Center for Financial Security
UNIVERSITY OF WISCONSIN-MADISON

Retirement & Disability Research Center

Stephanie Moulton
John Glenn College of Public Affairs, The Ohio State University

Donald Haurin
Department of Economics, The Ohio State University

Cäzilia Loibl
Department of Human Sciences, The Ohio State University

Housing Wealth and Economic Security in Retirement: Does Borrowing from Home Equity Increase Adherence to Prescription Drugs?

Center for Financial Security

University of Wisconsin-Madison

1300 Linden Drive
Madison, WI 53706

608-890-0229
cfs@mailplus.wisc.edu
cfs.wisc.edu

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Abstract

The primary source of wealth for many older adults, particularly for those with lower incomes who rely on Social Security for their income, is equity in the home. This study investigates the use of housing wealth as a resource to increase economic security for older adults. We focus on an indicator of severe economic insecurity—taking less medication than prescribed because of cost. We investigate the relationship between housing wealth and cost-related medication non-adherence (CRN) using data from the 1998—2016 waves of the US Health and Retirement Study. Our approach accounts for the exogenous and endogenous components of housing wealth, isolating the effect of liquidating housing wealth through borrowing. This analysis makes several novel contributions. First, we find a significant short-term effect of borrowing from a mortgage on reduced CRN—an effect that is particularly large for those with a recent health shock. Second, we find that the relationship between mortgage borrowing and CRN is stronger for homeowners age 65 and older relative to those age 50 to 65, and homeowners with low levels of financial assets. Third, our simulation estimates suggest that about two-thirds of homeowners in the boomer cohorts would have sufficient home equity in 2036 to borrow $50,000 at a loan-to-value limit of 80 percent. Taken together, our findings highlight the critical role of housing wealth for the economic security of SSA beneficiaries and the use of mortgage borrowing as a vehicle to smooth consumption following a health shock.

Keywords: Home Equity, Mortgage, Retirement, Medications

JEL Codes: D12, I20, G21, G40

1. Introduction

It has been well documented that older adults often treat housing wealth as precautionary savings for health shocks (Davidoff 2010; Nakajima & Telyukova 2009; Poterba & Venti 2017; Poterba et al. 2011; Venti & Wise 2004). For older adults with lower incomes, equity in the home is the primary source of wealth (Moulton and Haurin 2019). Yet, little is known about the extent to which housing wealth actually enables a household to smooth consumption and buffer the negative financial consequences of a health shock in older age. Housing wealth is illiquid and can only be used to smooth consumption if converted to a more liquid form. However, if older adults do not meet lender criteria, they are unable to access this source of wealth. In this paper, we investigate the role of housing wealth as a resource to increase economic security in older-aged adults. We focus on an indicator of severe economic insecurity—taking less medication than prescribed because of cost.

In a 2019 survey, 23 percent of older adults indicated that it was difficult for them to afford their prescription medications (Kirzinger et al. 2019). Prescription drug costs are particularly burdensome for those with lower incomes and costly medical conditions (Naci et al. 2014; Zhang et al. 2016). Even among older adults enrolled in the Low Income Subsidy under the Medicare Part D prescription drug program, more than one in five report skipping medications because of costs in the prior six months (Wei et al. 2013). The consequences of skipping medications can be severe, leading to increases in emergency room visits, hospitalizations, and preventable deaths (Campbell et al. 2020; Heisler et al. 2004; 2010; Sokol et al. 2005). Aside from implications for patients, medication non-adherence increases government health care costs (Heaton et al. 2003; Piña et al. 2020; World Health Organization 2003). One study found that non-adherence is associated with $100 billion in avoidable medical spending in the US each year (Kleinsinger 2018).

No prior study, to our knowledge, examines the relationship between housing wealth and cost-related non-adherence to prescription drugs. A few studies document a link between housing wealth and health consumption behaviors, including the use of long-term care services (Costa-Font et al. 2019) and take-up of recommended therapies following a cancer diagnosis (Gupta et al. 2018). Other studies examine housing wealth and indicators of physical and psychological health (Fichera & Gathergood 2016; Hamoudi & Dowd 2013; 2014). These studies exploit exogenous and unexpected changes in house prices as an instrument for changes in wealth—a strategy we also employ. However, these studies do not model the mechanisms that link housing wealth and health consumption, nor do they consider heterogeneous effects for vulnerable groups. Mortgage borrowing is a particularly important yet complex mechanism, as mortgage debt allows for the consumption of housing wealth but it can also create financial stress (Haurin, Loibl, and Moulton 2019). It is unlikely that homeowners borrow from home equity solely to pay for medication. However, borrowed home equity may be used to pay for larger health expenses, supplement income, or pay off higher-cost debts. This borrowing, in turn, increases cash flow and the ability to pay for expenses including medication.

We analyze the relationship between housing wealth and cost-related non-adherence (CRN) to medication using data from the Health and Retirement Study (HRS) from 2002—2016. This data set includes comprehensive survey information for adults age 50 and older such as extensive information on respondents' wealth and income, housing tenure, health status, and detailed socio-demographic characteristics. The HRS includes a question about taking less medication than prescribed because of the cost. Our first set of empirical specifications estimate the relationship between housing wealth and CRN for all homeowners in the HRS. We begin with a reduced form estimation of lagged FHFA House Price Index change on CRN, and then model the effects of lagged changes in home equity and mortgage borrowing separately as endogenous variables. Our instrumental variables are the FHFA House Price Index change at the ZIP code level and a measure of being borrowing constrained based on the respondent's home loan-to-value ratio (LTV). We find a large and statistically significant relationship between mortgage borrowing and reduced CRN—each $10,000 borrowed is associated with a 0.8 percentage point reduction in the probability of CRN two years after borrowing. Among homeowners who borrow, the average borrowed amount is $50,000, corresponding to a 4 percentage point reduction in CRN, a 60 percent reduction in the average CRN rate of 6.6 percent. The effect is economically larger for older adults, those relying on primarily social security for their incomes, and homeowners with less than $10,000 in non-housing financial assets.

Our second empirical specification models the effects of mortgage borrowing on CRN for those who experience a health shock. Following Poterba and Venti (2017), we measure a health shock as the first wave of a reported diagnosis of cancer, lung disease, diabetes, heart disease, stroke, or high blood pressure during the period 2006—2016. We follow respondents from the wave prior to their health shock for up to six waves after their health shock. As expected, we observe a significant increase in CRN following a health shock. For this group, each additional

$10,000 borrowed from a mortgage after a health shock is associated with a statistically significant 1.5 percentage point reduction in CRN. To put this effect size in context, a $10,000 increase in non-housing financial assets is associated with a 0.04 percentage point decrease in CRN following a health shock—indicating housing wealth can play an important role in reducing economic insecurity following a health shock. However, over the long term, borrowing from a mortgage increases housing costs in the form of a higher monthly mortgage payment. In the full sample, our results indicate that each $10,000 increase in annual housing costs is associated with a 1.22 percentage point increase in CRN. The effect of housing costs on CRN is larger for those relying on Social Security benefits for their incomes. For this group, an additional $10,000 in housing costs increases CRN by 4.62 percentage points.

Finally, using the estimates from our empirical specifications, we simulate the effects of higher mortgage debt held by younger cohorts of retirees on their future ability to borrow to buffer health shocks. The simulations show that between 68 and 76 percent of homeowners in the boomer cohorts would have sufficient home equity in 2026 to borrow $50,000 at a loan-to-value limit of 80 percent. This proportion is slightly higher in 2036, as loan-to-value ratios tend to decline with age. In 2036, we estimate that between 72 and 78 percent of homeowners in the boomer cohorts would have sufficient home equity to borrow $50,000 at an LTV limit of 80 percent.

Taken together, these results advance our understanding of the role of housing wealth for economic security in retirement. Our approach takes into account the exogenous and endogenous components of housing wealth, isolating the effect of liquidating housing wealth through borrowing on an indicator of severe economic insecurity—CRN. Our study is the first to estimate the effects of housing wealth on CRN, including for those with the onset of a new disease for whom financial risks may be most acute (Dalton and LaFave 2017; Gupta et al. 2018; Gilligan 2018). We identify economically larger effects for homeowners who rely predominately on Social Security benefits for their incomes, those who are older, and those with low levels of non-housing financial assets.

2. Literature Review

Our research is informed by two bodies of literature. First, we draw from the literature on cost-related non-adherence (CRN) to medication among older adults, with a particular focus on studies that inform the relationship between financial variables, wealth, and CRN for older adults. Next, we draw from the literature on housing wealth and consumption as well as studies that examine the relationship between housing wealth and health outcomes.

2.1 Cost-Related Prescription Drug Non-Adherence in Older Age

Skipping prescription medications because of cost is referred to in the literature as cost-related non-adherence, or CRN. While there is a broader literature that examines non-adherence to health treatments more generally, the CRN literature focuses specifically on cost-related factors that lead patients to cut back on medications. CRN is often used as a measure of severe economic distress (e.g. Walker et al. 2020). And, CRN may be associated with other financial hardships. For example, in a study of older homeowners with mortgages, Alley et al. (2011) found a positive association between being delinquent on a mortgage and CRN, indicative of a financial shock that contributed to both measures of economic hardship. A recent literature review documented the close association of CRN and food insecurity (Caouette et al. 2020).

The prevalence of CRN among older adults has declined slightly over time in response to the government's expansion of prescription drug coverage through Medicare Part D in 2006 and the Affordable Care Act in 2010 (Diebold 2018; Engelhardt 2016; Madden et al. 2008). Among Medicare beneficiaries, the unadjusted weighted prevalence of CRN in the prior two years was 14.1 percent in 2005, dropping to 11.5 percent after Part D implementation in 2006 (Madden et al. 2008). Economic hardship during the Great Recession led to an increase in CRN among older adults. A study by Naci et al. (2014) documents a 20 percent increase in CRN between 2009 and 2011 for older adults with four or more chronic conditions.

While most adults age 65 and older are enrolled in Medicare prescription drug plans, most plans still require out-of-pocket co-pays. Between 2011 and 2015 (post the 2010 ACA reforms), the average Medicare beneficiary paid $620 to $700 per year in out-of-pocket prescription drug costs (Park and Look 2020). These amounts are higher among older adults with a chronic disease. Using data from the 2014 HRS, Fong (2019) reports average annual out-of-pocket prescription drug costs of just over $1,000 among Medicare beneficiaries with lung disease, diabetes, or cardiovascular disease. Aside from higher drug costs, older adults experiencing a chronic disease also face higher out-of-pocket health expenditures that strain cash flow and make it more likely that they take less medication because of cost. Using data from the 2006–2010 waves of the HRS, Kelley et al. (2015) document average out-of-pocket health expenditures, totaling about $36,000 for older adults with heart disease or other chronic conditions in the last five years of their lives, about $29,000 for older adults with cancer, and more than $60,000 for older adults diagnosed with dementia.

