0.182	0.386
Mortgage borrowing ($100k), t-1 – t-2	0.046	0.216	0.096	0.358
Mortgage borrowing among borrowers ($100k), t-1 – t-2	0.417	0.523	0.528	0.690
Sold home (0/1), t-1 – t-2	0.033	0.180	0.038	0.192
Home equity extracted through sale ($100k), t-1 – t-2	0.013	0.160	0.018	0.178
Home equity extracted among sellers ($100k), t-1 – t-2	0.623	0.929	0.715	0.858
Combined equity extracted through borrowing and sale ($100k), t-1 – t-2	0.058	0.266	0.114	0.395
Home equity prior to diagnosis ($100k)[1]	2.114	2.151	1.611	1.693
Socioeconomic characteristics				
Annual household income prior to diagnosis ($100k)[1]	0.711	0.891	0.971	0.913
Annual household income ($100k), t-2	0.635	0.758	0.851	0.825
Net financial assets prior to diagnosis ($100k)[1]	2.917	7.025	1.549	2.971
Net financial assets ($100k), t-2	2.781	5.374	1.712	3.264
Net other assets prior to diagnosis ($100k)[1]	1.498	5.185	1.142	3.182
Net other assets ($100k), t-2	1.311	5.055	1.126	3.406
Non-housing debt prior to diagnosis ($100k)[1]	0.035	0.264	0.077	0.263
Non-housing debts ($100k), t-2	0.033	0.310	0.076	0.326
Health characteristics				
New cancer diagnosis (0/1)[1]	0.208	0.406	0.175	0.380
New diabetes diagnosis (0/1)[1]	0.281	0.450	0.385	0.487
New heart disease diagnosis (0/1)[1]	0.419	0.494	0.310	0.463
New lung disease diagnosis (0/1)[1]	0.150	0.357	0.177	0.381
Self-rated health prior to diagnosis[1]	3.346	0.963	3.248	1.035
Smoking status prior to diagnosis[1]	0.098	0.297	0.209	0.407
Comorbidities prior to diagnosis[1]	0.389	0.589	0.286	0.540
Self-rated memory prior to diagnosis[1]	2.907	1.027	2.972	1.104
Missing memory prior to diagnosis (0/1)[1]	0.034	0.181	0.043	0.203
Cognitive status prior to diagnosis[1]	9.762	3.620	10.834	3.833
CES-Depression scale prior to diagnosis[1]	1.105	1.634	1.517	2.053
Problems with activities of daily living prior to diagnosis[1]	0.146	0.505	0.198	0.637
No health insurance prior to shock (0/1)[1]	0.053	0.225	0.305	0.460
No health insurance (0/1), t-2	0.018	0.133	0.239	0.426
Medicare/VA coverage prior to shock (0/1)[1,2]	0.377	0.485	0.060	0.237
Medicare/VA coverage (0/1), t-2[2]	0.457	0.498	0.194	0.395
Medicaid coverage prior to shock (0/1)[1,2]	0.028	0.165	0.025	0.157
Medicaid coverage (0/1), t-2[2]	0.037	0.190	0.039	0.193
Private insurance coverage prior to shock (0/1)[1,2]	0.100	0.300	0.591	0.492
Private insurance coverage (0/1), t-2[2]	0.023	0.150	0.419	0.494

