Home Equity Mitigates the Financial and Mortality Consequences of Health Shocks: Evidence from Cancer Diagnoses*

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November 26, 2018

Abstract

This paper explores the relationship between home equity, financial distress, and cancer-related mortality. We find that highly-levered patients are more likely to refuse medical treatment and exhibit worse mortality in the aftermath of cancer diagnoses. Cancer is financially destabilizing for negative equity individuals—as measured by mortgage defaults, foreclosures, and bankruptcy—even among households with health insurance. By contrast, individuals with home equity are more likely to extract this equity in response to diagnosis, accept recommended therapies, do not exhibit financial distress, and have higher post-diagnosis survival rates. Our findings highlight the role of real estate in helping individuals buffer idiosyncratic shocks.

JEL classification: D14, D12, G33, I13, K35, R20
Keywords: Cancer, Health Shocks, Household Financial Fragility, Foreclosure, Medical Bankruptcy, Adverse Shocks, Leverage, Debt Overhang

*We are grateful to our discussants Sumit Agarwal, Pedro Gete, Paul Goldsmith-Pinkham, Tal Gross, Neale Mahoney, Oren Sussman, Jialan Wang, and Crystal Yang as well as comments from workshop participants at the University of Amsterdam (Business School), the American Law & Economics Association Annual Meeting, the University of Chicago (Economics and Law School), Oxford University, American College of Bankruptcy, AALS Annual Meeting, Columbia University (Economics, GSB, and Law School), NBER Summer Institute(Household Finance and Law & Economics), New York University (Stern), Stanford (GSB), the Texas Finance Festival, the NYC Real Estate Conference, the AREUEA National Conference, CUNY Graduate School, and the Fred Hutchinson Cancer Research Center for helpful comments. We also thank Equifax, DataQuick, BlackBox Logic, Zillow, the SNR Denton Fund, and the Fred Hutchinson Cancer Research Center for research support. Albert Chang and Dalya Elmalt provided excellent research assistance.

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Disclosure Statement (Arpit Gupta)

The author declares that he has no relevant or material financial interests that relate to the research described in this paper.

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Disclosure Statement (Catherine Fedorenko)

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I Introduction

Health shocks frequently result in large out-of-pocket expenditures, with over eight percent of households incurring direct healthcare costs exceeding $2,000 per year (see Gwet, Anderson and Machlin (2016)). The magnitude of these health-related expenses points to the importance of household wealth and access to credit markets as buffers against idiosyncratic health shocks, and potential determinants of subsequent patient financial and medical health. While it is well-understood that household wealth and socioeconomic status are closely correlated with health outcomes (Cutler, Lleras-Muney and Vogl, 2011), establishing the causal mechanisms and ruling out omitted background factors and reverse causation has proven to be a challenge. Many well-identified papers, which focus on developed countries with secure social safety nets, argue for a limited causal role of wealth shocks on health outcomes, even among patients facing serious health problems such as cancer.[1]

Our paper contributes to this literature by providing novel evidence on causal linkages between household wealth and life outcomes following cancer diagnoses, including compliance with the treatment recommendations of physicians, mortality, and financial distress. We focus on a particular source of household wealth—real estate—because it accounts for over forty percent of net worth among homeowners (Grinstein-Weiss, Key and Carrillo, 2015), and two-thirds of assets among the middle class (Wolff, 2012). Real estate has also seen dramatic price changes in recent years. While a number of papers have explored the implications of home prices changes on outcomes such as employment and default (Mian and Sufi, 2014), we present novel evidence that housing wealth has a causal impact on how households respond to personal health shocks. In particular, housing wealth enables individuals to extract equity (via refinanced mortgages or second liens) to pay for treatment and other medical expenses in the aftermath of cancer diagnoses.

[1] For instance, in the Swedish context Cesarini et al. (2016) and Erixson (2017) find no effect of exogenous windfall earnings on adult health outcomes. Finkelstein et al. (2012) find that health insurance does not improve measured physical health in Oregon, a state neighboring the one we examine. Schwandt (2018) finds evidence that changes in stock market wealth impact health outcomes among patients with hypertension, but no effect on patients with arthritis, diabetes, lung diseases, or cancer.

We study individuals who have undergone a health shock in the form of a cancer diagnosis. Our data allow us to identify the precise characteristics of the health shock (cancer stage, type, and recommended therapy) as well as the financial history of the patient prior to and after diagnosis. We find that negative-equity patients are more likely to refuse treatment recommended by physicians and have higher mortality rates following diagnosis. By contrast, we observe positive equity patients extracting equity from their properties and, in turn, experiencing greater longevity. We also find suggestive evidence that individuals also expand access to unsecured lending through credit cards without increasing spending on durable or non-durable goods. We emphasize, however, that collateralized lending—via refinanced mortgages or second liens—typically enables substantially greater access to funds of a magnitude sufficient to affect cancer prognosis.

Our estimates on the relationship between mortality and leverage persist when we control for a large number of medically relevant characteristics at the time of diagnosis, and under a variety of different specifications to rule out omitted factors related to household leverage choices. Our effects are very similar when accounting for cohort and time, or zip code and cohort fixed effects, which constrain leverage variation to come from different sources of cross-section and time-series variation in house prices. We also identify the effect of leverage on mortality directly by instrumenting the borrower's equity position using variation in neighborhood home prices during the three years prior to diagnosis. After controlling for residence zipcode and patient occupation as well as a battery of other covariates, this local house price variation can be viewed as plausibly exogenous to individual health condition. Our instrumental variables approach confirms that individuals are substantially more likely to comply with recommended therapies, and less likely to suffer mortality, when they are able to access housing wealth.

These results examine the pathway from pre-diagnosis financial access to post-diagnosis health outcomes. We also examine the link between health shocks and financial outcomes. We show that cancer diagnoses are financially destabilizing only for households with such high mortgage debt levels that they lack adequate home equity to serve as a financial buffer. Negative-equity patients are substantially more likely to default on their mortgage, file for bankruptcy, and subsequently experience foreclosure on their property. While it is unsurprising that debt default is one mechanism for coping with cancer diagnoses—which entail large out of pocket expenses, reduced labor supply, and a shortening of life horizon—we emphasize the magnitude of our results as well as the fact that they persist among individuals with formal medical health insurance.

Our work relates to an emerging literature attempting to isolate the causal relationship between debt or debt-related events (such as foreclosure) on mortality and health care events (such as emergency room trips). Examples include Ramsey et al. (2016), Currie and Tekin (2015), Argys, Friedson and Pitts (2016), Sachdeva (2018), and Pollack and Lynch (2009). We differ by analyzing novel channels which run through equity extraction and treatment choice among cancer patients.

Our research contributes to several other literatures as well. Extensive scholarship has explored the effects of shocks to health, mortality, and morbidity on consumption and investment decisions.[2] A subset of this literature examines the financial impact of idiosyncratic health shocks. Hubbard, Skinner and Zeldes (1995) was an early attempt to understand the effect of health shocks on financial outcomes, particularly among the elderly. Other examples from this literature include French and Jones (2004), who estimate that 0.1% of households experience a health shock that costs over $125,000 in present value; Ramsey et al. (2013), who find that cancer patients are at higher risk of bankruptcy than those without a cancer diagnosis; and Dobkin et al. (2018), who find that hospitalizations have a substantial adverse financial impact on insured households, as measured by out-of-pocket costs, lost income, reduced access to credit markets, and bankruptcy. Our empirical analysis contributes to this literature by highlighting the importance of personal leverage as an important driver of household default decisions.[3]

This paper is organized as follows: Sections II and III describe our data and empirical strategy. Section IV exploits plausibly exogenous variation in home equity to show that

[2]See Oster, Shoulson and Dorsey (2013) for a recent contribution.

[3]Our results also echo findings in the household finance literature. We find that a combination of negative shocks and high leverage best explain default patterns, similar to the "double-trigger" theory of mortgage default (see Bhutta, Dokko and Shan (2010)). We also highlight the trade-off between risk management and financing current investments in durable goods, such as housing and autos, as analyzed by Rampini and Viswanathan (2016). That trade-off persists even when households carry health insurance.

leverage accelerates time to death by reducing the financial "buffer" of home equity. Section V documents the financial consequences of cancer diagnoses, showing the critical role of home equity as a buffer, even for individuals with medical insurance coverage. Section VI discusses the implications of our findings and concludes.

II Data

Cancer represents one of the most common and costly health shocks. Roughly 40% of Americans can expect to face a cancer diagnosis over their lifetimes, and 20% of Americans will die due to cancer-related complications (Society (2013)). Cancer diagnosis rates are projected to increase both internationally and domestically over time due to medical progress in other fields, leaving individuals more susceptible to cancer risk. The cost of treating cancer has also been rising over time even faster then overall healthcare inflation, which in turn has been growing faster than economy-wide prices (See Mariotto et al. (2011) and Trogdon et al. (2012)).

Cancer severity is often measured using "stages." A cancer is *localized* if malignant cells are limited to the organ of origin ("primary tumor"), *regional* if the primary tumor has grown into other organs of the body, and *distant* if the primary tumor has produced new tumors that have begun to grow at new locations in the body. Because of this subtlety, it is well known that stage-coding is inconsistent (SEER Training Module 2014), with two stages potentially describing comparably severe cancers. There is yet another category of "unstaged" cancers, which are not given a formal staging by the investigating physicians. This often occurs when the cancer has spread so extensively through the patient's body that formal staging is not an informative exercise.