Using data from the 2010 Medicare Current Beneficiary Survey (MCBS), DeNardi et al. (2016) document that 20 percent of health care spending among older adults is financed out-of-pocket, with 65 percent covered by government and the remainder by private insurance. The prevalence of chronic disease among older adults increases health costs, with out-of-pocket prescription drug expenditures being the highest for cardiovascular disease, diabetes, and hypertension (Fong 2019). A study of Medicare Part D recipients found that 22 percent of the lowest-income individuals, who are automatically enrolled in the Medicare Part D Low-Income Subsidy, reported skipping medications because of cost in the prior six months (Wei et al. 2013). These dual eligible Medicaid and Medicare individuals often have complex health conditions that require costly medical treatments, and a large proportion is also people with disabilities, this making the transaction costs of filling prescriptions more difficult (Zhang et al. 2016).

A large body of literature examines factors that contribute to CRN. Piette et al. (2006) developed a conceptual model that has since been used as a framework for numerous empirical studies (e.g. Chung et al. 2019; Gupta et al. 2020; Piette et al. 2011; Zivin et al. 2010). In their model, “financial pressures” are the primary contributor to CRN, which for them include income, prescription drug coverage, out-of-pocket costs, and other health care costs. In a survey of US residents age 40 and older with a chronic disease, Piette et al. (2011) found that 79 percent of respondents with incomes below $25,000 per year reported CRN, compared to 14 percent of respondents with incomes above $125,000 per year. Their framework also incorporates non-financial factors that may moderate the relationship between financial pressures and CRN, such as individual sociodemographic characteristics, mental status, health literacy, clinician, and system barriers such as lack of trust, as well as beliefs about their medications including perceived need for medication, concerns about side effects, and knowledge about their medications. Interestingly, their model does not include indicators of wealth or savings, which are central to our study.

In a study of respondents age 65 and older in the 2017 National Health Interview Survey, Chung et al. (2019) empirically investigate factors that are associated with CRN. Statistically significant variables include unemployment, being uninsured, lower self-reported health, higher levels of mental distress and functional limitations, having multiple chronic conditions, being overweight, and being more likely to smoke. They measure income in categories as a percent of poverty and find that relative to those with incomes below 100 percent of poverty, respondents with incomes above 200 percent of poverty are about 50 percent less likely to report CRN, and respondents with incomes above 400 percent of poverty are 80 percent less likely to report CRN. These findings are in line with prior studies that indicate income is a significant predictor of CRN, even after controlling for prescription drug coverage and drug costs (Briesacher et al. 2007). However, their study is cross-sectional and they do not include indicators of financial or housing wealth.

Only a few studies of CRN include measures of wealth. Using data on older adults from the 2004 HRS, Ziven et al. (2010) include indicators of net worth to predict CRN in addition to income and other factors. They find that moving from the lowest net worth quartile (<$38,000) to the highest net worth quartile (>425,000) is associated with a 72 percent decrease in the odds of CRN. This is a larger effect than is observed for income, where moving from the lowest (<$14,000) to highest (>$48,000) income quartile is associated with a 40 percent lower odds of CRN. Their study highlights the importance of incorporating wealth in an understanding of CRN among older adults; however, their study is cross-sectional, which does not allow for the identification of causal effects.

In a panel data framework, Pool et al. (2017) use HRS data from 1992–2012 to identify the relationship between negative shocks to wealth and health among adults age 51 to 64. They define a negative shock to wealth as a decrease in household net worth of 75 percent or more over a two-year period (e.g., from one HRS wave to the next). They measure the financial effects of a wealth shock on CRN, and they measure the emotional effects of a wealth shock on reported depressive symptoms. They find a significant association between negative wealth shocks and an increase in depressive symptoms, but no significant relationship with CRN. However, wealth shocks are measured contemporaneously with CRN, and reverse causality may likely occur—a person experiencing a financial or health crisis may liquidate wealth to pay for health expenditures, including prescription drugs, resulting in a lower likelihood of CRN than a person unable to liquidate wealth. It is thus important to account for the endogeneity of wealth and its components when modeling effects on CRN.

To our knowledge, no prior studies measure the effects of housing wealth on CRN or the relationship between borrowing from a mortgage and CRN. This is a critical gap in the understanding of CRN given that a substantial proportion of the net worth of older adults is held in the equity in their homes. CRN is highest among lower-income older adults (Chung et al. 2019; Wei et al. 2013). Many of these lower-income older adults are homeowners, with housing wealth being their primary form of wealth (Moulton and Haurin 2019). Yet, this source of wealth is illiquid and can only be used for consumption if homeowners can convert this wealth into a more liquid form through borrowing or home sale.

2.2 Home Equity, Mortgage Borrowing, and Health Consumption

Paying for prescription drugs is a type of consumption that may be affected by housing wealth. We do not expect that homeowners borrow from home equity to directly pay for prescription drugs, but rather, we expect that borrowing from home equity increases cash available for all types of consumption, thereby reducing the likelihood that a homeowner takes less medication because of cost. There is an established literature in economics that identifies the relationship between housing wealth and consumption. Empirical results indicate that a 1 percent increase in home value contributes to an additional $0.04 to $0.08 in consumption (Angrisani et al. 2019; Bostic et al. 2009; Campbell and Cocco 2007). The standard assumption is that rising (falling) house prices increases (decreases) consumption, either indirectly by increasing wealth and making households feel richer (poorer) or directly by increasing (decreasing) borrowing capacity to use directly for consumption. Studies exploiting changes to house prices during the Great Recession find evidence in favor of borrowing capacity, as homeowners who were previously constrained and unable to borrower had a higher marginal propensity to consume from increases in housing wealth than previously unconstrained borrowers (Angrisani et al. 2019; Cooper 2013).

A few prior studies document a link between housing wealth and health consumption behaviors. Using data on older adults from the 1996—2010 waves of the HRS, Costa-Font et al. (2019) exploit the geographically heterogeneous shocks to house prices during the 2008 recession as an instrumental variable to analyze the relationship housing wealth and spending on long-term care services. They find a significant increase in the use of home health care, nursing home care, and informal care that can be causally attributed to increases in housing wealth. However, they do not model the mechanism through which housing wealth leads to health consumption (i.e., wealth effect or borrowing effect). We exploit a similar empirical strategy using the FHFA House Price Index as an exogenous instrument for mortgage borrowing to examine the relationship between borrowing from housing wealth and CRN.

A related set of studies examines changes in home equity following a health shock, with an assumption being that households liquidate home equity in response to the health shock either through borrowing or home sale. Dalton and LaFave (2017) use data from the 1999–2011 waves of the Panel Study of Income Dynamics to track changes in household wealth following a reported decline in activities of daily living (ADLs) associated with a chronic condition. In a panel regression framework with individual fixed effects, they find that the largest reduction in wealth, following the ADL decline, is housing wealth, with an estimated immediate decline of $12,000 for married respondents and about $5,000 for unmarried individuals. They further find that housing wealth is second only to formal health insurance for finance health-related consumption after a health shock. While they do not directly measure borrowing, they report a 22 percent increase in refinancing among homeowners newly diagnosed with a chronic condition.

Using data on respondents age 65 and older from the 1996—2014 waves of the HRS, Poterba et al. (2017) examine changes in total net worth in the wave when a new disease is first reported. They find variation in changes in net worth depending on the type of disease, with lung disease and stroke being associated with a statistically significant $29,000 and $25,000 reduction in total net worth immediately following the onset of the disease. They further break out their analysis 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, within one to two years after the onset of a diagnosis, and not modeling borrowing. Further, they do not examine the mechanisms underlying declines in housing wealth, nor do they model the relationship between declines in housing wealth and other health-related outcomes such as CRN.

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—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 depleted their net worth by four years following diagnosis, with an average decline of about $50,000. However, their results are primarily descriptive.

Most similar to our analysis, Gupta et al. (2018) analyze the relationship between cancer diagnosis, financial outcomes, and treatment adherence. Their data is limited to adults with a cancer diagnosis in one state (Washington) between 1996 and 2009, linked to cancer treatment and outcome data, public records property data, and mortgage data. 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.[1] 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. Our study extends this analysis to analyze the relationship between home equity, mortgage borrowing, and cost-related drug adherence 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 their study data.

3. Methods and Data

3.1 Aims and Empirical Specifications

Our first aim is to estimate the causal relationship between housing wealth, mortgage borrowing, and cost-related medication non-adherence (CRN). Our estimation is based on the household production function framework (Becker 1965; Todd & Wolpin 2003; 2006). The focal health services variable (S_{it}) for older adult i in period t represents an indicator of CRN. Health levels are

[1] 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.

H_{it} in period t-2. Funds for purchasing S are drawn from income (Y_{it-2}), liquid wealth (A_{it-2}), and new mortgage borrowing, which sets to zero any mortgage repayments (B_{it-1}). We control for an indirect effect of illiquid net housing wealth (E_i), which equals the difference between house value and mortgage debt at the wave a Health and Retirement Study (HRS) respondent first entered the HRS study, as well as annual housing costs (M_i), which equals the annualized amount of monthly mortgage, property tax, and insurance payments when a respondent first entered the HRS study. We fix net housing wealth and housing costs at the baseline survey wave as future values of these variables are endogenous to borrowing decisions. P_{it-2} is prescription drug prices, varying over time and by geography. X_{it-2} is a set of control variables, μ_i is a person-specific effect that captures unobserved individual factors, and η_{it} is a transitory shock. All models include year fixed effects as well as the geographic region of the respondent. Models are estimated using individual random effects, with clustered standard errors by household. We assume a linear form for estimation.[2]

$$S_{it} = \beta_0 + \beta_1 H_{it-2} + \beta_2 Y_{it-2} + \beta_3 A_{it-2} + \beta_4 B_{it-1} + \beta_5 E_i + \beta_6 M_i + \beta_7 P_{it-2} + \beta_8 X_{it-2} + \mu_i + \eta_{it} \qquad (1)$$

When estimating equation (1), all of the explanatory variables are predetermined at t-2 or the baseline HRS survey wave with the exception being new mortgage borrowing, which is a choice variable. We use two instruments to model new mortgage borrowing. Our first instrument for new borrowing is the lagged (t-1) local area period-to-period change in house prices (ΔHPI). 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). Our identifying assumption is that geographic variation in ΔHPI at a given point in time is unrelated to CRN, except through its effect on borrowing. Our second instrument is an indicator of being borrowing constrained at t-2, which we measure as having a loan-to-value (LTV) ratio of 90 percent or higher as it is difficult to be approved for additional borrowing with LTVs above 90 percent.[3]

[2] We use STATAs “xtivreg” command for our estimation. An alternative is to treat the outcome as binary using a probit specification. However, panel data models allowing for an endogenous variable and binary outcome are relatively new (e.g., STATAs extended regression models) and did not converge with our specifications.
[3] We test alternative instruments, including an indicator of monthly housing costs to monthly income being greater than 36 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 60 percent, 70 percent, and 80 percent LTV. LTV thresholds above 70 percent are statistically associated with lower levels of mortgage borrowing, however the 90

We expect the short-run effect of new mortgage borrowing to decrease CRN ($\beta 4 < 0$). This occurs because the loan proceeds are liquid and they increase spendable funds. In alternative specifications, we explore the long-run effect of borrowing by substituting different lag structures for borrowing (B_{it-1}) in equation (1), adjusting the lags of other explanatory and instrumental variables accordingly.