Combination public and private coverage prior to shock (0/1)[1,2]	0.441	0.497	0.019	0.137
Combination public and private coverage (0/1), t-2[2]	0.465	0.499	0.110	0.313
Spouse problems with activities of daily living, t-2	0.174	0.686	0.160	0.616
Spouse self-rated health, t-2	2.165	1.751	2.573	1.655
Spouse has cancer (0/1), t-2	0.125	0.330	0.082	0.274
Spouse has diagnosis (0/1), t-2	0.140	0.347	0.164	0.370
Spouse has heart disease (0/1), t-2	0.195	0.397	0.154	0.361
Spouse has lung disease (0/1), t-2	0.073	0.260	0.071	0.257
Spouse death (0/1), t-2	0.030	0.170	0.013	0.115
Spouse comorbidities, t-2	0.992	1.168	0.930	1.098
Demographic characteristics				
Black (0/1)[1]	0.084	0.277	0.095	0.293
Other race (0/1)[1]	0.026	0.158	0.061	0.239
White (0/1)[1]	0.890	0.313	0.844	0.363
Hispanic ethnicity (0/1)[1]	0.055	0.228	0.101	0.301
Male (0/1)[1]	0.507	0.500	0.408	0.492
Immigrant (0/1)[1]	0.075	0.263	0.088	0.284
Less than high school degree (0/1)[1]	0.183	0.387	0.129	0.335
GED (0/1)[1]	0.049	0.216	0.062	0.242
High school degree (0/1)[1]	0.337	0.473	0.294	0.456
Some college (0/1)[1]	0.217	0.413	0.284	0.451
Four year college (0/1) [1]	0.213	0.410	0.230	0.421
Age in wave of diagnosis[1]	72.723	5.777	58.640	4.266
Age, t-2	74.279	6.052	60.666	5.466
Married or partnered prior to diagnosis (0/1)[1]	0.755	0.430	0.828	0.377
Married or partnered (0/1), t-2	0.706	0.456	0.812	0.391
Separated, divorced, or widowed prior to diagnosis (0/1)[1]	0.230	0.421	0.147	0.354
Separated, divorced, or widowed (0/1), t-2	0.277	0.448	0.165	0.371
Never married prior to diagnosis (0/1)[1]	0.016	0.125	0.024	0.154
Never married (0/1), t-2	0.017	0.127	0.023	0.149
Number of living children prior to diagnosis[1]	3.421	2.083	2.958	1.857
Number of living children, t-2	3.427	2.117	3.006	1.898
Household size prior to diagnosis[1]	2.064	0.834	2.563	1.206
Household size, t-2	2.018	0.871	2.427	1.165
Urban residence prior to diagnosis (0/1)[1]	0.454	0.498	0.471	0.499
Urban residence (0/1), t-2	0.448	0.497	0.461	0.499
Suburban residence prior to diagnosis (0/1)[1]	0.250	0.433	0.219	0.413
Suburban residence (0/1), t-2	0.254	0.435	0.220	0.415
Rural residence prior to diagnosis (0/1)[1]	0.296	0.456	0.311	0.463
Rural residence (0/1), t-2	0.299	0.458	0.319	0.466
New England region prior to diagnosis (0/1)[1]	0.034	0.181	0.031	0.172
New England region (0/1), t-2	0.033	0.179	0.031	0.172
Mid-Atlantic region prior to diagnosis (0/1)[1]	0.105	0.306	0.108	0.311
Mid-Atlantic region (0/1), t-2	0.105	0.306	0.105	0.307