Cancer diagnoses generate direct and indirect costs. Direct cancer costs relate to the cost of treatment and can represent substantial expenses relative to household income. Cancer treatments typically involve some combination of drugs, surgery, radiation, and hormonal therapy. Formal health insurance should cover many of these treatments, but individuals are also exposed to out-of-pocket costs such as co-pays and deductibles. Prior to 2006, for example, older patients (over 65) often had limited insurance coverage of cancer drugs unless they purchased supplemental Medicare plans (in 2006, this situation changed with the enactment of Medicare Part D). Indirect costs include the time required to undergo screening and therapy, transportation to hospitals and clinics, and child or nursing care. Evidence suggests that 6.5% of cancer expenses among the non-elderly ($1.3 billion) are paid out-of-pocket (Howard, Molinari and Thorpe (2004)). Over 40% of cancer patients stop working after initial treatment (De Boer et al. (2009)).

Costs are substantial even among individuals with public or private insurance. Among Medicare beneficiaries, for example, out-of-pocket costs average $4,727 annually (Davidoff et al. (2013)). Among non-elderly cancer patients, Bernard, Farr and Fang (2011) found that 13% of individuals incurred out-of-pocket costs exceeding 20% of annual income. The percentage is much higher among individuals with public insurance (24% of income) and those with health insurance not provided by their employer (43%).[4]

II.A Data Construction

We link cancer diagnosis data from Washington State to bankruptcy filings, property records, mortgage payment data, and credit reports. Our cancer data are provided by the Cancer Surveillance System of Western Washington, which collects information about all cancer diagnoses in 11 counties on the western side of the state. These data are a subset of the National Cancer Institute's Surveillance Epidemiology and End Results (SEER) program. Our data include about 270,000 diagnoses occurring during calendar years 1996 through 2009. About 110,000 of these diagnoses involved patients between ages 24 and 64.

These cancer data were linked to federal bankruptcy records by the Fred Hutchinson Cancer Research Center via a probabilistic algorithm based on the patient's name, gender, address, and last four Social Security Number digits (see Ramsey et al. (2013)). The bankruptcy records include any consumer bankruptcy filing under chapters 7, 11, or 13 of the Bankruptcy Code.

[4]The magnitude of indirect costs arising from cancer diagnoses suggests that our work may have some applicability to countries with more universal health coverage, at least to the extent that formal insurance mechanisms are insufficient to fully mitigate the financial consequences of cancer diagnoses.

We further link the cancer data to property records maintained by DataQuick to create a "Property Database." The DataQuick records are transaction-based and provide information about every sale, mortgage, foreclosure, or other transaction affecting a property address during calendar years 2000 through 2011. We link these property records to the cancer data based on the patient's property address. This Property Database can be used to study the relationship between cancer diagnoses and foreclosure starts.

We augment the Property Database by linking it to mortgage payment data and credit reports for patients with privately securitized mortgages. BlackBox LLC provided the mortgage payment data, which includes information about the balance, LTV, borrower FICO, and other characteristics of the mortgage at origination as well as the borrower's post-origination payment history. These data cover the period January 2000 through July 2014, and are restricted to the universe of private-label securitized loans. Equifax provided the credit reports, which include monthly information about the borrower's credit score, utilization of revolving lines of credit (mainly credit cards), total debt burden, and other characteristics. These data cover the period from June 2005 through July 2014.[5] We linked the Property Database to the BlackBox and Equifax records using mortgage origination date, origination balance, zip code fields, and other mortgage fields (mortgage type and purpose) that are common to all datasets.

After linking these databases (SEER cancer registry, bankruptcy filings, DataQuick property records, and the BlackBox and Equifax databases), we subset on individuals between ages 21 and 80 at the time of diagnosis. Younger patients are unlikely to file for bankruptcy; older patients have extremely high mortality rates subsequent to diagnosis. Additionally, we exclude cancer diagnoses that involving benign and in situ stage cancer diagnoses (early stage cancers that have not spread to surrounding tissue) as well as diagnoses discovered only upon death or autopsy. The former cancers represent trivial health shocks; the latter confound death and diagnosis, making it impossible to infer the impact

[5] Equifax performed the linkage between its records and the BlackBox data. Because this linkage was imperfect, we retained a linkage only if Equifax reported a "high merge confidence" (based on a proprietary algorithm) or if the BlackBox and Equifax records listed the same property zip code (suggesting a common residence between the subject of the credit report and the holder of the mortgage. Additional information about the BlackBox and Equifax databases, and the merge algorithm, can be found in Mayer et al. (2014) and Piskorski, Seru and Witkin (2015).

of diagnosis on financial stability. Finally, a number of patients have multiple cancer diagnoses. If the diagnoses were "synchronous"—occurring within a three month period—we treat them as a single event and assign a diagnosis date equal to the first-diagnosed cancer. Synchronous cancers are frequently manifestations of one underlying cancer.[6] If a patient suffered multiple, non-synchronous cancers (diagnoses occurring over a period longer than three months), we included in our analysis any cancer diagnosis that was not followed by another diagnosis during the subsequent three years. These restrictions explain why the "Full Sample" we use for base analysis contains fewer observations (about 220,000) than our complete dataset (about 270,000). The Deeds Sample, consisting of data that merge between SEER and property records, contains around 64k observations.

Figure I provides a visual description of our data creation process. Appendix A provides a more complete description of the data and information about the merge algorithms.

II.B Summary Statistics

Table I presents summary statistics for the cancer patients in our study. The first two columns summarize the Full Sample, defined as the SEER data linked to bankruptcy records, with restrictions as outlined in the Data Construction section. The second two columns summarize the subsample linked to Deeds property records ("Deeds Sample"). In the Full Sample, the mean age is 61, with a wide standard deviation: ages 32 through 80 are within two standard deviations of the mean. About sixty percent of patients are married, roughly half are male, and over a third had health insurance through Medicare or Medicaid. Although Table I indicates that only 9.5 percent of individuals carried private insurance (14.7 percent in the Deeds Sample), health insurance information is missing for nearly half of the sample. Most of the individuals with missing information likely had some form of health insurance: Those age 65 and older are covered by Medicare; among those aged 18 to 64, prior studies indicate that between 8 and 14 percent had no health insurance coverage in Washington State (Ferguson and Gardner (2008)).

[6]We assign these cancers the highest stage among the multiple stages present (localized, regional, or distant). We also assign the site of the cancer to the "Other" category if the sites of the synchronous cancers differ.

Table I also presents information about the "occupation" of individuals in our sample. This information is included in the SEER database and derived from a hospital intake form that asks patients to describe their occupation, not whether they are currently employed in that occupation. We interpret this information as a proxy for the patient's human capital investment. Using an algorithm supplied by the Washington State Department of Health (Ossiander and Milham (2006)), we categorized patient responses into broad categories: Professional, Clerical, Laborer, Other, Not Employed, and Missing. The Not Employed category includes individuals who indicated that they lacked employment status at the time they completed the intake form.[7]

Table II shows the annual number of cancer diagnoses by stage at diagnosis. As described above, cancer diagnoses can be staged—from least to most severe—as localized, regional, and distant. Nearly half of diagnoses are localized; regional and distant cancers account for most of the remaining diagnoses. In the analysis below, we include unstaged cancers in the "distant" category because these cancers tend to have a very high mortality rate.

III Empirical Strategy

Changes in household leverage can affect health outcomes through multiple channels. Changes in leverage, for example, could affect stress, which in turn affects health. In our initial specifications, we explore the effect of plausibly exogenous variation in household leverage on health decisions and mortality rates. Next, we seek to isolate the causal effects of cancer diagnoses on financial fragility, as measured by consumer defaults. The key focus in both sets of specifications is on the role of leverage: both in the first set of specifications in posing financial constraints to individuals which prevent them from making longevity-promoting decisions, as well as in presenting a debt overhang which results in financial distress in combination with health shocks.

[7] We classify individuals as "unemployed" if they fail to indicate an occupation, but do indicate marital status. We assume that, if an individual fails to answer both the occupation and marital status questions, he or she is refusing to complete the form. If the individual indicates marital status, but leaves occupation blank, we think it reasonable to assume that the individual is leaving it blank because he or she is unemployed.

III.A Effect of Home Equity on Mortality

We test the effects of leverage on longevity. We do this by testing the effects of shocks to mortgage equity on treatment decisions and ultimate health. To do this, we estimate a Cox proportional hazards model:

$$\lambda(t|X_i) = \lambda_0(t)\exp(X_i \cdot \beta) \tag{1}$$

This individual-level analysis estimates duration to death following cancer diagnosis as a function of patient and property level covariates X_i. The key variable of interest is the value of home equity at diagnosis, as measured by the patient's current CLTV ("CCLTV"). Variation in CCLTV can, of course, be driven by unobservable patient characteristics that are correlated with health outcomes. These include how long the patient has maintained the mortgage (which may reflect background wealth, education, or other characteristics, but also affects loan amortization) and the particular year and region in which the property was purchased (which may be correlated with personal characteristics, but also affects home value). Following Bernstein and Struyven (2017) and Bernstein (2018), we estimate three alternative specifications that account for endogenous sources of variation in CLTV: (1) loan age, (2) region (zip code) $\times$ cohort, and (3) cohort $\times$ time effects. Specification (1) soaks up variation in equity attributable to differences across homeowners in mortgage amortization. Specification (2) accounts for variation attributable to the timing of the purchase and the region in which the home is located (a "cohort" is defined as a group of borrowers who originated mortgages during the same calendar year). The residual variation in this specification is attributable to *within-cohort* variation home prices. Finally, specification (3) accounts for within-cohort cohort variation over time, which captures the possibility that reactions to economic conditions (such as the Great Recession) vary by cohort. This specification uses the residual cross-sectional variation in house prices.