We estimate several alternative specifications for equation (1). As is conventional in the literature, we estimate a reduced form relationship between lagged HPI change and CRN, replacing B_{it-1} with the one wave prior ΔHPI at t-1, treated as exogenous. We expect a weak relationship, as we expect that borrowing is the primary way that increases in house prices influence CRN (Cooper 2013). In a separate specification, we replace B_{it-1} with change in home equity as of t-1, treated as endogenous using the same set of instruments as we use for borrowing. This specification is common in the literature; however, it confounds the relationship between house price increases, mortgage borrowing, and CRN. Changes in home equity result from house price changes and changes in mortgage debt—both of which have different expected effects on CRN. For example, an increase in house prices increases home equity, which is expected to decrease CRN. However, an increase in a mortgage through borrowing decreases home equity, but is expected to decrease CRN. Our expectations for the relationship between lagged changes in home equity and CRN are thus ambiguous.

Our second aim is to estimate the extent to which borrowing from home equity enables older adults to buffer the effects of a health shock on CRN. We limit our sample to those with a health shock. We define a health shock at time T as the wave in which a respondent reports being diagnosed with one of six diseases: cancer, lung disease, diabetes, heart disease, stroke, or high blood pressure. For the shocked sample, we estimate CRN beginning one wave prior to the health shock (T-1) and in all available periods after the health shock (T+n). We control for annual housing costs (M_{iT-2}) and home equity (E_{iT-2}) as of the survey wave prior to the health shock, as borrowing after a health shock could affect these values. We allow all other explanatory variables to vary over time (t-2). We measure mortgage borrowing (B_{it-1}) as a change in the mortgage balance from t-2 to t-1, this being treated as endogenous.[4] The coefficient of interest is β_4, which measures the

percent threshold has the strongest relationship with future borrowing and thus is the threshold we use for our primary specifications.

[4] As a robustness test, we limit the definition of new mortgage borrowing to mortgage increases greater than 5 percent of the balance at t-2 or at least $1,000. This definition recodes about 10.1 percent of homeowners in our

effect of borrowing in the waves after the health shock ($Post_{iT\geq0}$).[5] We also include a vector of indicators that measure the wave since the health shock ($PostWave_{it\geq T}$), thereby controlling for trends in CRN after a health shock. As with equation (1), all models include year fixed effects as well as the geographic region of the respondent. Models are estimated using individual random effects, with clustered standard errors by household. We assume a linear form for estimation.

$$S_{it} = \beta_0 + \beta_1 H_{it-2} + \beta_2 Y_{it-2} + \beta_3 A_{it-2} + \beta_4 B_{it-1} * Post_{iT\geq0} + \beta_5 E_{iT-2} + \beta_6 M_{iT-2} + \beta_7 P_{it-2} + \beta_8 X_{it-2} + \beta_9 PostWave_{it\geq T} + \mu_i + \eta_{it} \quad (2)$$

We assume all of the explanatory variables in equation (2) are predetermined as of the baseline period two waves prior to the health shock (T-2) or at t-2, with the exception of mortgage borrowing. We model borrowing as endogenous including the same instruments described in equation (1). The coefficient for borrowing in equation (2) measures the short-term effects of borrowing after a health shock among those who experience a health shock at some point during our sample period, relative to health shocked individuals who do not borrow. Our identifying assumption is that changes in house prices affect the likelihood of borrowing, and that the timing of changes in house prices and the timing of a health shock among those who experience a health shock are unrelated.

Our third aim is to explore the heterogeneous effects of borrowing on CRN for particular subgroups. The first subgroup of interest is those for whom Social Security benefits are their primary source of income, compared to a subgroup of individuals who have a larger proportion of income from other sources. We define Social Security income as being the primary source of income if it comprises 90 percent or more of the household's income in a given period. Because real Social Security income is relatively stable over time, this group may have less ability to increase income from other sources to supplement consumption. We also estimate subsample regressions for those who are age 65 and older, compared to the subsample of individuals younger than age 65, as those over age 65 are eligible for Medicare which may affect CRN. Our third

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sample as non-borrowers due to very small increases in mortgage debt from one wave to the next. Our results are nearly identical with this revised definition (available upon request), which suggests our main specification is not biased by small increases in mortgage debt.

[5] The net effect of mortgage borrowing prior to the health shock is captured in the baseline measure of home equity (E_{iT-1}).

subsample of interest is defined based on the level of non-housing financial assets, splitting our sample into those with more or less than $10,000 in non-housing financial assets (lagged two waves). We expect that the effect of borrowing from housing wealth on CRN to be greater for those unable to supplement their consumption from other forms of non-housing wealth. We re-estimate equation (1) for these subgroups.

For individuals with a health shock, we also re-estimate equation (2) for those with and without other disease diagnoses in the wave prior to the shock (T-1), as individuals with comorbidities have been shown to be at higher risk of CRN (Chung et al. 2019). However, it is not clear if borrowing will have a larger or smaller effect on CRN for this group, as these individuals may have more severe conditions that make CRN less responsive to the same dollar increase in liquidity through borrowing. Madden et al. (2008) found that while the expansion of Medicare Part D in 2006 decreased CRN in the senior population as a whole, there was no significant decrease in CRN for those with multiple chronic conditions.

Our final aim is to simulate how cohort differences in mortgage borrowing behaviors affect economic security later in life, as measured by CRN. Here, we are particularly interested in understanding how higher levels of mortgage debt among younger cohorts might affect their future borrowing potential and thus estimated CRN. Using estimates from our models in equation (1), we project the future likelihood of CRN (through 2026 and 2036) for the Baby Boomers cohorts in the HRS (age 51 through 68 as of 2016). Our upper bound projections simulate that the upward trend in the rate of mortgage borrowing among the Baby Boomers continues for the next 20 years, while our lower bound projections expect that the rate of growth in mortgage borrowing reverts to that for the original HRS study cohort (age 75-85 as of 2016). These projections, combined with assumed values for other explanatory variables, yield a set of predictions of future risk of CRN among Baby Boomers for a 20-year period.

3.2 Data: Health and Retirement Study

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 (Health and Retirement Study) 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 1998–2016 with geographic identifies, as well as the RAND HRS Longitudinal File 2016 (v2) which includes imputations for missing data on financial variables used in our analysis.[6]

To estimate equation (1), our first sample includes home-owning respondents 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.[7] CRN is measured as of 2006—2016 survey waves.[8] We further restrict the sample to homeowners who did not move in the prior three waves and remained in an "intact" household during our study period. If a respondent moves or experiences a split with their spouse or partner, we follow the respondent until the wave they report the move or split. Focusing on respondents from intact households, a common approach in housing research (Begley and Chan 2019), creates a more homogenous sample because households tend to experience changes in housing wealth through relocation and the purchase of a new home or changes in marital status. We drop homeowners living in a mobile home, nursing home, or institutional settings. We also drop older adults those who defaulted on mortgage debt in the 2008, 2010, 2012, or 2014 waves.[9] Our final sample consists of 12,454 unique respondents, with 39,538 respondent-wave observations.[10]

For equation (2), we apply the same sample restrictions as above but further limit the sample to HRS respondents with a health shock. Of those in our prior sample, 65 percent have a new health shock during our study period. We define a respondent as having a health shock when they self-report being newly diagnosed with diabetes (N=2418), heart disease (N=2901), hypertension (N=4008), stroke (N=1223), lung disease (N=1312), or cancer (N=1,923) during the

[6] 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.
[7] 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.
[8] While CRN is measured in every HRS survey wave beginning in 1998, our control variables for prescription drug coverage are only included in the HRS beginning in the 2002 survey wave. We lag our control variables two waves in our models, and thus begin measuring CRN as of the 2006 survey wave.
[9] 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.
[10] The sample sizes are slightly different when we replace our indicator of mortgage borrowing with house price change or with home equity change due to missing data.

period 2002–2016. For respondents with multiple shocks during our study period, we model the baseline wave (T) as the first wave they are newly diagnosed with one of the six diseases during our study period. This results in the first health shock being skewed towards earlier waves of the HRS, 20.1 percent of first health shock in 2002, 18.2 percent in 2004, 18.2 percent in 2006, 14.7 percent in 2008, 11.7 percent in 2010, 8.1 percent in 2012, 5.5 percent in 2014, and 3.6 percent in 2016. Our final sample for this estimation strategy consists of 7,875 unique respondents, with 25,462 respondent-wave observations.

3.3 Variable Construction and Sample Characteristics

Appendix A reports summary statistics for our sample variables for the full estimation sample in equation (1) and the sample with a health shock used to estimate equation (2). CRN is measured in the HRS based on a question about whether the individual took fewer medications because of costs in the prior two years. In the HRS, respondents were asked in each interview, "Sometimes people delay taking medication or filling prescriptions because of the cost. At any time in the last two years, have you ended up taking less medication than was prescribed for you because of the cost?" (N188). CRN was coded 1 if they answered yes and zero if they answered no. "Do not know" answers and refusals were set to missing. In our full estimation sample, 6.6 percent of respondents reported experiencing CRN within the past two years. This is slightly higher in the sample with a health shock, where 7.5 percent of respondents reported CRN within the past two years.

Home equity is calculated as the difference between respondents' estimate of the home value and their outstanding mortgage balance. The change in home equity is calculated as the difference between two waves. All dollar values are adjusted for inflation to 2016 dollars. The sample mean change in home equity over the period is $7,660.[11] New mortgage borrowing is calculated as the amount of the increase in the self-reported mortgage balance on the primary residence between two waves (Bhutta & Keys 2016; Moulton et al. 2016). Negative values, which present 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

[11] The overall positive sample mean home equity change is driven by large positive average changes in home equity during the peak of the housing boom between 2006 and 2008. Average changes in home equity are negative from 2010-2014, the period affected by the 2008 housing crisis and its aftermath. The sample mean home equity change is again positive in 2016.

(HELOCs), second mortgages, and other mortgages on the primary residence. We use the not 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. We also create a binary measure of new mortgage borrowing, which is coded as 1 in the wave of mortgage borrowing and 0 in the other waves. Outliers are set to missing, including households with home equity or mortgage debt amounts greater than $2,000,000 in years t-1 or t-2 (6 cases) and households that borrow more than $1,000,000 from year t-1 to t-2 (1 case). In our full sample, 15.1 percent of homeowners borrow over a two-year period (from one wave to the next) with an average borrowed amount of $49,324. The sample mean amount borrowed (including $0 for non-borrowers) is $7,450.