East North Central region prior to diagnosis (0/1)[1]	0.169	0.375	0.179	0.383
East North Central region (0/1), t-2	0.166	0.372	0.177	0.381
West North Central region prior to diagnosis (0/1)[1]	0.113	0.316	0.073	0.261
West North Central region (0/1), t-2	0.112	0.316	0.074	0.262
South Atlantic region prior to diagnosis (0/1)[1]	0.242	0.428	0.240	0.427
South Atlantic region (0/1), t-2	0.245	0.430	0.244	0.430
East South Central region prior to diagnosis (0/1)[1]	0.067	0.250	0.073	0.261
East South Central region (0/1), t-2	0.067	0.249	0.074	0.262
West South Central region prior to diagnosis (0/1)[1]	0.102	0.303	0.105	0.306
West South Central region (0/1), t-2	0.103	0.304	0.104	0.306
Mountain region prior to diagnosis (0/1)[1]	0.049	0.215	0.067	0.251
Mountain region (0/1), t-2	0.051	0.220	0.070	0.255
Pacific region prior to diagnosis (0/1)[1]	0.120	0.325	0.124	0.329
Pacific region (0/1), t-2	0.119	0.323	0.122	0.327
County unemployment prior to diagnosis (%)[1]	5.620	2.146	5.758	2.243
County unemployment rate, t-2	7.017	2.675	7.253	2.752
Change in unemployment rate, t-2 – t-3	0.833	2.233	0.722	2.343
Year and wave since/of diagnosis				
Wave of the shock, t+1	0.254	0.435	0.225	0.417
Wave of the shock, t+2	0.265	0.441	0.254	0.435
Wave of the shock, t+3	0.187	0.390	0.168	0.374
Wave of the shock, t+4	0.143	0.351	0.148	0.355
Wave of the shock, t+5	0.083	0.275	0.100	0.300
Wave of the shock, t+6	0.050	0.218	0.073	0.259
Wave of the shock, t+7	0.019	0.136	0.032	0.176
Wave biomarker measured 2006	0.117	0.321	0.100	0.300
Wave biomarker measured 2008	0.152	0.359	0.141	0.348
Wave biomarker measured 2010	0.167	0.373	0.156	0.363
Wave biomarker measured 2012	0.185	0.389	0.168	0.374
Wave biomarker measured 2014	0.213	0.409	0.227	0.419
Wave biomarker measured 2016	0.165	0.371	0.209	0.407
Wave of diagnosis 2002[1]	0.235	0.424	0.260	0.438
Wave of diagnosis 2004[1]	0.231	0.421	0.223	0.416
Wave of diagnosis 2006[1]	0.187	0.390	0.203	0.402
Wave of diagnosis 2008[1]	0.146	0.353	0.122	0.328
Wave of diagnosis 2010[1]	0.118	0.323	0.076	0.265
Wave of diagnosis 2012[1]	0.058	0.234	0.084	0.277
Wave of diagnosis 2014[1]	0.025	0.156	0.033	0.178
Wave of diagnosis 2016[1]	0.000	0.000	0.000	0.000
Instrumental variables				
Change in zip code FHFA house price inflation (%), t-1 – t-2	-0.011	0.225	-0.008	0.222
Loan-to-value ≥ 80% (0/1), t-2	0.025	0.155	0.073	0.260
Zillow zip code house value index ($100k), t-2	2.176	1.565	2.135	1.527
Unique respondents =	2,663		1,414	

N person-waves =	4,120	2,342

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
Notes:
[1] Time-invariant variable, measured as of the wave prior to the health shock
[2] We also included a dummy variable for other types of public health insurance (e.g., Veteran's Administration, CHAMPUS, etc.) not listed above. The percent of the sample in this category is too small to present due to disclosure limitations.

Appendix C: Random-effects linear probability model predicting the disease being uncontrolled on home equity held prior to the diagnosis, Diagnosed Age 65+