Of course, these specifications may not fully account for endogenous correlates of household-level variation in CLTV. We deploy an instrumental variable (IV) specification to address potential confounds. Our strategy follows Amromin, Eberly and Mondragon

(2016) and exploits zipcode-level changes in home prices prior to diagnosis as a plausibly exogenous source of variation. In the first stage, we regress CCLTV on the change zip-level home price indices during the three-year period prior to diagnosis:

$$CCLTV_{it} = \alpha + \beta \cdot -\Delta HP_{i,t-36\rightarrow t} + \mathbf{X'_{it}}\gamma + \varepsilon_{it} \tag{2}$$

Here, β captures the role of local home price shocks on mortgage equity. We express the change in house prices as the negative of house price change, so a positive β coefficient can be interpreted as a decline in house prices leading to rises in home equity. X_{it} includes typical patient-level information plus an interaction between cancer stage and cancer type in order to account for other cancer characteristics that may ultimately drive outcomes.

In the second stage, we regress CCLTV against an indicator of whether the patient refused treatment:

$$Refused_{it} = \alpha + \beta \cdot CCLTV_{it} + \mathbf{X'_{it}}\gamma + \varepsilon_{it} \tag{3}$$

Putting the first stage and second stage together, our IV specification tests whether local home price shocks (the instrument) drive (a) an individual's propensity to refuse necessary treatment care through (b) the channel of home equity. Access to home equity improves financial capacity to pay for and finance cancer care through a variety of outcomes, including by facilitating home equity extraction (which could be used to finance that care).

The underlying assumption is that home price shocks affect treatment decisions only through the channel of improved home equity. This assumption is false if a household's purchasing capacity expands as its home appreciates in value via channels that do not involve home equity directly. We address that possibility by testing a reduced-form specification, regressing treatment decisions on home prices directly:

$$Refused_{it} = \alpha + \beta \cdot -\Delta HP_{i,t-36\rightarrow t} + \mathbf{X'_{it}}\gamma + \varepsilon_{it} \tag{4}$$

Here, β captures the effect of *all* mechanisms by which rising local home prices may affect the treatment choices of individuals. To the extent that local home price variation is exogenous to individual health for cancer patients, these channels should isolate the role of greater housing wealth on individual propensities to proceed with recommended cancer treatment.

III.B Effect of Health Shocks on Financial Outcomes

Having established the channel connecting wealth and health, we next estimate a standard event-study difference-in-difference (DD) regression to investigate the role of health shocks on financial outcomes, following Almond, Hoynes and Schanzenbach (2011) and Autor (2003):

$$O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it} \tag{5}$$

Here, O_{it} is an outcome measure. In most specifications, it will be a binary equal to one if patient i exhibits a measure of distress (e.g., foreclosure) during calendar year t. θ_t is a matrix of calendar year fixed effects.[8] The matrix X_{it} includes a variety of controls, which vary with the database used for the analysis. In all regressions, we include patient age, marital status, gender, race, occupation, health insurance status, indicators for whether the patient suffered synchronous cancers or had a previous cancer diagnosis, and county fixed effects. In analysis using the BlackBox or Equifax data, the controls include time from origination, static information taken at time of origination (balance, CLTV, and details about the purpose and type of mortgage), and dynamic information updated monthly (such as credit score, estimated income, and interest rate).

The identifying assumption in our model is that, conditional on observables, the *timing* of cancer diagnosis is unrelated to the individual's financial condition. We focus for this reason only on individuals diagnosed with cancer in our sample, and compare individuals diagnosed at different times. Common trends—due to time and geographical drivers of financial distress—are differenced out in our sample design. We present evidence consistent with our identifying assumption in Section V.A below.

[8] We do not include individual fixed effects because our dependent variable is binary and we are typically studying the first occurrence of an event (such as foreclosure or bankruptcy). In this setting, with non-repeating events, fixed effect analysis is not feasible (Andress, Golsch and Schmidt (2013).

The coefficients of interest are μ_k, which measure the change in the outcome variable during the s calendar years prior to and following the diagnosis in year T_i, where s is typically 5. Years $[-s, -1]$ reflect the s pre-treatment years, while the interval $[0, s-1]$ is the post-treatment window. These coefficients are measured relative to the (omitted) year prior to the diagnosis. Standard errors are clustered by patient.

If outcome O_{it} occurs during year t, data for that patient is censored in all subsequent years. This censoring renders our framework similar to a discrete time hazard model, as in Mayer et al. (2014). Additionally, if patient i dies during year t, data for that patient is also censored in all subsequent years. Finally, the model is only estimated during years for which we are confident that the patient lived in the property in question as determined by sale transactions data.

IV Effects of Home Equity on Health Outcomes

Our initial goal is to evaluate the role of home equity as a buffer—a form of self-insurance—against health shocks. We begin in Figure II by plotting the hazard of mortality across levels of equity. Panel A plots the Kaplan-Meier (unconditional) survival curve by CCLTV (the ratio of mortgage debt to home value at the time of diagnosis). Individuals with CCLTV greater than 100 have no home equity at diagnosis. Panel A shows that, as CCLTV increases, survival rates decline monotonically, consistent with the hypothesis that home equity mitigates the financial impact of cancer on mortality rates. Panel B plots the survival curve from a Cox model that includes the same controls included throughout this paper, including property, loan, borrower, and cancer characteristics. We see a predictable narrowing of differences between the survival curves, but continue to observe a monotonic and statistically significant reduction in mortality rates as CCLTV increases.[9]

The narrowing of differences between the survival curves, as we move from Panel A to B, points to important heterogeneity across patients as well as the possibility that variation in CCLTV is correlated with background characteristics that are correlated with health

[9] Although the analysis in Panels A and B is performed using the entire Deeds Sample, we obtain the same results when we subset on individuals for whom we can verify medical insurance coverage, as shown in Appendix Figure A.I.

outcomes. We explore the sources of variation in CCLTV in Table III. Column 1 reports coefficients from the Cox model underlying the coefficients in Panel B of Figure II.[10] Because this specification already accounts for loan age, the residual variation in CCLTV is attributable to variation across patients and over time in home price changes. The next two columns restrict the source of variation in home price changes. Because Column 2 adds region (zip code) $\times$ cohort, our estimates here are identified from within-cohort, within-region variation in home prices over time. Column 3 includes cohort $\times$ time effects, allowing the CCLTV estimates to be identified off of variation within-cohort, within-year across regions. Across specifications, however, the hazard of death increases monotonically with CCLTV and the magnitudes are largely invariant to the strategy for controlling variation in CCLTV. For example, the hazard rate for individuals with no home equity (CCLTV$>$100) is about 17 percentage points higher than the rate for individuals with substantial home equity (CCLTV $\leq$ 60).

Columns 4 through 6 rerun the survival analysis on the subset of patients with "high expected survival." We identify this subset based on a separate duration model, predicting mortality based on observable patient and demographic information at the time of diagnosis. Patients with above-median predicted survival times are included in the "high expected survival" subset. Perhaps unsurprisingly, we find much stronger effects of leverage on morality in this subset. For those with low survival rates, expected survival times are so low that leverage matters little; life expectancies are short whether or not they receive recommended therapies. Thus, home equity matters most among individuals who are have relatively high expected survival rates, provided they receive therapy.

The final columns (7–9) of Table III rerun our analysis on the subset of individuals with verifiable health insurance coverage. Due to sample size constraints, we do not condition on individuals with high life expectancy. Nonetheless, we continue to find large effects of leverage on mortality.

There are several pathways by which leverage could cause an increase in mortality rates. We hypothesize that one important pathway is that high leverage affects limits a patient's

[10]Note these tables display the survival model coefficients, not hazard ratios.

ability to access financial markets and fund medical care. Figure III presents a preliminary exploration of this hypothesis. We explore medical outcomes across bins of individual home equity at the time of diagnosis, as measured by CCLTV. Panels A and B show that patients are less likely to perform, and more likely to refuse, recommended medical treatment performed if they have negative equity (CCLTV $\geq$ 100).[11] Correspondingly, five-year cancer survival rates are lower among negative equity patients. These results highlight the role of leverage and mortgage equity in facilitating patient care and subsequent longevity.

We explore this hypothesis more carefully in Panel B of Table III. Here we estimate the effect of leverage on an individual's decision to refuse recommended treatment recommended. The controls are the same as in Panel A, where we estimated the effect of leverage on mortality. Individuals with negative equity are 0.0084 percentage points more likely to refuse treatment than those with sizable home equity. This is equal to a 21 percent increase over the baseline probability of refusing treatment (3.86 percent). Although the effect is not statistically significant, it is large in magnitude and consistent across specifications, regardless of how we constrain the variation in CCLTV. We obtain comparable results when we subset on individuals with high expected survival and those with verifiable medical insurance, as the final columns show. In Appendix Table A.I, we also find that individuals with worse equity positions are less likely to have recommended treatment performed, a difference which is especially stark among individuals with negative equity. Taken as a whole, these results suggest that mortality may be worsened among patients who, due to negative home equity, are less able to access financial markets to borrow and fund medical care.

To be sure, we cannot rule out the potential endogeneity of leverage, even after systematically controlling for sources of variation in CCLTV. We can, however, address this potential endogeneity using the instrumental variable strategy described in equations 2 through 4. Table IV reports estimates from this strategy. The controls here remain the same as in all prior specifications.

The first stage of the analysis in Table IV uses home price changes during the 36 months prior to diagnosis to predict current combined loan-to-value at the time of diagnosis. Un-

[11] We look at both treatment performance and treatment refusal because, in our data, some patients are not recommended to receive a particular treatment.

surprisingly, we observe a strong effect of home price shocks on equity positions, implying that a one standard deviation decrease in house prices results in a 0.11 standard deviation increase in current CLTV. In Column 2, we regress CCLTV against the decision to refuse treatment, finding that individuals with greater leverage are more likely to refuse treatment, consistent with the results in Panel B of Table III. Column 4 presents the instrumented relationship between housing equity and refusal of treatment. Our estimates are sizable, indicating that a one standard deviation in leverage—instrumented by housing shocks—is associated with a -0.029 percentage point decrease in the likelihood of refusal of treatment, which is strongly correlated with subsequent longevity. To put this estimate into perspective, note that treatment is refused by 3.86% of patients in the Full Sample (see Panel B of Table III). Additionally, a one-standard deviation change in CCLTV is equal to 51 points (see Table I). The refusalal rate falls by .057 percentage points for every one point drop in CCLTV.