Changes in house prices are measured as percentage changes in the Federal Housing Finance Agency (FHFA) five-digit ZIP code level House Price Index (HPI) from t-2 to t-1 (FHFA 2020).[12] The HPI is available for 18,053 ZIP codes in the US, about 43.2 percent of all ZIP codes as of 2019 (Bogin et al. 2019). Observations with missing data on HPI at the 5-ZIP code level are replaced with annual county estimates, or state non-metro averages (averaged over four quarters per year) if a county is missing. The HPI is considered largely exogenous of an individual household's choices as it is averaged across a ZIP code and presents a broad measure of changes in single-family house prices (FHFA 2020). During our sample period, the average HPI change is -0.005 percent. Our second instrument measures whether a homeowner is borrowing constrained, defined as having a loan-to-value (LTV) ratio of 90 percent or more. During our sample period, 2.9 percent of respondents were borrowing constrained.

In all our models, we control for a standard set of demographic and socioeconomic variables that are associated with CRN (Piette et al. 2006; Wei et al. 2013). The controls are all lagged as of wave t-2 unless otherwise noted. Household-level controls include home equity level as of the baseline period, annual housing costs (mortgage payments plus taxes and insurance) as of the baseline period, and non-housing wealth (liquid and illiquid). We also include non-housing debt and include an indicator of whether household income is below 130 percent of the Federal Poverty Level. We measure income as total household income in our primary specification, and in alternative specifications, break income into separate variables by source (i.e., Social Security

[12]Percentage HPI change t-2 to t-1=(deflated HPI t-1-deflated HPI t-2)/deflated HPI t-2*100%

Retirement and Disability Income, earned income, and other sources).[13] Other household level controls are household size and geography (Census region of the country).

Respondent-level controls include age, gender, education, immigration status, race, ethnicity, educational attainment, number of living children, and marital status. In the full sample, 84 percent of respondents are white, 11.5 percent of respondents are black, 8.5 percent are Hispanic, and 5 percent are of another race. We also control for the presence of health insurance and an indicator of receipt of the Low-Income Subsidy. We control for prescription drug coverage, constructing types of coverage following Levy and Weir (2009) to include prescription drug coverage by employer, Medicaid, Medicare HMO, Medicare Part D, Medigap, other source, or no prescription drug coverage. We control for the cost of prescription drugs using the Bureau of Labor Statistics (BLS) Medical Care Cost Index, together with geographic variations in drug prices (MaCurdy et al. 2009). We link the cross-sectional drug expenditure in 34 Prescription Drug Plan (PDP) regions in 2008 (MaCurdy et al. 2009) to the BLS Medical Care Cost Index in 27 Metropolitan Statistical Areas to obtain time-varying county-level prescription drug costs.

We control for health status using several variables, the first being an indicator of self-reported health, which is measured on a scale of 1 to 5 with 5 being excellent, 4 being very good, 3 being good, 2 being fair, and 1 being poor. Other health controls include a count of difficulty with activities of daily living (walking across a room, dressing, getting out of bed, bathing, eating), with 0 being having no difficulty and 5 being having difficulty with all five ADLs. We include a vector of control variables corresponding to six common chronic diseases (cancer, stroke, lung disease, hypertension, diabetes, and heart disease), coded 1 if a respondent reports being previously diagnosed with the disease. We also control for an indicator of depression, using the Center for Epidemiological Studies-Depression (CESD) scale with scores ranging from 0 to 60 and higher scores indicating greater depressive symptoms, as depression is linked to CRN in other studies (Oates et al. 2020), as well as an indicator of whether the person smokes.

Following the literature on CRN, we also control for a measure of cognitive status based on word recall, which 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

[13] The results are robust to including a single measure of income or measuring income by its components. Results of the alternative income specification are available from the authors upon request.

2006).[14] To account for unobserved local economic shocks that may be correlated with both mortgage borrowing and CRN, 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).

4. Results

4.1 Descriptive Trends

We begin by examining the relationship between cost-related medication non-adherence (CRN) and home equity as well as trends in CRN before and after a health shock among our analytic sample. Figure 1 plots rates of CRN across the distribution of inflation-adjusted home equity for each year between 2006 and 2016.[15] The graph suggests an inverse relationship between CRN and home equity that is generally consistent in shape across years. The association is particularly strong at the lower end of the home equity distribution, where moving from the lowest to the second-lowest category results in a 1.7 to 6.3 percentage-point reduction in CRN. Unsurprisingly, at most home equity levels CRN is highest in 2006, the year of the Medicare Part D prescription drug expansion. For some levels of home equity, CRN is highest in 2010 during the Great Recession. This is consistent with prior research that found an increase in CRN among older adults during the Great Recession period (Naci et al. 2014).

[14] In alternative specifications we control for an indicator of financial literacy (Duca & Kumar 2014), with no change in our results. This is not our preferred specification given missing data on financial literacy in particular survey waves.
[15] Figure 1 is limited to members of the analytic sample that are age 65 or older to account for the influence of age composition changes due to younger cohorts added to the HRS in later years. We note that the inclusion of respondents younger than 65 does not alter the results. The means are weighted using HRS respondent weights to be representative of the older adult population in the US.

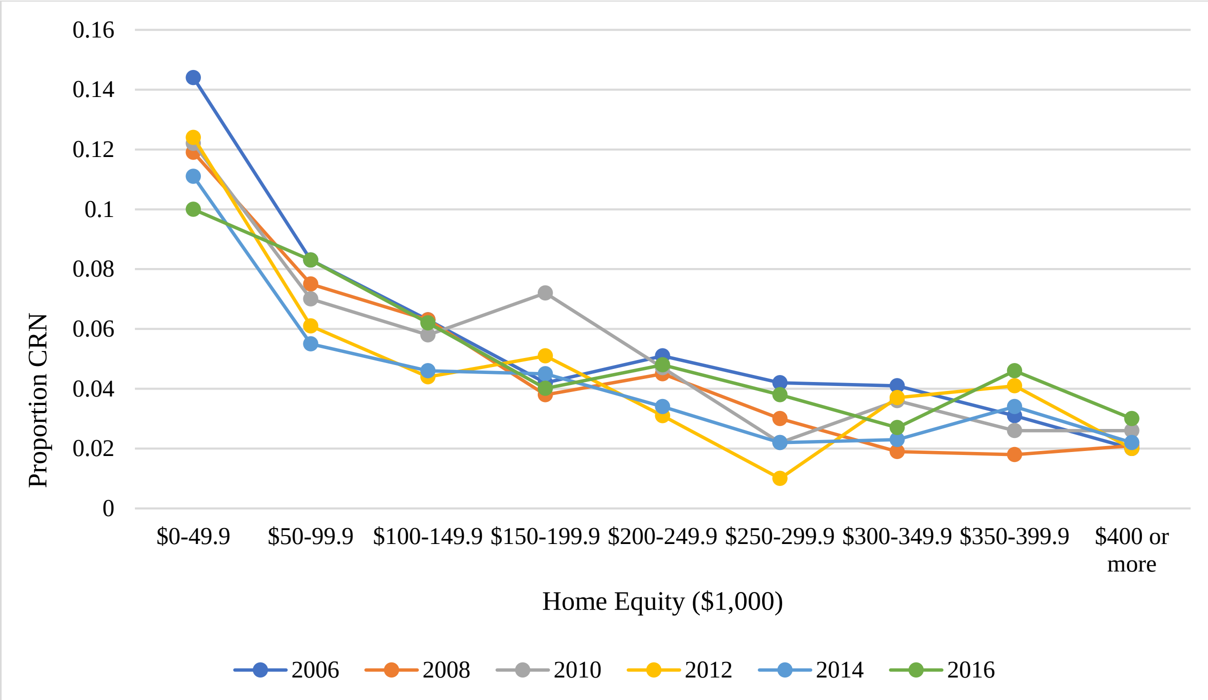

Figure 1
Notes: CRN and home equity among homeowners age 65 and older, 2006-2016 Health and Retirement Study

Figure 2 charts the change in the predicted probability of CRN before and after a health shock for the health shock sample, adjusted for age, health insurance coverage, and year of the shock. The reference period is two waves prior to the health shock -- all changes are relative to this period. The x-axis denotes the wave since the shock, with negative values indicating the number of waves before the shock; zero marking the wave of the shock; and positive values indicating waves after the shock. Error bars represent 95 percent confidence intervals. Figure 2 shows a statistically significant 0.021 increase in the probability of CRN in the year of a health shock. This elevated level of CRN remains positive and significant in the waves following a shock. The trend suggests that health shocks increase the risk of CRN for older adult homeowners. Figure 3 plots the change in the probability of CRN three waves (six years) before and after a health shock by diagnosis type. The positive effect of a health shock on CRN is evident across all diagnoses, although small sample sizes for particular disease types increase the width of the confidence interval.