	Beta	Robust S.E.
Housing characteristics		
Home equity prior to diagnosis ($100k)	-0.003	0.003
Socioeconomic characteristics		
Annual household income prior to diagnosis ($100k)	0.004	0.009
Net financial assets prior to diagnosis ($100k)	0.001	0.001
Net other assets prior to diagnosis ($100k)	0.003+	0.002
Non-housing debt prior to diagnosis ($100k)	0.020	0.029
Health characteristics		
New cancer diagnosis	0.140***	0.035
New diabetes diagnosis	0.122***	0.035
New heart diagnosis	0.281***	0.034
New lung disease diagnosis	0.201***	0.036
Self-rated health prior to diagnosis	-0.019*	0.008
Smoking status prior to diagnosis	0.061*	0.025
Comorbidities prior to diagnosis	0.001	0.012
Self-rated memory prior to diagnosis	0.019*	0.008
Missing memory prior to diagnosis	-0.012	0.055
Cognitive status prior to diagnosis	-0.004	0.002
CES-Depression scale prior to diagnosis	0.006	0.005
Problems with activities of daily living prior to diagnosis	-0.025+	0.014
Spouse problems with activities of daily living prior to diagnosis	-0.003	0.011
Spouse self-rated health prior to diagnosis	-0.001	0.006
Spouse has cancer prior to diagnosis	0.007	0.022
Spouse has diabetes prior to diagnosis	0.043*	0.021
Spouse has heart disease prior to diagnosis	-0.021	0.019
Spouse has lung disease prior to diagnosis	0.010	0.029
No health insurance prior to diagnosis	-0.068*	0.034
Medicaid coverage prior to diagnosis	-0.009	0.047
Private insurance coverage prior to diagnosis	-0.002	0.030
Combination public-private coverage prior to diagnosis	-0.018	0.015
Demographic characteristics		
Black	-0.001	0.026
Other race	-0.055	0.044
Hispanic ethnicity	-0.003	0.037
Male	-0.009	0.015
Immigrant	-0.007	0.030
GED	-0.009	0.037
High school degree	-0.039+	0.022
Some college	-0.075**	0.024
Four-year college	-0.102***	0.024
Age in wave of diagnosis	-0.033	0.025

Age in wave of diagnosis-squared	0.0002	0.0002
Separated, divorced, or widowed prior to diagnosis	0.023	0.028
Never married prior to diagnosis	-0.049	0.054
Number of children prior to diagnosis	0.006+	0.004
Household size prior to diagnosis	0.010	0.010
Urban residence prior to diagnosis	-0.020	0.018
Suburban residence prior to diagnosis	-0.044*	0.019
New England region prior to diagnosis	-0.014	0.045
Mid-Atlantic region prior to diagnosis	0.065*	0.031
East North Central region prior to diagnosis	-0.027	0.027
West North Central region prior to diagnosis	-0.025	0.033
South Atlantic region prior to diagnosis	0.005	0.026
East South Central region prior to diagnosis	-0.020	0.035
West South Central region prior to diagnosis	-0.033	0.030
Mountain region prior to diagnosis	-0.059+	0.035
County unemployment rate prior to diagnosis	0.001	0.005
Year and wave since/of diagnosis		
Wave of the shock, t+1	0.071	0.046
Wave of the shock, t+2	0.150	0.093
Wave of the shock, t+3	0.227	0.138
Wave of the shock, t+4	0.292	0.185
Wave of the shock, t+5	0.347	0.231
Wave of the shock, t+6	0.428	0.278
Wave of the shock, t+7	0.496	0.323
Wave biomarker measured 2008	-0.067	0.051
Wave biomarker measured 2010	-0.076	0.095
Wave biomarker measured 2012	-0.178	0.139
Wave biomarker measured 2014	-0.201	0.189
Wave biomarker measured 2016	-0.297	0.228
Wave of diagnosis 2004	-0.287	0.298
Wave of diagnosis 2006	-0.312	0.250
Wave of diagnosis 2008	-0.187	0.204
Wave of diagnosis 2010	-0.173	0.161
Wave of diagnosis 2012	-0.148	0.113
Wave of diagnosis 2014	-0.080	0.068
Constant	1.423	0.976
N person-waves =	5,056	

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners age 65+ newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

Appendix D. Random-effects linear probability models predicting the disease being uncontrolled on home equity held prior to the diagnosis by type of diagnosis

	Cancer		Diabetes		Heart disease		Lung disease	
	Beta	Robust S.E.	Beta	Robust S.E.	Beta	Robust S.E.	Beta	Robust S.E.
Home equity prior to the diagnosis ($100k)	-0.005	0.004	0.003	0.005	0.001	0.005	-0.017	0.011
N person-waves =	1,317		1,619		2,583		908	

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to individuals newly diagnosed with cancer, diabetes, heart disease, or lung disease at age 65 or older from 2002-2016 and were homeowners in the wave prior to the diagnosis.
Note: All models include all controls in Appendix C.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