A less restrictive, reduced-form specification is found in Column 3 of Table IV. Here we regress local changes in home prices against the likelihood that individuals refuse treatment. Again, we find a large effect, showing that house price shocks affect treatment choices, potentially through multiple channels, including direct equity extraction.

Our IV strategy here follows Adelino, Schoar and Severino (2015) and Bernstein, McQuade and Townsend (2015), who analyze the effects of exogenous shocks to house prices on various outcomes. Due to the idiosyncratic nature of cancer diagnoses, we expect little ex-ante relationship between house price shocks and medical prognoses, except through the channels which impact housing equity. We test for the exogeneity of our house price instrument in figure A.II. In this figure, we rerun the reduced-form specification, equation 4, but change the outcome to measure patient health and demographics, including cancer stage, patient occupation, and insurance status. We find no statistically significant relationship between our house price instrument and any of these background variables, suggesting that our instrument is picking up a quasi-exogenous shock to households.

Overall, our results suggest a powerful role for household leverage in determining individual treatment decisions and mortality. We believe that the likely mechanisms underlying this finding include both out-of-pocket costs of therapy and lost income of cancer patients and their families. Our results suggest that home equity can serve as an important buffer for individuals facing adverse health shocks. This result is subject to the usual caveat that drivers of mortgage equity may not be purely exogenous to individuals. However, we focus on variation in home equity from a variety of different channels and obtain comparable results, suggesting that housing wealth may be a causal driver of treatment decisions.

V Effects of Cancer Diagnoses on Financial Outcomes

Our analysis of pre-existing financial condition on subsequent health outcomes highlighted the role of leverage as a contributing factor behind individual decision-making in the aftermath of cancer diagnosis. Leverage remains the focus in this section, which focuses instead on the impact of cancer diagnoses on household financial outcomes. We document that individuals with untapped liquidity through home equity are better able to withstand cancer diagnoses. This analysis helps identify the channels discussed above by which leverage can affect mortality.

V.A Average Effects

Figure IV plots yearly coefficients from our event-study model, equation 5, using three outcome variables: notice of default, foreclosure, and bankruptcy. Notices of default correspond to a publicly available statement notifying homeowner-borrowers that if they fail to repay money owed, lenders may foreclose on the real estate. It therefore corresponds to a situation of sizable mortgage delinquency, typically after a borrower has missed three or more months of payments. A foreclosure occurs when the lender seizes the property (most foreclosures in Washington state are non-judicial proceedings). Thus, while defaults largely capture individual decisions to stop payment, foreclosures capture a joint decision by the individual to remain delinquent on the mortgage and by the lender to seize the property. Because notices of default and foreclosures are observable only among individuals who own homes and have taken mortgages, we use the Deeds Sample to study these outcomes. Bankruptcy, by contrast, is observable for all individuals, regardless of homeownership status, allowing us to use the Full Sample. A bankruptcy occurs when an individual files a petition with the relevant court, but is usually done after the individual has defaulted and often done in order to halt pending creditor collection efforts, such as a foreclosure.

Figure IV plots the coefficients of interest, μ_k for the five years before and after diagnosis, with the year before as the excluded category. Year zero corresponds to the calendar year of diagnosis. The model is shown separately for stage one cancers, and cancers staged two or higher. Plots on the left of Figure IV include all patients; plots on the right examine the subset of medically insured individuals.

Across specifications, the key coefficients in Figure IV are generally insignificant prior to the treatment year. This is important because it helps validate our identifying assumption that a cancer diagnosis is indeed an unexpected event for households and not predicted, for instance, by other changes in household variables also driving financial fragility. This might happen, for instance, in the presence of "comorbidities," i.e., other diseases that typically arise in conjunction with cancer diagnoses (emphysema, for example, often arises in conjunction with lung cancer). The existence of comorbidities may drive financial distress independently of the cancer prior to the time of diagnosis. If so, we should observe financial stress increasing prior to the cancer diagnosis.

The lack of economic and statistical significance of prior coefficients is most evident when analyzing the outcomes of foreclosure and bankruptcy; and in analyzing foreclosures and default. We find some evidence for pre-trends when examining the outcome of default, among cancers staged 2+, in the full (not restricted to medically insured) sample, especially in years -3 and year -5 before the diagnosis. These specifications would suggest that we are *under*-estimating the impact of cancer diagnoses on financial distress, as some financial distress could be materializing prior to the diagnosis for these patients. However, the balance of our pre-coefficient trends do not exhibit differential pre-trends suggestive of financial hardship prior to cancer diagnosis. By contrast, yearly coefficients after diagnosis are frequently positive and significantly different from zero, suggesting a causal relationship between cancer diagnosis and measures of financial stress.

To provide a better quantitative sense of our results, Tables V and VI report the yearly coefficients μ_k, but suppress remaining controls to simplify the presentation. At the bottom of each table, we report the cumulative estimated effect for the five years after diagnosis ("Treatment 5 Years"). Again, these estimates are measured relative to the year prior to diagnosis. Additionally, the bottom of the table reports the average outcome probability (default, foreclosure, or bankruptcy) during the year prior to diagnosis ("Ref. Prob. 1 Year") and the cumulative probability during the five years prior to diagnosis ("Ref. Prob. 5 Years").

Table V examines financial defaults as measured by notices of default (columns 1–2) and foreclosures (columns 3–4), regardless of the individual's insurance status. Recall from Table I that about 50% of individuals in our Deeds Sample have unknown insurance coverage. While our measures of insurance status are incomplete (because we lack good estimates on truly uninsured people), we can identify subpopulations that are well insured medically: individuals with documented private medical insurance in our data, as well as individuals over 65 (who typically qualify for Medicare). Columns 5–6 (notices of default) and 7–8 (foreclosure) report estimates from analysis on this subpopulation. All estimates in Table V are based on the Deeds Sample.

Columns 1 and 2 show a substantial, sustained increase in the probability of default and foreclosure during the five years following diagnosis (as summarized by "Treatment 5 years" at the bottom of Table V). The default rate increases 0.007 percentage points for stage one ("localized") cancers, a 100 percent increase in the frequency of defaults relative to the five year baseline. We find effects of comparable relative magnitude for higher stage cancers (an increase of 0.0081 percentage points relative to a baseline of 0.0091 percent). Though we observe large effects across all cancer stages, we do find that timing varies. Among higher stage cancers, we observe an increase in foreclosure rates beginning in the second post-diagnosis year. Among less severe cancers (localized and regional), significant effects appear in the third year following diagnosis. Overall foreclosure rates are large in relative magnitude: representing a relative increase of 156 percent among stage one cancers, and 96 percent among higher stage cancers. Note also that all results are censored at mortality.[12]

[12]Results are higher when we do not impose this restriction.

When we restrict our analysis to individuals for whom we can confirm medical insurance coverage—columns 5 through 8—we continue to find strong evidence of financial distress induced by cancer diagnoses. For example, the estimated cumulative five-year effect amounts to a 92 percent increase in the relative probability of experiencing severe mortgage default among stage one cancers. Other estimates are similar in magnitude, regardless of whether we condition on insurance status. Because we do not measure uninsured status well, these numbers cannot be interpreted as evidence that insurance status is unimportant in determining default rates. Rather, we interpret our results as suggesting that *even* medically insured individuals appear to respond to cancer diagnoses by defaulting on debts, particularly on their mortgages. Our results here are consistent with those in Dobkin et al. (2018).

Table VI reruns the analysis using bankruptcy filings as the outcome measure. Columns 1 and 2 use the Full Sample, 3 and 4 subset on the Deeds Sample (the same sample used in the previous regressions), and 5 and 6 subset further on households (in the Deeds Sample) for whom we can verify medical insurance coverage. In the Full Sample, we observe small (and insignificant) effects of cancer diagnoses on bankruptcy filings, regardless of insurance coverage. Effects are larger when we limit the analysis to the Deeds sample (which matches with mortgage records through address), especially among stage one cancers. In column (3), we find that cancer diagnoses lead to a significant cumulative increase in bankruptcy filings of 0.005 percentage points in the five years after diagnosis, which represents about a 24 percent increase relative to the baseline filing rate. The effect is even larger—a 58 percent increase (a 0.007 increase relative to the 0.012 baseline rate)—when we subset on individuals with insurance. We find much smaller estimates of the effect on bankruptcy filings (a cumulative five year increase of 0.00058) among cancers staged two or higher. Although it may seem surprising to find larger effects for less severe cancers, we believe this pattern reflects the effects of mortality expectations on how households respond to cancer diagnosis. Individuals with longer life expectancies (stage 1 cancers) are more likely to file for bankruptcy than those with shorter life expectancies (stages and higher). The latter are more likely to default and undergo foreclosure than to file for bankruptcy, as we discuss next.[13]

These findings establish our baseline results: cancers are financially destabilizing as measured by defaults, foreclosures, and (depending on the specification) bankruptcies.