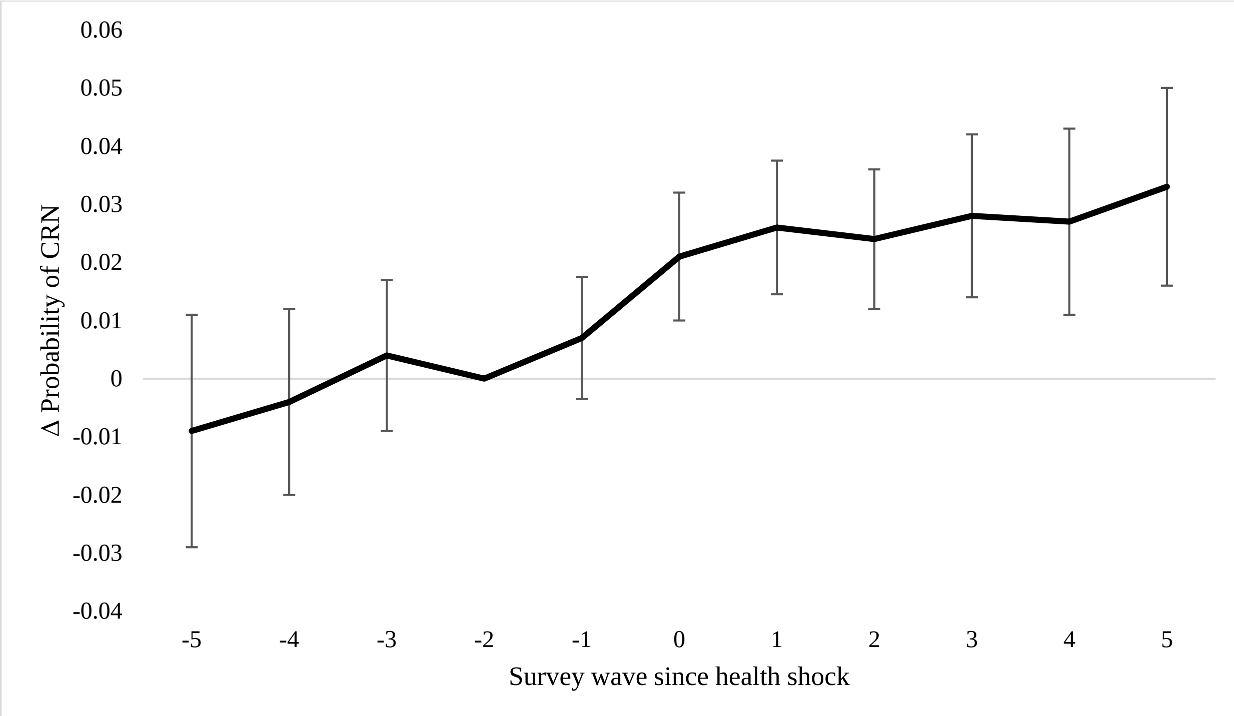

Figure 2
Notes: CRN before and after health shock, Health and Retirement Study

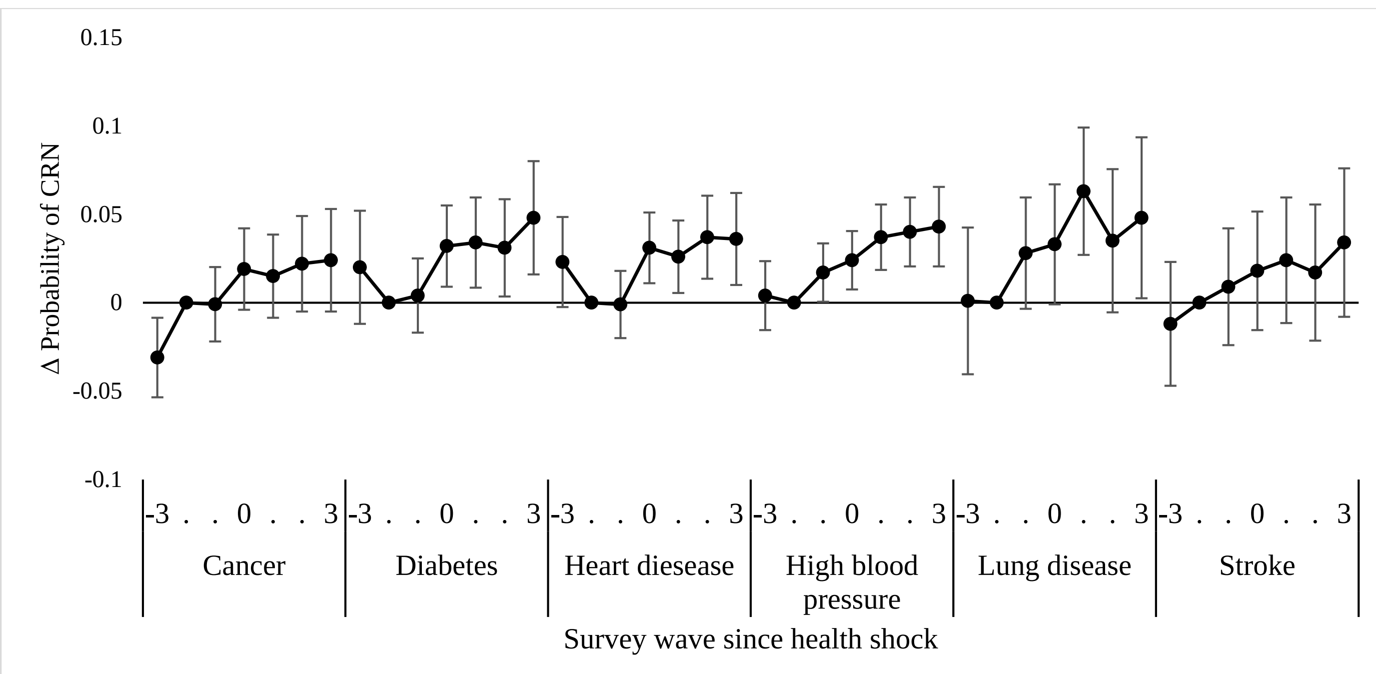

Figure 3
Notes: CRN before and after health shock by diagnosis, Health and Retirement Study

4.2 Housing Wealth, Borrowing, and CRN: Full Sample

The results for key coefficients from our first specification (equation 1) are presented in Table 1. Complete results for all sample variables for the model (3) are presented in Appendix B. The first model (1) reports the results from the reduced form estimation where CRN is regressed on lagged ΔHPI, treated as exogenous. The results indicate a statistically significant but economically small effect of changes in house prices on CRN, where a 100 percent increase in lagged ΔHPI is associated with a 2.3 percentage point reduction in the probability of CRN. During our sample period, the median ΔHPI was quite small (-0.02 percent); however, the top and bottom 5^{th} of the distribution in our sample experienced increases (and decreases) in HPI of 23 percent or more, which our results suggest would be associated with a 0.529 percentage point decrease (or increase) in the probability of CRN. The results from the ΔHPI specification are consistent with those from Costa-Font et al. (2019) who found that increases in house prices during the Great Recession were associated with increased consumption of long-term care services among older adults. However, these results do not provide insights into the mechanisms behind this association.

Model (2) presents the results for a specification that replaces the ΔHPI with the lagged change in home equity. We treat home equity change as endogenous given that change in the mortgage balance through borrowing is an endogenous choice, using lagged ΔHPI as an instrument in the first stage. The results indicate that a $100,000 lagged increase in home equity is associated with a 0.7 percentage point reduction in the probability of CRN; however, this result is not statistically significant. The insignificant relationship between home equity and CRN is not surprising, as home equity confounds the expected effects from house price changes with the effects from changes in mortgage balances.

Our third model (3) is our preferred specification, where the lagged amount of new mortgage borrowing is treated as an endogenous choice using lagged ΔHPI and an indicator of being borrowing constrained as instruments in the first stage. Here, we find that a $10,000 increase in the amount borrowed from a mortgage is associated with a 0.84 percentage point reduction in the probability of CRN, or a 0.41 percentage point reduction in the probability of CRN for the average borrowed amount (among borrowers) of $49,324. It is not surprising that the change in borrowing is statistically significant while the change in home equity is not—particularly if the mechanism through which home equity reduces CRN is direct access to liquidity (Cooper et al.

2013). The results for model 3 also indicate that a $10,000 increase in annual housing costs is associated with a 1.22 percentage point increase in the probability CRN. Thus, while our results indicate a short-term reduction in CRN from the amount borrowed (home equity liquefied), the effects will be moderated by an increase in the annual housing costs associated with the increased mortgage payment.

Other significant controls positively predicting CRN include being female, younger, being in worse health, or reporting difficulties with activities of daily living. Those with prior disease diagnoses are also more likely to report CRN. Having prescription drug coverage, and having friends and family nearby is negatively associated with CRN. Of note, black homeowners are more likely to report CRN, with a 1.6 percent higher reported likelihood than for white homeowners. Interestingly, the first stage regression results indicate that black homeowners are also significantly more likely to borrow from home equity than white homeowners (Appendix B).

We re-estimate the mortgage borrowing specification for a subsample of homeowners for whom Social Security consists of more than 90 percent of their total income (model 4), and a subsample of homeowners who have other income sources (model 5). The results indicate that the relationship between borrowing and CRN is economically larger for the social security income subsample; however, the relationship is not statistically significant, likely due in part to the smaller sample size. Of note, the relationship between housing costs and CRN is much higher for those relying primarily on social security income, where a $10,000 increase in annual housing costs is associated with a 4.62 percentage point increase in the probability CRN. The average CRN for this group is 9.84; thus, a $10,000 increase in housing costs is expected to increase the risk of CRN by 47.0 percent.

We also re-estimate the mortgage borrowing specification for a subsample of homeowners age 65 and older (model 6) and a subsample of homeowners below age 65 (model 7). The results show the association between mortgage borrowing and CRN is stronger for relatively older adults. Finally, we re-estimate our model for a subsample of homeowners with very low financial assets ($10,000 or less) (model 8) and a subsample with higher financial assets (more than $10,000) (model 9). We find that the association between mortgage borrowing and CRN is stronger for homeowners with low financial assets, although it is notable that the association between annual housing costs and CRN is also larger for this group.

In an alternative set of specifications (not shown), we estimate the long term effect of borrowing on CRN by substituting different lag structures for our measure of borrowing. The results of these specifications indicate that the effect of borrowing on CRN is short-tern, with the size of the coefficient reduced by half by two waves post borrowing and dropping to marginal statistical significance ($p<0.10$), with no significant effect by three waves post borrowing.[16]

Table 1 also reports the coefficients for our instruments from the first stage regressions for models 2 through 7, as well as the results of standard instrument tests that we implement for each of our endogenous specifications. In each case, under-identification tests are statistically significant, allowing us to reject the null hypothesis that our specifications are not well identified. Tests for over-identification are not statistically significant, indicating that our specifications are not over-identified. Under-identification tests are based on Anderson canonical correlations tests (ACC). Over-identification tests are based on Sargan-Hanson statistics (SH). Our instruments do not appear to be weak as the Cragg-Donald Wald F statistic is 198.7 for the home equity change model (2), and 183.5 for the new mortgage borrowing model (3), both well above the rule of thumb of 10 (Stock & Yogo 2005). The coefficients for our instruments are also as expected, with lagged ΔHPI being positively and significantly associated with both home equity change and mortgage borrowing, and being borrowing constrained being negatively and significantly associated with mortgage borrowing.

[16] Results of the long-run specifications available from the authors upon request.