Appendix E: Two-stage least squares random-effects linear probability models predicting the disease being controlled on post-diagnosis mortgage borrowing

Outcome variable	Second stage: Disease uncontrolled (0/1), t		First stage: Mortgage borrowing ($100k), t-1 – t-2	
	Beta	Robust S.E.	Beta	Robust S.E.
Housing characteristics				
Mortgage borrowing ($100k), t-1 – t-2	-0.925*	0.457		
Socioeconomic characteristics				
Annual household income ($100k), t-2	-0.003	0.013	-0.003	0.005
Net financial assets ($100k), t-2	0.0002	0.002	0.001	0.001
Net other assets ($100k), t-2	0.0001	0.001	0.001	0.001
Non-housing debt, t-2	-0.014	0.020	0.004	0.013
Health characteristics				
New cancer diagnosis	0.107*	0.042	-0.009	0.015
New diabetes diagnosis	0.119**	0.041	-0.001	0.016
New heart diagnosis	0.260***	0.040	-0.015	0.015
New lung disease diagnosis	0.224***	0.042	0.006	0.016
Self-rated health prior to diagnosis	-0.016	0.011	-0.003	0.005
Smoking status prior to diagnosis	0.051+	0.030	-0.009	0.013
Comorbidities prior to diagnosis	0.011	0.015	0.006	0.007
Self-rated memory prior to diagnosis	0.014	0.011	0.002	0.005
Missing memory prior to diagnosis	-0.036	0.061	0.022	0.034
Cognitive status prior to diagnosis	-0.004	0.003	-0.0001	0.001
CES-Depression scale prior to diagnosis	0.010+	0.006	0.002	0.003
Problems with activities of daily living prior to diagnosis	-0.032+	0.018	-0.011*	0.005
Spouse problems with activities of daily living, t-2	-0.022+	0.013	-0.001	0.004
Spouse self-rated health, t-2	-0.002	0.008	-0.003	0.004
Spouse cancer, t-2	-0.012	0.031	-0.006	0.015
Spouse diabetes, t-2	-0.013	0.032	-0.007	0.015
Spouse heart disease, t-2	-0.046	0.032	-0.002	0.014
Spouse lung disease, t-2	-0.026	0.039	-0.019	0.015
Spouse death, t-2	0.008	0.043	-0.004	0.016
Spouse comorbidities, t-2	0.035+	0.018	0.006	0.008
No health insurance, t-2	-0.078	0.051	0.030+	0.015
Medicaid coverage, t-2	-0.009	0.050	-0.040*	0.016
Private insurance coverage, t-2	-0.083	0.067	0.019	0.026
Combination public-private coverage, t-2	-0.005	0.017	0.025	0.037
Demographic characteristics			-0.005	0.004
Black	0.033	0.039	0.037+	0.022
Other race	-0.049	0.053	0.017	0.038
Hispanic ethnicity	-0.016	0.045	0.011	0.029
Male	0.001	0.020	-0.004	0.011