V.B Financial Fragility and Household Leverage

The analysis thus far conceals important heterogeneity across patients. Table VII reexamines the effect of cancer diagnoses on foreclosure, but subsets on individuals for whom we can verify medical insurance coverage as well as the origination date and balance of a mortgage in the Deeds database.[14] Column 1 restricts on individuals for whom we can measure a combined loan to value ratio (CLTV), defined as total mortgage debt (including both first and second mortgages) divided by the purchase price of the home. This regression—which is the same specification reported in the preceding tables—establishes a benchmark to verify that we obtain comparable results on the subsample with mortgage information. Column 1 suggests that default rates increase by .015 percentage points following diagnosis, a 75 percent increase relative to the baseline rate (.02). This "average effect" here is comparable to what we report in Table V for insured individuals, though the underlying default rate is substantially higher when we subset on individuals with CLTV information.

This "average effect" is driven by the subset of households that are highly levered, as columns 3 and 5 of Table VII show. Column 3 uses a measure of CLTV taken at origination; column 5 uses an estimate of the current CLTV (CCLTV) at the time of diagnosis. Cancer is destabilizing only for patients who have no home equity (CLTV $\geq$ 100) at mortgage origination. Among these patients, we observe a very large increase—2 percentage points—in the foreclosure probability during the five years following diagnosis, over a 200 percent increase relative to the baseline (.01). The foreclosure rate declines among patients with home equity at origination (CLTV$<$100), as column 2 shows. Default and bankruptcy rates

[13]In Appendix B we set out a theoretical model of the choice between bankruptcy and default and foreclosure; we show that the choice is driven, in part, by life expectancies. Appendix C presents results consistent with our model.

[14]We cannot observe the origination date and balance of a mortgage originated prior to around 2000. Our data track transactions after that date. We obtain comparable results when we do not subset on individuals for whom we can verify medical insurance coverage.

are also higher among highly levered individuals, relative to those with equity. We find similar patterns when we use CCLTV to identify highly-levered households. Although the CCLTV results are often insignificant, this is unsurprising because our measure of. CCLTV measure is imprecise: We impute the current mortgage balance (assuming straight-line amortization) and the current home value (using zip-code price indices, which do not cover all transactions in our data).[15] We believe the CLTV-based results are complemented by the magnitudes of the CCLTV-based results.

These estimates suggest that home equity—and access to liquidity generally—is an important channel through which patients (insured or uninsured) cope with the financial stress of health shocks. We can study this channel more directly by looking at patients' use of credit following cancer diagnosis. Panel D of Table VII predicts the annual probability that a patient refinances a first mortgage or takes on a second mortgage as the dependent outcome. Although we see a (insignificant) decline in credit use by the average patient during the years following a diagnosis (column 1), the decline is driven entirely by patients with high levels of leverage (column 3). By contrast, we observe a substantial rise in equity extraction among the population with positive equity in their homes. Our effects are economically large, suggesting cancer diagnosis leads to as many as 17 percent of affected individuals with positive equity to extract some of it.

Our main findings are summarized in Figure V, which computes the percentage increase in each outcome—default, foreclosure, bankruptcy, and access to new credit—by cancer stage, medical insurance, and household leverage. Our key findings are that (1) cancer diagnoses are financially destabilizing, (2) these effects persist among the medically insured, and (3) they are concentrated among highly levered individuals, while individuals with more equity are instead able to access credit. Together, these results highlight the role of leverage in exacerbating the intensity of other shocks, and the potential role for home equity to act as a form of self-insurance for individuals facing idiosyncratic shocks.

As a robustness check, we examine in Figure VI how the yearly coefficients change under alternate specifications that account for potentially endogenous drivers of variation

[15] Appendix A describes the imputation process in more detail.

in home equity. As discussed above, in Section III.A, these endogenous drivers include loan age, borrower cohort and region, and the year in which we observe the borrower's cancer diagnosis in our data. Figure VI shows how our foreclosure estimates vary as we constrain the variation in current CLTV to account for potential endogeneity. Specification (1) adds a control for loan age, (2) adds region (zip code) $\times$ cohort controls, and (3) adds cohort $\times$ time controls. Panel A uses the Full Sample, with the right-hand side using the subset of patients with CCLTV greater than 100. Panel B focuses on the insured subset, again with the right-hand side restricting to patients with high CCLTV. We find comparable estimates across all three specifications.

Finally, we explore other post-diagnosis outcomes by exploiting the linkage to Blackbox and Equifax data in Table VIII. Recall that the Blackbox data include detailed payment information about private-label securitized loans, and these data have been linked to Equifax credit reports, including credit card usage. Because this subsample is relatively small (5,000 individuals), as Figure I illustrates, we do not further subset on individuals for whom we can verify medical insurance coverage. Panel A of Table VIII looks at measures of default and shows a substantial increase in the probability that a borrower misses three or more payments on their mortgage during the three years following diagnosis. Effects are negligible prior to diagnosis, but exceed 2 percentage points during the second and third years following diagnosis. Although we also find an increase in defaults on installment and revolving debts, the effects are significant for revolving (in year three) but not installment debt. Revolving debts include credit card balances; installment debt includes automotive and student loans.

Panel B of Table VIII uses the Blackbox-Equifax sample to examine credit access and usage following cancer diagnosis. We find significant declines in credit scores, but also an economically large though statistically insignificant increase in credit limits of over $1,600 by the third year after diagnosis, which is driven by an increase in new cards (an increase of 0.5 additional credit cards in the year of diagnosis). While our analysis here is limited due to the small sample size, it suggests that cancer diagnoses induce greater demand for credit, both secured and unsecured, and that lenders supply credit despite worsening repayment rates and credit scores in this population. These results also point to the key role of real estate assets: Because home equity serves as collateral for new lending, it facilitates substantially greater access to credit than unsecured credit.[16]

These results isolate a pathway—home equity—from cancer diagnoses to severe financial distress. Cancer is destabilizing for households who have exhausted their home equity, not among those who have retained this financial buffer. These findings help rationalize our finding that, for households who lack home equity, the financial consequences of cancer could affect treatment decisions and, in turn, mortality.

VI Conclusion

Our results point to the central importance of credit markets, and real estate assets in particular, as a buffer against health events and other adverse financial shocks. Even households with health insurance face sizable out-of-pocket costs after a cancer diagnosis. These costs are destabilizing when a household has taken on high pre-diagnosis leverage. The household is not only effectively priced out of the credit market, but also exposed to higher mortality risk because the household may be unable or unwilling to pay for recommended therapies.

Our research is subject to several caveats. First, we document patterns of financial distress surrounding severe medical events, but do not make claims about the strategic nature of those defaults. Nor do we make any normative claims about the desirability of foreclosure among affected households. Bankruptcy, default, and foreclosure are commonly viewed as manifestations of severe financial distress, with adverse consequences for debtors and creditors alike. An alternative view might see these outcomes as manifestations of strategical calculations by households. Because a cancer diagnosis reduces

[16] Appendix C explores the heterogeneity of our results by occupation, cancer severity, and expected survival. We show there that effects on default, foreclosure, and bankruptcy are driven, in large part, by patients listing "clerical" or "laborer" occupations. Tentative evidence suggests that effects are largest for lung and thyroid cancers and for patients receiving radiation-based therapy. The effects, however, vary by outcome. Bankruptcy effects are largest for patients with above-average survival rates, such as thyroid patients. Default and foreclosure effects are largest for those with below-average life expectancies. Importantly, the difference between low- and high-survival patients is larger when we subset on individuals aged 26 through 60, who are plausibly more financially fragile because they are less likely to benefit from public insurance, and when we subset on households with no home equity, confirming that home equity plays an important role in mitigating the financial impact of cancer. These findings are important, we believe, because they provide further evidence to rule out potential confounds, such as a correlation between leverage and cancer severity.

a patient's life expectancy, for example, a rational household might strategically default on long-term debts such as mortgages. Under this interpretation, our results on leverage form an analogue to the "double trigger" theory of household default: Default may be the result of both (i) an adverse shock (cancer diagnosis) that reduces ability to pay and (ii) an adverse financial position (negative equity) that limits the household's desire to repay.

Additionally, we look exclusively at the effects of cancer diagnoses on financial management (defaults, foreclosures, bankruptcies). We are unable to test whether cancer diagnoses affect broader wealth and consumption choices.

Nonetheless, our results present a sharp contrast with much of the prevailing literature on household financial fragility and health insurance because we that highly levered individuals face a higher probability of financial default even in the presence of medical insurance. While medical insurance is clearly an important buffer for households facing severe medical shocks, our results show that household financial fragility depends on much more than the existence of such insurance. Many individuals with insurance file for bankruptcy or experience foreclosure (particularly if they are heavily levered); many individuals without insurance never file for bankruptcy or foreclosure (particularly if they have equity). Household capital structure is, at the very least, an additional, important, and underemphasized driver of default decisions among medically distressed households.

Consistent with the idea that real estate assets serve as an important buffer for individuals faced with idiosyncratic shocks, we find that borrowers with positive equity are likely to extract this equity after diagnosis, and appear to be more likely to undergo treatment and live longer as a result. These results provide evidence of the real effects of financial markets on an important tangible household outcome: life expectancy.

Our findings on the relationship between debt and mortality connect to important potential public policies, both for policymakers and physicians. Governments can influence household assets and leverage through a variety of channels, including credit supply and leverage restrictions.[17] The optimal therapy for a patient could depend on the patient's financial condition, especially if debt burdens may discourage a patient from completing a

[17] Texas, for example, prohibits refinanced mortgages with a principal balance that exceeds 80 percent of the home value, as discussed in Kumar (2017).

relatively high-cost therapy. We conclude that financial markets play an important role in helping individuals smooth the expenses associated with adverse health events, and there remains considerable scope for such efforts even in environments of full medical insurance.

References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2015. "House prices, collateral, and self-employment" *Journal of Financial Economics*, 117(2): 288–306.