Table 1. Linear probability model regression results predicting CRN, Health and Retirement Study 2006—2016

	(1)	(2) Full Sample	(3)	(4) SSRI ≥ 90% Income	(5) Other Income Sources	(6) Age 65 plus	(7) Age 50-64	(8) Financial Assets <= $10k	(9) Financial Assets > $10k
FHFA HPIΔ (100%, exogenous) t-1	-0.023*								
	(0.012)								
Home equity Δ ($100k, endogenous) t-1		-0.007							
		(0.006)							
Mortgage borrow ($100k, endogenous) t-1			-0.084*	-0.262	-0.060	-0.135+	-0.027	-0.144+	0.011
			(0.043)	(0.229)	(0.041)	(0.078)	(0.046)	(0.085)	(0.044)
Home value, ($100k) baseline	-0.003***								
	(0.001)								
Home equity, ($100k) baseline		-0.003***	-0.004***	-0.008*	-0.004***	-0.004***	-0.005***	-0.010***	-0.002**
		(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Annual housing costs, ($100k) baseline		0.024	0.122**	0.462*	0.092*	0.176**	0.044	0.188*	0.019
		(0.023)	(0.048)	(0.230)	(0.046)	(0.067)	(0.063)	(0.089)	(0.049)
Instrumental Variables (First Stage)									
Percentage FHFA HPI Δ t-2 to t-1		1.90***	0.053+	0.089*	0.048	0.065+	0.030	0.061*	0.047
		(0.146)	(0.028)	(0.038)	(0.034)	(0.035)	(0.043)	(0.030)	(0.039)
Constrained (LTV>90%) (0,1) t-2			-0.236***	-0.141***	-0.252***	-0.196***	-0.272***	-0.173***	-0.285***
			(0.029)	(0.030)	(0.034)	(0.035)	(0.036)	(0.016)	(0.053)
Instrument Tests									
Cragg-Donald Wald F-statistic		198.7	183.5	29.3	160.6	76.9	85.2	113.5	105.6
Underidentification test		167.2***	68.5***	17.0***	55.7***	33.2	49.4	91.6***	30.3***
Overidentification test		0	1.215	0.001	0.993	0.006	N/A	0.312	NA
N (individual-years) =	39,346	38,453	39,538	5,763	33,570	27,757	11,781	10,548	28,990
n (individuals) =	12,389	12,079	12,454	3,133	11,498	8,873	5,601	4,966	9,672

Notes: All models estimated with individual random effects. Standard errors clustered by household in parentheses. Dollar denominated variables are adjusted for inflation to 2016 dollars. Control variables included but not shown include all explanatory variables in Appendix A, lagged as of t-2.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

4.3 Housing Wealth, Borrowing, and CRN after a Health Shock

Table 2 reports the key results from equation 2, limited to the sample of homeowners who experience a health shock during our study period. Here, borrowing is measured in the periods after the onset of a new diagnosis and is treated as endogenous. Model 1 reports the results for the full shocked sample, indicating that a $10,000 increase in borrowing after a health shock is associated with a 1.67 percentage point reduction in the probability of CRN, or an 8.46 percentage point reduction in the probability for the average borrowed amount of $50,723 among borrowers with a health shock. Our models also control for home equity and annual housing costs as of two waves prior to the health shock (T-1). Here, a $10,000 increase in annual housing costs is associated with a 0.8 percentage point increase in the risk of CRN.

Table 2 also reports the results from our health shock specification for two different sets of subsamples. The first subsample is split based on the age of the homeowner in the wave prior to their health shock, with model 2 reporting results for those age 65 and older and model 3 reporting results for those under age 65. The results suggest that the relationship between mortgage borrowing and CRN is stronger among homeowners who experience their first health shock at an older age. We also split the sample based on whether or not a homeowner was already diagnosed with a disease in the wave prior to the onset of their health shock (models 4 and 5). Consistent with prior literature that documents a positive relationship between comorbidities and CRN, we find that the association between mortgage borrowing and CRN is stronger for homeowners that had an existing disease prior to a health shock, where a $10,000 increase in borrowing is associated with a 2.4 percentage point decrease in the risk of CRN ($p<0.10$).

As with our full specification, we split the sample by whether or not social security is the primary source of income (models 6 and 7), and whether or not the homeowner had $10,000 or more in non-housing financial assets (models 8 and 9). The coefficient for borrowing on CRN is larger for those relying on social security income and those with less than $10,000 in financial assets; however, the estimates are not statistically significant.

The results of the standard instrument tests for the endogenous specifications again indicate that our equations are well-identified, passing both the under-identification and over-identification tests, and our instruments are not weak. The Cragg-Donald Wald F statistic for our primary specification in model 1 is 74.6. The coefficients for our instruments are also as expected, with being borrowing constrained being negatively and significantly associated with mortgage borrowing, and lagged ΔHPI being positively (though not significantly) associated with mortgage borrowing.

Appendix C reports the full results for all of the control variables included in model 1, for both the first stage predicting mortgage borrowing and the second stage predicting CRN. There are a few noteworthy observations. First, with regard to financial variables, higher levels of financial wealth are associated with lower levels of CRN. However, the effect size is very small. With regard to demographic characteristics, being female, non-white, and having more children are associated with higher levels of CRN. Poorer self-rated health is associated with an increase in CRN, as is having an increase in problems with ADLs. With regard to comorbidities prior to health shock, being diagnosed with lung disease, hypertension, heart disease, and being depressed is associated with higher rates of CRN. Prescription drug coverage from an employer, Medicaid, Medicaid HMO, or other source is associated with significantly lower rates of CRN relative to individuals without insurance coverage. The post-shock wave indicators demonstrate an elevated increase in the risk of CRN in the periods following a health shock relative to the wave before the shock, similar to the trends noted in Figure 2. In the first stage, the amount borrowing is also significantly higher in the periods following a health shock compared to the wave prior to the shock (the omitted wave indicator), similar to findings in prior studies that indicate a positive relationship between health shocks and spending from housing wealth (Dalton and LaFave (2017; Poterba et al. 2017).

Table 2. Linear probability regression models predicting CRN, Homeowners with a health shock, HRS 2004—2016

	(1) Full Sample	(2) Age 65 plus	(3) Age 50 to 65	(4) No co-morbidities	(5) Has co-morbidities	(6) SSRI ≥ 90% Income	(7) Other Income Sources	(8) Financial Assets <=$10k	(9) Financial Assets > $10k
(Mortgage borrowing $100k, t-1)*Post	-0.167*	-0.185+	-0.079	-0.088	-0.242+	-0.487	-0.139	-0.237	-0.029
	(0.086)	(0.112)	(0.088)	(0.095)	(0.129)	(0.458)	(0.090)	(0.147)	(0.105)
Home equity level, baseline ($100k)	-0.004***	-0.003*	-0.006**	-0.004	-0.004*	-0.004***	-0.003***	-0.005	-0.003**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)
Annual housing cost, baseline ($100k)	0.088*	0.136*	0.015	0.766	0.075	0.391	0.076+	0.200*	0.023
	(0.040)	(0.054)	(0.046)	(0.049)	(0.057)	(0.458)	(0.040)	(0.086)	(0.044)
Instrumental Variables (First Stage)									
Percentage FHFA HPI Δ t-2 to t-1	0.040+	0.055	0.028	0.011	0.066+	0.034	0.043	0.025	0.048
	(0.024)	(0.036)	(0.037)	(0.027)	(0.037)	(0.027)	(0.030)	(0.032)	(0.034)
Constrained (LTV>90%) (0,1), t-2	-0.157***	0.210***	-0.212***	-0.208***	-0.153***	-0.088***	-0.155***	-0.134***	-0.184***
	(0.013)	(0.033)	(0.024)	(0.027)	(0.016)	(0.019)	(0.014)	(0.018)	(0.022)
Instrument Tests									
Cragg-Donald Wald F-statistic	74.6	57.6	52	55.4	38.2	9.888	56.9	36.6	40.8
Underidentification test	100.0***	30.1***	57.3***	42.8***	56.6***	18.2***	85.0***	44.9***	42.6***
Overidentification test	0.265	0.818	2.94+	0.708	0.082	0.054	0.268	0.005	1.205
N (individual-years) =	25,462	15,708	9,754	12,236	13,226	4,515	20,947	7,469	17,993
n (individuals) =	7,875	4,840	3,035	3,604	4,271	2,430	7,154	3,295	6,028

Notes: All models are estimated with individual random effects. Standard errors clustered by household in parentheses. Dollar-denominated variables are adjusted for inflation to 2016 dollars. Control variables included but not shown include all explanatory variables in Appendix A, lagged as of the wave prior to the health shock (T-1).

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

4.4 Simulations

Our first set of simulations use the estimates from equation (1) to predict the future CRN of the early and mid-baby boomer cohorts, born between 1948 and 1959. We begin by predicting the regression adjusted CRN for these cohorts in 2016. We then age the cohort by 10 or 20 years (respectively) and predict for each observation in our sample (1) the future probability of being borrowing constrained in 2026 or 2036, (2) the future borrowing amount in 2026 or 2036, and (3) the future probability of CRN in 2026 or 2036, accounting for the newly predicted borrowing amount. We estimate an upper and lower bound for future CRN, depending on the extent to which baby boomers continue to borrow from a mortgage at their predicted rate in future periods (lower bound), or if they reduce their borrowing amount by two-thirds (upper bound), borrowing at a level more similar to the older HRS cohort (born between 1931 and 1941). In our simulations, future CRN is predicted based on future age and future mortgage borrowing (modeled as endogenous with future borrowing constraints). However, we hold all other model covariates such as income, assets, self-reported health, and prescription drug coverage at their 2016 values for a given person. While this is an oversimplification, it allows us to focus on the age-adjusted future predicted CRN accounting for predicted future borrowing.

CRN is projected to decline with age, corresponding to the negative coefficient of age on CRN in Appendix B. In our simulations, age is the predominant factor that drives predicted future CRN from a high of 0.089 in 2016 to a low of 0.029 in 2036, assuming the boomer cohort follows their regression adjusted trajectory for borrowing in future periods. However, if their level of borrowing decreases in future periods by two-thirds—a level more similar to the older HRS cohorts in our model in 2016, we predict that their CRN will be slightly higher in 2026 and 2036. For example, in 2026, predicted CRN is 0.059 if borrowing continues the predicted boomer trajectory, and increases to 0.064 if boomers reduce future borrowing to be similar to that of the older HRS cohort. Thus, despite boomers having a higher stock of mortgage debt when they enter retirement than older cohorts, they have higher predicted flows of new borrowing in the future than the older cohorts, assuming their borrowing behaviors continue the trajectory observed through 2016. In our simulations, this higher flow of new borrowing for the average boomer offsets the borrowing constraints imposed by higher predicted future LTVs that reduce the borrowing amount for a subset of the boomer cohort in future periods.[17]

Our second set of simulations estimate the proportion of boomers who will have sufficient home equity to borrow from in the future, such as in response to a future health shock. The results from our health shock regressions indicate that of those who borrow, the average amount borrowed following a health shock is $50,000. For each individual in the boomer cohort in our sample, we predict the extent to which they would be able to borrow $50,000 in 2026 or 2036, based on their projected future LTVs in those periods.[18] We consider two different binding LTV constraints: 80 percent, which is a common underwriting limit for forward mortgages such as home equity lines of credit (HELOCs); or 50 percent, which is a typical limit on the maximum LTV for a reverse mortgage. If a boomer's projected future mortgage debt plus an additional $50,000 is less than the LTV limit, then we predict that they would have sufficient home equity to borrow in the future. Figure 4 summarizes the results of these simulations.

[17] Our simulations hold monthly mortgage costs at the baseline levels used in our regressions (e.g., when the person entered the HRS study), which assumes that the payment amount does not decline with age (e.g., a 30 year fixed mortgage has a set payment amount, even if the balance on the mortgage declines).
[18] To estimate future LTVs, we use our regression sample to predict the effect of age on LTV for the boomer cohort during our study period. The coefficient for age is -0.006. We then multiply this coefficient by 10 or 20 (-0.06 and -0.12, respectively) and subtract this amount from the 2016 LTVs for each individual in our sample, including the late Baby Boomer cohort who enter the sample in 2016, resulting in predicted 2026 and 2036 LTVs.