Immigrant	0.038	0.041	0.022	0.027
GED	-0.024	0.043	0.025	0.017
High school degree	-0.032	0.026	0.007	0.007
Some college	-0.049	0.033	0.035*	0.014
Four-year college	-0.080*	0.031	0.026*	0.013
Age, t-2	-0.014	0.029	-0.024*	0.010
Age-squared, t-2	0.0001	0.0002	0.0001*	0.0001
Separated, divorced, or widowed, t-2	0.035	0.036	-0.012	0.018
Never married, t-2	-0.092	0.065	-0.038+	0.022
Number of living children, t-2	0.007	0.004	0.002	0.002
Household size, t-2	0.025+	0.013	0.014+	0.007
Urban residence, t-2	0.017	0.023	0.020*	0.009
Suburban residence, t-2	0.001	0.025	0.022*	0.010
New England region, t-2	-0.023	0.053	-0.004	0.030
Mid-Atlantic region, t-2	0.026	0.039	-0.011	0.023
East North Central region, t-2	-0.046	0.035	-0.013	0.018
West North Central region, t-2	-0.052	0.042	-0.015	0.022
South Atlantic region, t-2	-0.002	0.033	0.010	0.021
East South Central region, t-2	-0.040	0.045	-0.029	0.020
West South Central region, t-2	-0.060	0.040	-0.025	0.023
Mountain region, t-2	-0.079+	0.042	-0.007	0.026
County unemployment rate, t-2	-0.005	0.006	-0.0004	0.002
Change in unemployment rate, t-2 – t-3	0.001	0.007	0.002	0.003
Year and wave since/of diagnosis				
Wave of the shock, t+1	0.162	0.388	0.166	0.203
Wave of the shock, t+2	0.124	0.328	0.136	0.172
Wave of the shock, t+3	0.105	0.262	0.096	0.137
Wave of the shock, t+4	0.056	0.201	0.065	0.105
Wave of the shock, t+5	0.038	0.142	0.056	0.072
Wave of the shock, t+6	0.020	0.095	-0.001	0.045
Wave biomarker measured 2008	-0.009	0.073	0.039	0.037
Wave biomarker measured 2010	0.054	0.134	0.075	0.070
Wave biomarker measured 2012	0.042	0.196	0.094	0.104
Wave biomarker measured 2014	0.161	0.266	0.138	0.139
Wave biomarker measured 2016	0.147	0.323	0.158	0.170
Wave of diagnosis 2004	0.288	0.340	0.168	0.175
Wave of diagnosis 2006	0.179	0.278	0.152	0.142
Wave of diagnosis 2008	0.216	0.212	0.111	0.107
Wave of diagnosis 2010	0.160	0.150	0.095	0.074
Wave of diagnosis 2012	0.073	0.090	0.064	0.044
Constant	0.350	1.227	0.681	0.457
Instrumental variables				
Change in zip code FHFA house price inflation (%), t-1 – t-2			0.038*	0.017
Loan-to-value ≥ 80% (0/1), t-2			-0.099***	0.023

Zillow zip code house value index ($100k), t-2		0.002	0.003
N person-waves =	4,120	4,120	
First stage instrument tests			
Cragg-Donald F statistic	9.259		
Under-identification	13.283**		
Hansen-J statistic	1.339		

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

Appendix F: Two-stage least squares random-effects linear probability models predicting the disease being controlled on post-diagnosis mortgage borrowing by type of diagnosis

	Cancer		Diabetes		Heart disease		Lung disease	
	Beta	Robust S.E.	Beta	Robust S.E.	Beta	Robust S.E.	Beta	Robust S.E.
Mortgage borrowing ($100k), t-1 – t-2	-0.908	1.523	-0.233	0.451	0.677	2.857	-0.390	0.492
Instrumental variables								
Change in zip code FHFA house price inflation (%), t-1 – t-2	0.024	0.032	0.113+	0.064	0.003	0.016	0.078	0.049
Loan-to-value ≥ 80% (0/1), t-2	-0.052	0.033	-0.182**	0.060	-0.021	0.021	-0.145**	0.051
Zillow zip code house value index ($100k), t-2	-0.003	0.005	0.009	0.011	0.0002	0.003	0.010	0.011
N person-waves =	1,040		1,358		2,038		773	
First stage instrument tests								
Cragg-Donald F statistic	0.641		7.905		0.236		5.800	
Under-identification	2.732		4.941		0.903		5.404	
Hansen-J statistic	0.806		7.772*		3.507		Not reported[1]	

Source: 2006-2016 waves of the Health and Retirement Study. Sample is restricted to homeowners newly diagnosed with cancer, diabetes, heart disease, or lung disease from 2002-2016.
Notes: All models include all controls in Appendix E.
[1] Hansen-J statistic not reported due to covariance matrix of moment conditions not being full rank.
***p<0.001, **p<0.01, *p<0.05, +p<0.10 (two-tailed)

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