Almond, Douglas, Hilary W. Hoynes, and Diane Whitmore Schanzenbach. 2011. "Inside the War on Poverty: The Impact of Food Stamps on Birth Outcomes" *The Review of Economics and Statistics*, 93(2): 387–403.

Amromin, Gene, Janice Eberly, and John Mondragon. 2016. "The Housing Crisis and the Rise in Student Debt" *Working Paper*.

Andress, Hans-Jurgen, Katrin Golsch, and Alexander W. Schmidt. 2013. *Applied Panel Data Analysis for Economic and Social Surveys* Springer.

Argys, Laura M., Andrew I. Friedson, and M. Melinda Pitts. 2016. "Killer Debt: The Impact of Debt on Mortality" *Working Paper*.

Autor, David H. 2003. "Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing" *Journal of Labor Economics*, 21(1): 1–42.

Bernard, Didem S.M., Stacy L. Farr, and Zhengyi Fang. 2011. "National Estimates of Out-of-pocket Health Care Expenditure Burdens among Nonelderly Adults with Cancer: 2001 to 2008" *Journal of Clinical Oncology*, 29(20): 2821–2826.

Bernstein, Asaf. 2018. "Negative Equity, Household Debt Overhang, and Labor Supply" *Working Paper*.

Bernstein, Asaf, and Daan Struyven. 2017. "Housing Lock: Dutch Evidence on the Impact of Negative Home Equity on Household Mobility" *Working Paper*.

Bernstein, Shai, Timothy McQuade, and Richard R. Townsend. 2015. "Does Economic Insecurity Affect Employee Innovation?" *Working Paper*.

Bhutta, Neil, Jane Dokko, and Hui Shan. 2010. "The Depth of Negative Equity and Mortgage Default Decisions" *Journal of Finance (forthcoming)*.

Boscoe, Francis P, Christopher J Johnson, Recinda L Sherman, David G Stinchcomb, Ge Lin, and Kevin A Henry. 2014. "The Relationship between Area Poverty Rate and Site-specific Cancer Incidence in the United States" *Cancer*, 120(14): 2191–2198.

Cesarini, David, Erik Lindqvist, Robert Östling, and Björn Wallace. 2016. "Wealth, Health, and Child Development: Evidence from Administrative Data on Swedish Lottery Players" *The Quarterly Journal of Economics*, 131(2): 687–738.

Currie, Janet, and Erdal Tekin. 2015. "Is there a Link between Foreclosure and Health?" *American Economic Journal: Economic Policy*, 7(1): 63–94.

Cutler, David M, Adriana Lleras-Muney, and Tom Vogl. 2011. "Socioeconomic Status and Health: Dimensions and Mechanisms" In *The Oxford Handbook of Health Economics*.

Davidoff, A.J., M. Erten, T. Shaffer, J.S. Shoemaker, I.H. Zuckerman, N. Pandya, M.-H. Tai, X. Ke, and B. Stuart. 2013. "Out-of-pocket Health Care Expenditure Burden for Medicare Beneficiaries with Cancer" *Cancer*, 119(6): 1257–1265.

De Boer, I A.G., T. Taskila, A. Ojajarvi, F.J. van Dijk, and J.H. Verbeek. 2009. "Cancer Survivors and Unemployment: A Meta-Analysis and Meta-Regression" *JAMA*, 301(7): 753–762.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J. Notowidigdo. 2018. "The Economic Consequences of Hospital Admissions" *American Economic Review*, 108(2): 308–52.

Erixson, Oscar. 2017. "Health responses to a wealth shock: evidence from a Swedish tax reform" *Journal of Population Economics*, 30(4): 1281–1336.

Ferguson, Deron, and Erica Gardner. 2008. "Estimating Health Insurance Coverage Using Hospital Discharge Data and Other Sources" *Health Care Research Brief No. 48*.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and Oregon Health Study Group. 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year*" *The Quarterly Journal of Economics*, 127(3): 1057–1106.

French, Jeric, and John B. Jones. 2004. "On the Distribution and Dynamics of Health Care Costs" *Journal of Applied Econometrics*, 19(6): 705–721.

Grinstein-Weiss, Michal, Clinton Key, and Shannon Carrillo. 2015. "Homeownership, the Great Recession, and Wealth: Evidence from the Survey of Consumer Finances" *Housing Policy Debate*, 25(3): 419–445.

Gwet, Philippe, Jerrod Anderson, and Steven R. Machlin. 2016. "Out-of-Pocket Health Care Expenses in the U.S. Civilian Noninstitutionalized Population by Age and Insurance Coverage, 2014" *Agency for Healthcare Research and Quality Statistical Brief*, 646–653.

Howard, David H., Noelle-Angelique Molinari, and Kenneth E. Thorpe. 2004. "National Estimates of Medical Costs Incurred by Nonelderly Cancer Patients" *Cancer*, 100(5): 883–891.

Hubbard, R. Glenn, Jonathan Skinner, and Stephen P. Zeldes. 1995. "Precautionary Saving and Social Insurance" *Journal of Political Economy*, 103(2): 360–399.

Kitahara, Cari M, and Julie A Sosa. 2016. "The Changing Incidence of Thyroid Cancer" *Nature Reviews Endocrinology*, 12(11): 646–653.

Kumar, Anil. 2017. "Do Restrictions on Home Equity Extraction Contribute to Lower Mortgage Defaults? Evidence from a Policy Discontinuity at the Texas Border" *American Economic Journal: Economic Policy (forthcoming)*.

Mariotto, Angela B., K. Robin Yabroff, Yongwu Shao, Eric J. Feuer, and Martin L. Brown. 2011. "Projections of the Cost of Cancer Care in the United States: 2010–2020" *Journal of the National Cancer Institute*.

Mayer, Christopher, Edward Morrison, Tomasz Piskorski, and Arpit Gupta. 2014. "Mortgage Modification and Strategic Behavior: Evidence from a Legal Settlement with Countrywide" *American Economic Review*, 104(9): 2830–57.

Mian, Atif, and Amir Sufi. 2014. "What explains the 2007–2009 drop in employment?" *Econometrica*, 82(6): 2197–2223.

Morrison, Edward R. 2014. "Coasean Bargaining in Consumer Bankruptcy" In *Ronald H. Coase*. , ed. Omri Ben Shahar. Chicago, IL:University of Chicago Law School.

Morrison, Edward R., and Antoine Uettwiller. 2017. "Consumer Bankruptcy Pathologies" *Journal of Institutional and Theoretical Economics*, 173(1): 174–196.

Ossiander, Eric M., and Samuel Milham. 2006. "A computer system for coding occupation" `fortress.wa.gov/doh/occmort/OCCMORT/OM_sasprog.htm`.

Oster, Emily, Ira Shoulson, and E. Ray Dorsey. 2013. "Limited Life Expectancy, Human Capital and Health Investments" *The American Economic Review*, 103(5): 1977–2002.

Piskorski, Tomasz, Amit Seru, and James Witkin. 2015. "Asset Quality Misrepresentation by Financial Intermediaries: Evidence from RMBS Market" *Journal of Finance*, 70(6).

Pollack, Craig Evan, and Julia Lynch. 2009. "Health status of people undergoing foreclosure in the Philadelphia region" *American journal of public health*, 99(10): 1833–1839.

Rampini, Adriano A., and S. Viswanathan. 2016. "Household Risk Management" National Bureau of Economic Research.

Ramsey, Scott D., Aasthaa Bansal, Catherine R. Fedorenko, David K. Blough, Karen A. Overstreet, Veena Shankaran, and Polly Newcomb. 2016. "Financial Insolvency as a Risk Factor for Early Mortality Among Patients With Cancer" *Journal of Clinical Oncology*, 34(9): 980–986.

Ramsey, Scott D., David Blough, Anne Kirchhoff, Karma Kreizenbeck, Catherine Fedorenko, Kyle Snell, Polly Newcomb, William Hollingworth, and Karen Overstreet. 2013. "Washington State cancer patients found to be at greater risk for bankruptcy than people without a cancer diagnosis" *Health Affairs*, 32(6): 1143–1152.

Sachdeva, Kunal. 2018. "Liquidity and Longevity, Bequest Adjustments Through the Life Settlement Market" *Working Paper*.

Schwandt, Hannes. 2018. "Wealth Shocks and Health Outcomes: Evidence from Stock Market Fluctuations" *Working Paper*.

Society, American Cancer. 2013. "Lifetime Risk of Developing or Dying From Cancer"

Stoler, Avraham, and David Meltzer. 2012. "Mortality and Morbidity Risks and Economic Behavior" *Health Economics*, 22(2): 132–143.

Trogdon, Justin G., Florence K.L. Tangka, Donatus U. Ekwueme, Gery P. Guy Jr., Isaac Nwaise, and Diane Orenstein. 2012. "State-level Projections of Cancer-related Medical Care Costs: 2010 to 2020" *The American Journal of Managed Care*, 18(9): 525.

White, Michelle J., and Ning Zhu. 2010. "Saving Your Home in Chapter 13 Bankruptcy" *Journal of Legal Studies*, 39(1): 33–61.

Wolff, Edward N. 2012. "The asset price meltdown and the wealth of the middle class" *Working Paper*.