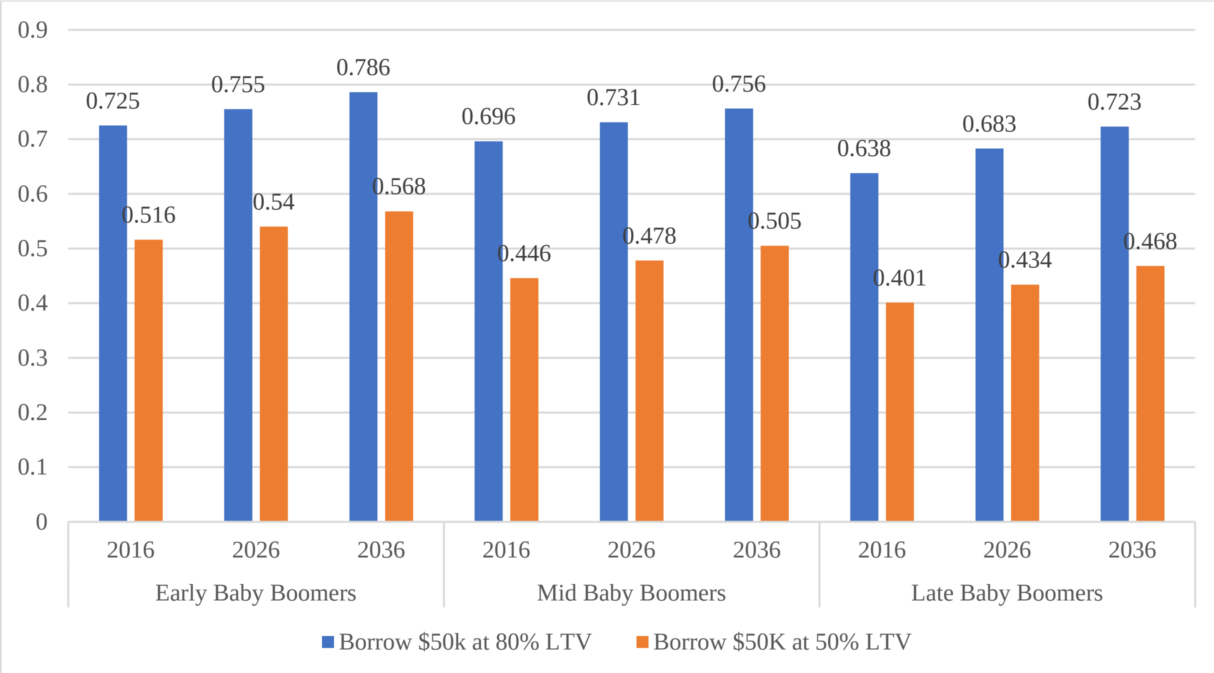

Figure 4
Notes: Predicted probability of sufficient home equity to borrow $50,000

Our simulations suggest that between 68 and 76 percent of homeowners in the boomer cohorts would have sufficient home equity to borrow $50,000 at an LTV limit of 80 percent in 2026, with 43 to 54 percent of homeowners having sufficient equity to borrow the same amount at an LTV limit of 50 percent. This proportion is slightly higher in 2036, as LTVs are predicted to decline with age. In 2036, we estimate that between 72 and 78 percent of homeowners in the boomer cohorts would have sufficient home equity to borrow $50,000 at an LTV limit of 80 percent, with between 47 and 57 percent having enough equity to borrow the same amount at 50 percent LTV. These estimates should be interpreted as upper bounds, as they do not account for additional constraints, such as the ability to afford a monthly payment for a forward mortgage or the ability to meet credit-based underwriting standards. Further, our simplifying assumption to hold control variables at their 2016 levels is likely unrealistic; characteristics such as health and income will likely change with age. Nonetheless, the simulation estimates provide some indication that borrowing from home equity is likely to be an option for a non-negligible proportion of the baby boomer cohorts in future years.

5. Discussion

As many as 80 percent of adults age 70 and older own their home and the wealth accumulated in the home is the largest asset for a larger share of older adults. However, this wealth cannot be easily accessed to buffer economic insecurity. It requires selling the home and downsizing or borrowing against the equity in the home to liquefy this wealth—something that historically, older adults tend to be reluctant to do. A large volume of prior research indicates that older adults tend to not spend down housing wealth in retirement, except in response to a shock, such as the death of a spouse or an adverse health event (Davidoff 2010; Nakajima & Telyukova 2009; Poterba & Venti 2017; Poterba et al. 2011; Venti & Wise 2004). Indeed, these studies suggest that housing wealth serves as a form of precautionary savings for health shocks. While this may be the case, few empirical studies examine whether or not housing wealth—when liquefied through borrowing—helps older adults smooth consumption and prevent negative outcomes, such as skipping prescription medications because of cost. This is the focus of our study.

To our knowledge, our study is the first to document that new borrowing through a mortgage reduces the likelihood that older adults delay taking medication or filling prescriptions because of the cost—at least in the short term. This finding makes sense when considering that the average borrower in our sample extracts $50,000 in home equity, which can increase cash flow in the short term by paying down expenses or supplementing income. This finding advances the understanding of the wealth components that are associated with cost-related non-adherence (CRN) beyond the role of net worth (e.g., Ziven et al. 2010). By exploiting the panel nature of the Health and Retirement Study (HRS) and instrumenting for mortgage borrowing, we show that it is important to account for the endogeneity of wealth and its components when modeling effects on CRN, thus refining earlier research (Pool et al. 2017).

Second, we find that the effect of mortgage borrowing on CRN is particularly pronounced following a health shock, providing some evidence that home equity indeed serves as a form of precautionary savings that buffers the negative consequences of a health event. Following the onset of a disease, borrowing $50,000 is associated with an 8.35 percentage point reduction in the risk of CRN in the two years following borrowing. This borrowing helps to offset the average increase in CRN observed for homeowners in our sample following the onset of a new disease. While borrowed funds could be used to pay for prescription drugs directly, they may also be used to pay for other health-related expenses and supplement lost income associated with the onset of a new disease, thereby increasing overall cash flow. This finding parallels cancer-related research that showed equity extraction, modeled as endogenous as in our study, is associated with a 23 percentage point increase in cancer treatment adherence (Gupta et al. 2018).

Third, we observe a significant positive relationship between housing costs and CRN. The costs of repayment of mortgage debt over the long term can offset some of the positive effects of increased cash-flow from borrowing in the short term. For example, consider a typical homeowner who extracts $50,000 on a 20-year home equity line of credit (HELOC) at an interest rate of 5 percent. For the first ten years, the monthly payment is interest only, at around $200 per month, followed by a ten year period of payments of $530 per month. The increase in annual housing costs associated with borrowing $50,000 on a HELOC would thus be $2,400 per year for the first ten years, increasing to $6,360 per year for the next ten years. The net effect of borrowing $50,000 on CRN in the short term would be a predicted decrease in the risk of CRN of 3.9 percentage points (0.084*50 – 0.12*2.4). However, our results indicate that the effect of borrowing on CRN is no longer statistically significant by three waves (six years) after borrowing, yet the borrower still experiences an elevated risk of CRN of 0.29 percentage points (first ten years) and 0.76 (second ten years) due to the higher monthly housing costs.

While the effects of an increase in housing costs on CRN may be small for the average borrower, the same dollar increase in annual housing costs is associated with a much larger increase in the risk of CRN for those who rely primarily on Social Security benefits for their income. For this group, the increased risk of CRN associated with $2,400 per year repayment is 1.1 percentage points, followed by 2.9 percentage points for the $6,360 per year repayment period. This suggests a role for policy options that provide older adults with access to home equity without increasing monthly housing costs—such as reverse mortgages. Reverse mortgages require no repayment until the loan is due, typically upon the death of the borrower.

Fourth, our final contribution is simulating the extent to which younger cohorts of older adults will have sufficient home equity to borrow from in the future, given they are carrying larger amounts of mortgage debt into retirement. The ability (or inability) to borrow may affect their future economic security, as measured by CRN. Our simulation results project that about two-thirds of the baby boomer generation will have sufficient home equity to borrow $50,000 through a forward mortgage in 2036, and about half will have sufficient home equity to borrow an additional $50,000 through a reverse mortgage. These are reduced form estimates that do not account for additional frictions to borrowing, such as the ability to qualify for a mortgage, and thus should be interpreted as an upper bound. Additional research can incorporate information on credit constraints to better project future access to mortgage borrowing.

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Appendix A: Summary Statistics

	Full Sample		Homeowners with a Health Shock	
	Mean	SD	mean	SD
Cost-related non-adherence to medication (0,1), t	0.066	0.249	0.075	0.263
Amount of new mortgage borrowing ($100,000), t-2 to t-1	0.075	0.339	0.073	0.341
Any new borrowing (0,1), t-2 to t-1	0.151	0.358	0.144	0.351
Borrowing constrained (LTV>90%) (0,1), t-2	0.029	0.166	0.026	0.160
Home equity level (in $100,000), baseline	2.155	2.532	2.085	2.460
Home equity change (in $100,000), t-2 to t-1	0.077	1.537	0.056	1.685
Percentage FHFA HPI, t-2 to t-1	-0.005	0.154	-0.011	0.153
Annual housing cost (in $100,000), baseline	0.080	0.105	0.076	0.103
Household total income (in $100,000), t-2	0.821	1.204	0.735	1.077
Financial assets (in $100,000), t-2	2.906	6.763	2.690	6.405
Net other assets (in $100,000), t-2	1.773	7.266	1.571	6.586
Non-housing debt (in $100,000), t-2	0.049	0.367	0.045	0.283
Under 130 Federal Poverty Line (0,1), t-2	0.088	0.283	0.099	0.298
Household size (1-15), t-2	2.173	1.036	2.165	1.053
Region: Northeast New England (0,1), t-2	0.038	0.191	0.037	0.188
Region: Northeast Mid-Atlantic (0,1), t-2	0.105	0.306	0.103	0.303
Region: Midwest East North Central (0,1), t-2	0.177	0.382	0.170	0.376
Region: Midwest West North Central (0,1), t-2	0.087	0.282	0.089	0.285
Region: South Atlantic (0,1), t-2	0.231	0.422	0.240	0.427
Region: South East South Central (0,1), t-2	0.064	0.246	0.067	0.249
Region: South West South Central (0,1), t-2	0.105	0.307	0.110	0.313
Region: West Mountain (0,1), t-2	0.059	0.236	0.055	0.227
Help with future needs (0,1), t-2	0.568	0.495	0.541	0.498
Problems with activities of daily living (0-5), t-2	0.251	0.778	0.317	0.874
Age (33-102), t-2	70.00	9.398	72	8.860
Male (0,1), t-2	0.433	0.495	0.455	0.498
Immigrant (0,1), t-2	0.095	0.293	0.093	0.290
White (0,1), t-2 (reference category)	0.836	0.370	0.830	0.376
Black (0,1), t-2	0.115	0.319	0.123	0.328
Other race (0,1), t-2	0.048	0.215	0.047	0.212
Hispanic (0,1), t-2	0.085	0.279	0.090	0.285
Less than high school (0,1), t-2 (reference category)	0.148	0.355	0.168	0.374
GED (0,1), t-2	0.040	0.196	0.045	0.207
High school diploma (0,1), t-2	0.314	0.464	0.316	0.465
Some college (0,1), t-2	0.238	0.426	0.236	0.425
College or more (0,1), t-2	0.260	0.439	0.235	0.424
Number of living children (0-20), t-2	3.113	1.992	3.195	2.013
Married (0,1), t-2 (reference category)	0.732	0.443	0.717	0.451
Separated, divorced, or widowed (0,1), t-2	0.244	0.429	0.261	0.439
Never married (0,1), t-2	0.025	0.155	0.022	0.146
Self-reported health (1-5), t-2	3.231	1.032	3.033	1.021
Self-reported memory (1-5), t-2	2.876	1.036	2.815	1.068
Cognition test score (0-20), t-2	9.557	3.854	9.119	3.878
Prescription coverage: Employer (0,1), t-2	0.470	0.499	0.433	0.495