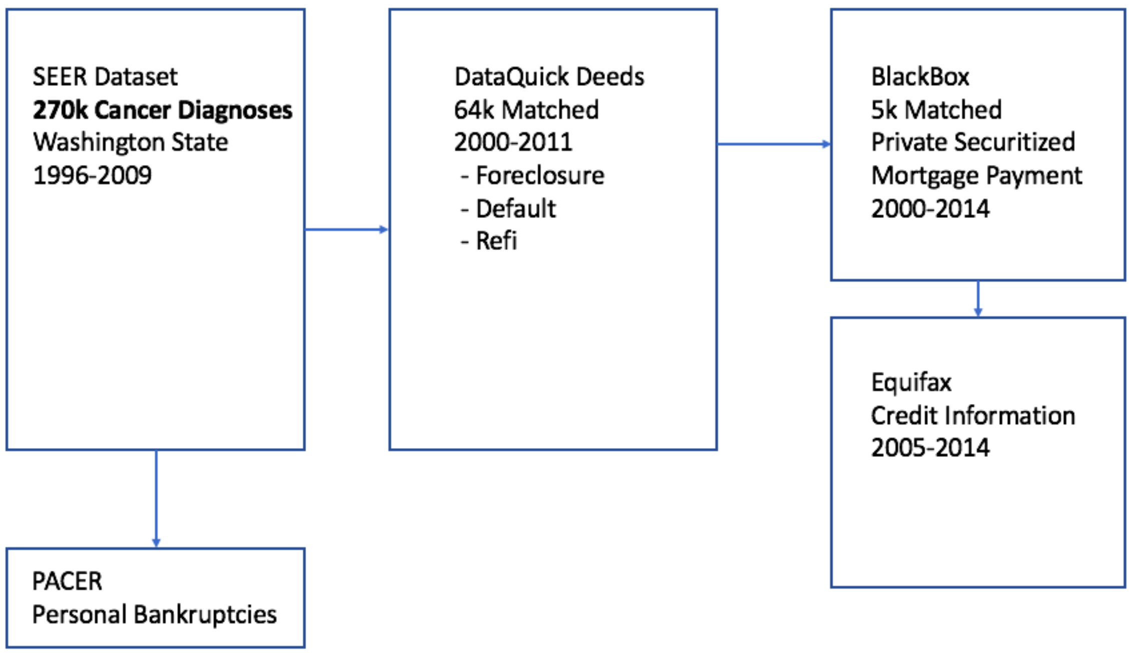
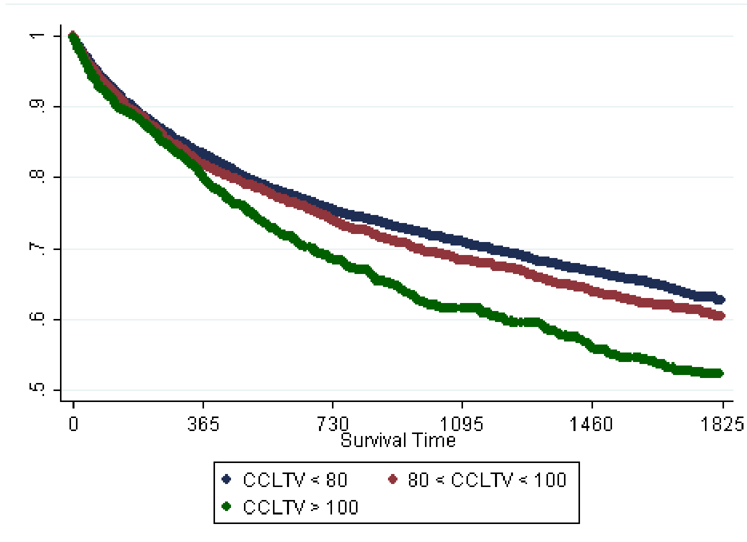
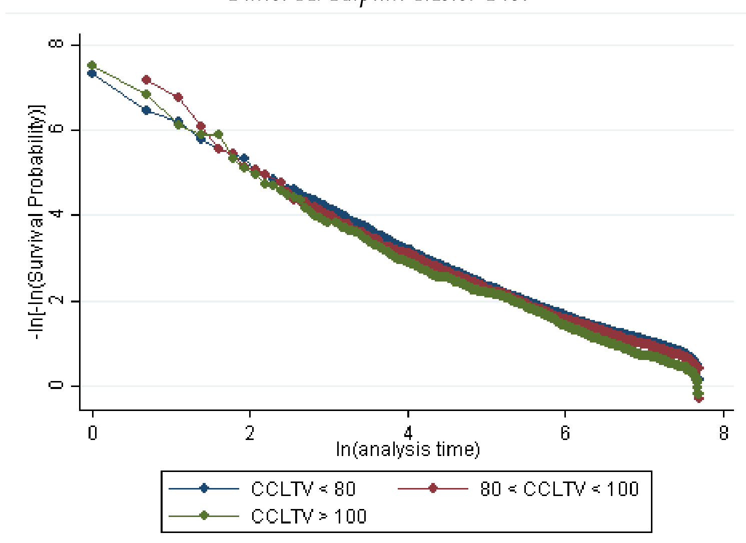


FIGURE I: Illustration of Merged Datasets

This figure illustrates the connections between the datasets used in this study. The core dataset is the SEER dataset containing diagnosis and treatment information on cancer patients in Western Washington State. This dataset is combined with individual bankruptcy information to produce the Full Sample. This composite dataset is also merged with Deeds data using home address, which provides information on household leverage as well as default and foreclosure information. Deeds data are also linked for some observations to BlackBox and Equifax, which contain information on defaults on privately securitized mortgages, as well as associated credit bureau information



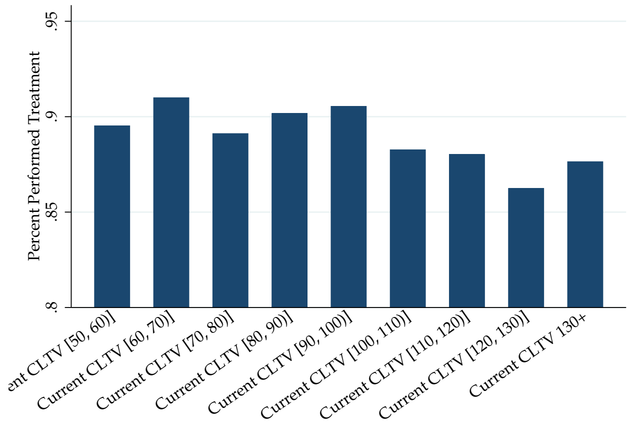
Panel A: Kaplan-Meier Plot



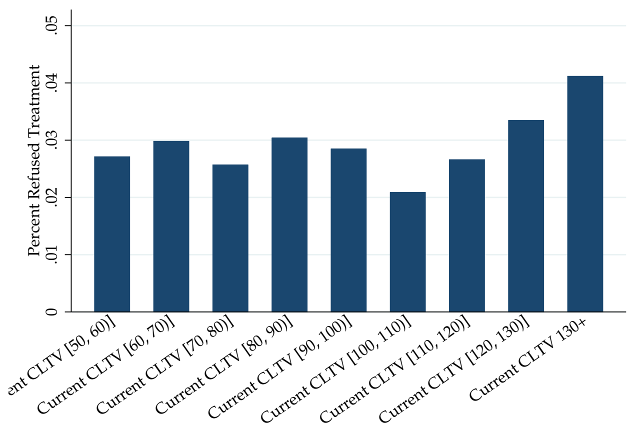
Panel B: Cox regression

FIGURE II: Survival Analysis and Housing Equity

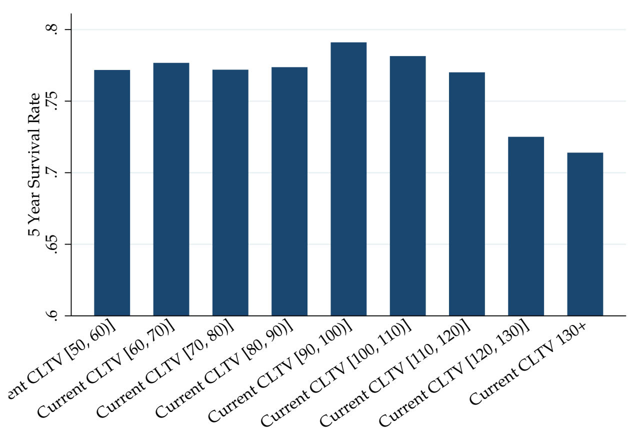
Panel A illustrates a Kaplan-Meier survival curve across levels of home equity. Panel B is a survival analysis Cox regression including all typical controls. The coefficient on negative equity is statistically significant at a 5% level.



Panel A: Equity and Performed Treatment



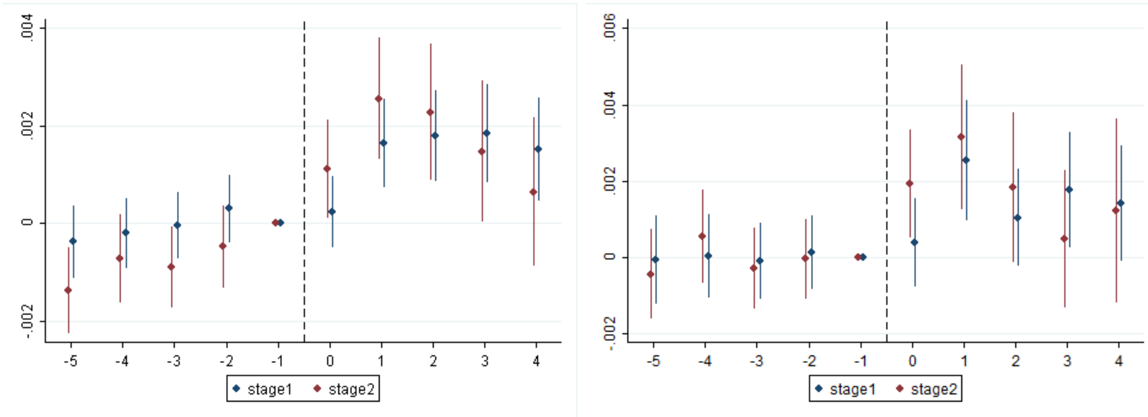
Panel B: Equity and Refusal of Treatment