Prescription coverage: Medicaid (0,1), t-2	0.036	0.186	0.044	0.205
Prescription coverage: Medicare HMO (0,1), t-2	0.167	0.373	0.187	0.390
Prescription coverage: Medicare Part D (0,1), t-2	0.173	0.378	0.193	0.395
Prescription coverage: Medigap (0,1), t-2	0.035	0.185	0.034	0.182
Prescription coverage: Other (0,1), t-2	0.035	0.185	0.039	0.194
Prescription coverage: None (0,1), t-2 (reference category)	0.083	0.275	0.069	0.253
Full Low Income Subsidy for Part D (0,1), t-2	0.027	0.162	0.032	0.177
Partial Low Income Subsidy for Part D (0,1), t-2	0.004	0.062	0.005	0.072
Receiving SSDI (0,1), t-2	0.032	0.177	0.036	0.187
Health Insurance (0,1), t-2	0.897	0.304	0.927	0.261
Cancer (0,1), t-2	0.173	0.378	0.237	0.425
Stroke (0,1), t-2	0.065	0.247	0.099	0.299
Lung disease (0,1), t-2	0.094	0.292	0.139	0.346
Hypertension (0,1), t-2	0.604	0.489	0.730	0.444
Diabetes (0,1), t-2	0.223	0.416	0.311	0.463
Heart disease (0,1), t-2	0.259	0.438	0.355	0.479
CESD depression scale (0-8), t-2	1.139	1.749	1.268	1.834
Smoking (0,1), t-2	0.091	0.287	0.097	0.296
Prescription drug price index (0.875 - 1.446), t-2	1.128	0.124	1.131	0.121
County unemployment rate (2- 28.8), t-2	6.800	2.606	6.924	2.631
Change in county unemployment rate (-6 - 10.2), t-2	-0.109	2.319	-0.080	2.359
Number of Observations	39,538	39,538	25,462	25,462
Number of Unique Respondents	12,454	12,454	7,875	7,875

Notes: Ranges for variables in parentheses. Dollar-denominated variables are adjusted for inflation to 2016 dollars.

Appendix B: Full Sample, Complete First, and Second Stage LPM Results

	(1) Second Stage: CRN	(2) First Stage: Borrowing
Mortgage borrowing ($100k) (endogenous), t-1 to t-2	-0.084*	
Home equity, baseline ($100k)	-0.004***	-0.010***
Annual housing cost, baseline ($100k)	0.122*	1.063***
Household total income, t-2 ($100k)	-0.002+	-0.006+
Financial assets, t-2 ($100k)	-0.000	0.000
Net other assets, t-2 ($100k)	-0.000	0.001
Non-housing debt t-2 ($100k)	0.003	-0.001
Under 130% Federal Poverty Line, t-2	0.011+	0.007
Household size t-2	0.003	0.008*
Help with future needs, t-2	-0.006*	-0.001
Problems with activities of daily living, t-2	0.021***	0.005+
Age, t-2	-0.003***	-0.001*
Male, t-2	-0.019***	0.007**
Immigrant, t-2	-0.001	0.005
Black, t-2	0.016*	0.022**
Other race, t-2	0.008	0.041
Hispanic, t-2	-0.001	0.006
GED, t-2	0.018	0.008
High school diploma, t-2	-0.006	0.004
Some college, t-2	-0.008	0.010
College or more, t-2	-0.019**	-0.006
Number of living children, t-2	0.003**	0.002
Missing information on number of living children, t-2	0.093+	-0.001
Separated, divorced, or widowed, t-2	0.010*	0.005
Never married, t-2	-0.011	0.000
Self-reported health, t-2	-0.011***	-0.002
Self-reported memory, t-2	-0.001	0.001
Missing information on self-reported memory, t-2	-0.008	0.006
Cognition test score, t-2	-0.000	0.000
Prescription drug coverage: Employer, t-2	-0.034***	0.002
Prescription drug coverage: Medicaid, t-2	-0.039**	0.016
Prescription drug coverage: Medicare HMO, t-2	-0.017**	0.001
Prescription drug coverage: Medicare Part D, t-2	-0.016*	0.011
Prescription drug coverage: Medigap, t-2	-0.014+	0.023+
Prescription drug coverage: Other, t-2	-0.026**	0.006
Full Low Income Subsidy for Part D, t-2	-0.004	0.013
Partial Low Income Subsidy for Part D, t-2	0.007	0.000
Receiving SSDI t-2	0.034**	-0.006
Health Insurance t-2	0.006	-0.003
Cancer, t-2	-0.007+	0.005
Stroke, t-2	-0.013+	-0.007

Lung disease, t-2	0.031***	0.007
Hypertension, t-2	0.014***	0.001
Diabetes, t-2	0.015**	-0.002
Heart disease, t-2	0.018***	0.004
CESD depression scale, t-2	0.010***	-0.001
Smoking, t-2	0.007	-0.003
Prescription drug price index, t-2	-0.083+	-0.242**
County unemployment rate, t-2	0.000	-0.005***
Change in county unemployment rate, t-2 to t-1	0.004**	0.000
Instrumental Variables		
Percentage FHFA HPI, Δ t-2 to t-1		0.053*
Borrowing constrained (LTV>90%), t-2		-0.175***
Constant	0.404***	0.391***
N (individual-years) =	39,538	39,538
n (individuals) =	12,454	12,454

Notes: Model estimated with individual random effects. Standard errors clustered by household. Dollar-denominated variables are adjusted for inflation to 2016 dollars. The model includes year and region fixed effects.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Appendix C: Health Shocked Sample, First and Second Stage LPM Results

	(1)	(2)
	Second Stage: CRN	First Stage: Borrowing
Mortgage borrowing, t-2 to t-1 ($100k)*Post	-0.167*	
Home equity level,baseline ($100k)	-0.004***	-0.002
Annual housing cost, baseline ($100k)	0.088*	0.416***
Household total income, t-2 ($100k)	-0.001	0.001
Financial assets, t-2 ($100k)	-0.0004**	-0.000
Net other assets, t-2 ($100k)	-0.000	0.000
Non-housing debt, t-2 ($100k)	0.005	0.007
Help with future needs, t-2	-0.003	0.004
Problems with activities of daily living, t-2	0.019***	0.001
Separated, divorced, or widowed, t-2	0.014*	0.001
Never married, t-2	-0.012	-0.002
Self-reported health, t-2	-0.010***	0.002
Receiving SSDI, t-2	0.020	-0.008
Cancer, t-2	-0.003	0.012+
Stroke, t-2	-0.008	0.003
Lung disease, t-2	0.021**	-0.002
Hypertension, t-2	0.009*	0.004
Diabetes, t-2	0.007	0.001
Heart disease, t-2	0.013**	-0.001
CESD depression scale, t-2	0.010***	0.003*
Smoking, t-2	0.003	-0.000
Under 130 Federal Poverty Line at t-2	0.003	-0.012+
Household size, t-2	0.004	0.012***
Age, t-2	-0.004***	-0.001***
Male, t-2	-0.018***	0.005
Immigrant, t-2	0.002	-0.005
Black, t-2	0.021*	0.016*
Other race, t-2	0.027+	-0.015
Hispanic, t-2	0.001	0.019+
GED, t-2	0.015	0.010
High school diploma, t-2	-0.008	0.003
Some college, t-2	-0.006	0.020**
College or more, t-2	-0.017*	0.013+
Number of living children, t-2	0.004**	0.001
Missing information on number of children, t-2	0.122*	0.124
Self-reported memory, t-2	0.000	0.003
Missing information on self-reported memory, t-2	0.007	0.042*
Cognition test score, t-2	0.000	-0.000
Prescription drug coverage: employer, t-2	-0.035***	0.006
Prescription drug coverage: Medicaid, t-2	-0.040**	0.01
Prescription drug coverage: Medicare HMO, t-2	-0.017*	-0.001

Prescription drug coverage: Medicare Part D, t-2	-0.014	0.007
Prescription drug coverage: Medigap, t-2	-0.017+	-0.000
Prescription drug coverage: Other, t-2	-0.027*	0.012
Full Low Income Subsidy for Part D, t-2	0.012	0.01
Partial Low Income Subsidy for Part D, t-2	0.032	-0.022*
Any health insurance, t-2	0.008	-0.004
Prescription drug price index, t-2	-0.051	-0.203*
County unemployment rate, t-2	0.002	-0.003+
Change in county unemployment rate, t-2	0.006***	-0.003
Wave after health shock (T+0) (0,1)	0.010+	0.003*
Wave after health shock (T+1) (0,1)	0.032**	0.105***
Wave after health shock (T+2) (0,1)	0.016+	0.089***
Wave after health shock (T+3) (0,1)	0.020+	0.093***
Wave after health shock (T+4) (0,1)	0.018+	0.084***
Wave after health shock (T+5+) (0,1)	0.021*	0.077***
Instrumental Variables		
Percentage FHFA HPI Δ t-2 to t-1		0.032
Borrowing constrained (LTV>90%), t-2		-0.100***
Constant	0.353***	0.202*
N (individual-years) =	25,462	25,462
n (individuals) =	7,875	7,875

Notes: Model estimated with individual random effects. Standard errors clustered by household. Dollar-denominated variables are adjusted for inflation to 2dollarsamodel model includes year and region fixed effects.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Center for Financial Security

School of Human Ecology
University of Wisconsin-Madison

1300 Linden Drive
Madison, WI 53706

608-890-0229
cfs@mailplus.wisc.edu
cfs.wisc.edu