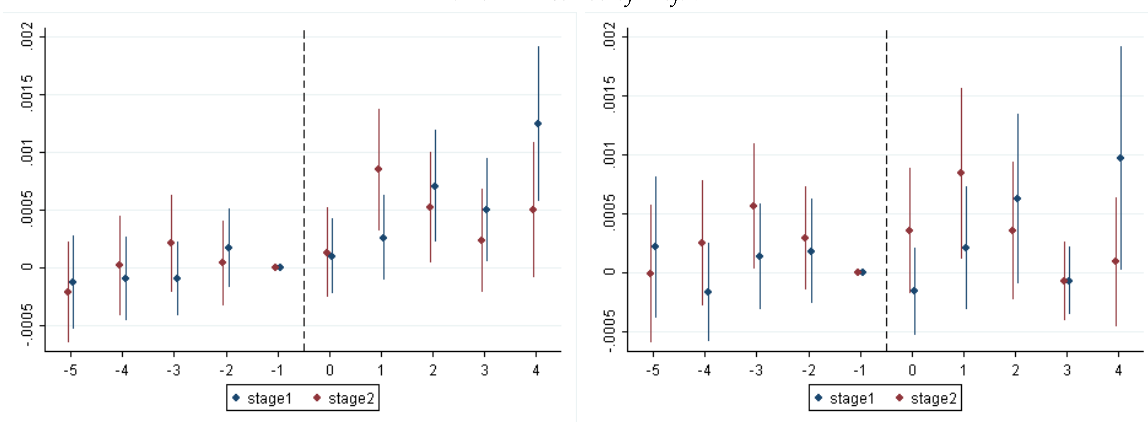
Panel B: Equity and Five-Year Survival

FIGURE III: Home Equity and Medical Outcomes

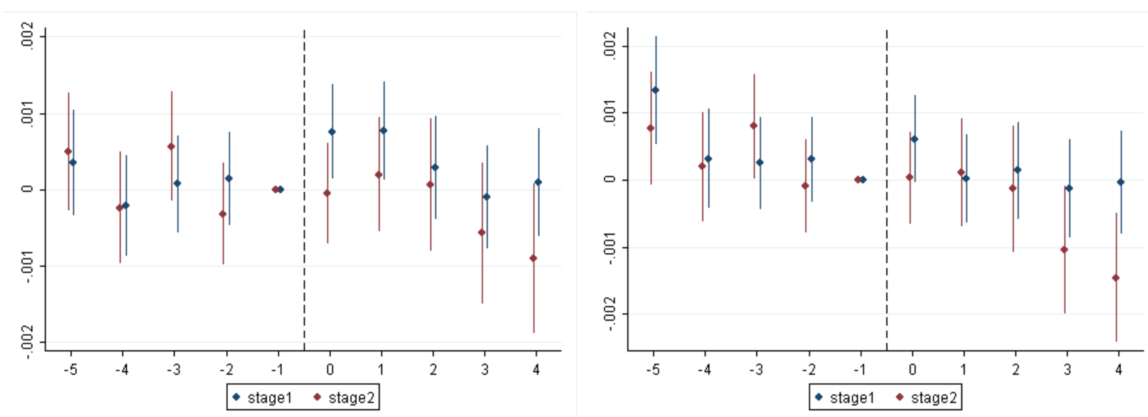
This figure examines health decisions and outcomes by mortgage equity at the time of diagnosis (current CLTV). Figure A plots the probability of performing therapy by current CLTV. Panel B examines the probability of refusing treatment, which is not the inverse of the probability of performing therapy because not all patients are recommended to complete a therapy. Finally, Figure C plots cancer survival rates against current CLTV.



Panel A: Notice of Default



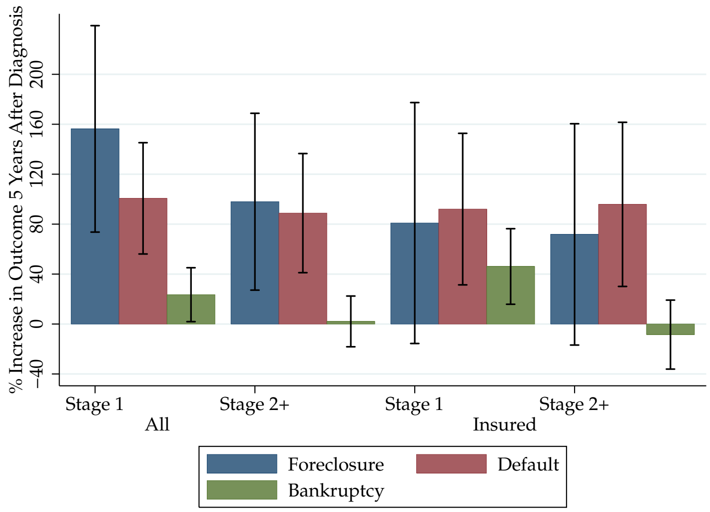
Panel B: Foreclosure



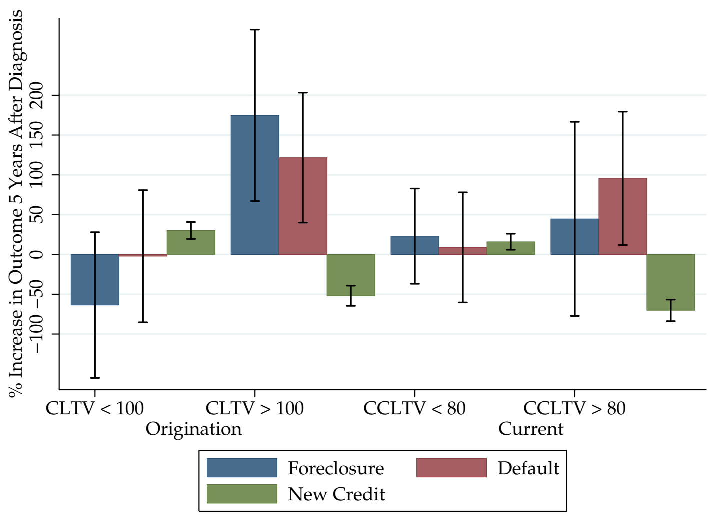
Panel C: Bankruptcy

FIGURE IV: Yearly Coefficients from Panel Event Study

These graphs plot the yearly coefficients from the event study regression in equation 5. Stage 2 refers to cancers staged 2 or higher. Graphs on the left examine all patients; graphs on the right examine the medically insured subset.



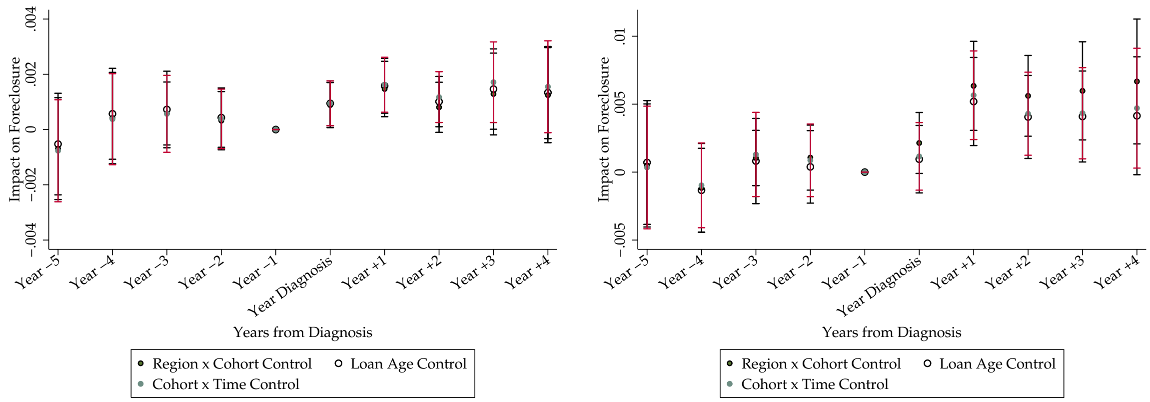
Panel A: Main Effects by Staging and Insurance



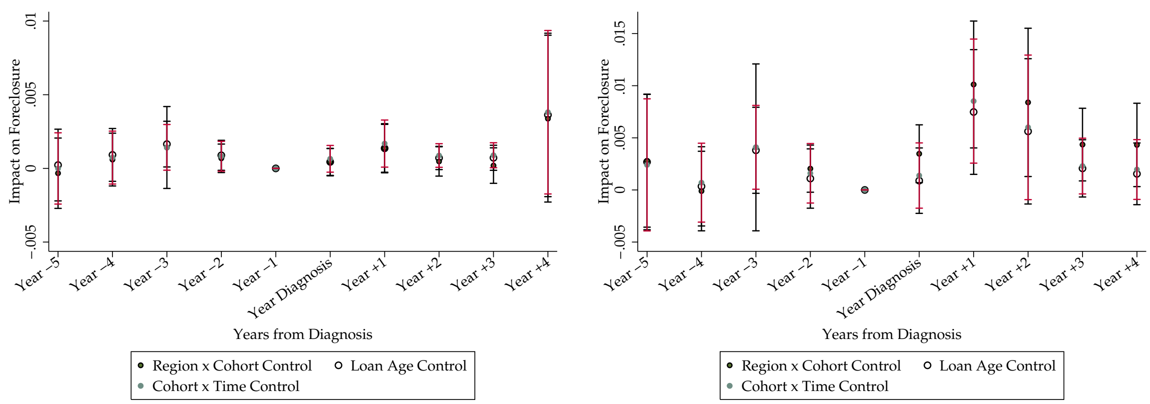
Panel B: Main Effects by Leverage

FIGURE V: Quantification of Main Effects

This figure summarizes the yearly effects reported in Table V, VI, and VII. Each column reports the percentage increase in each outcome variable, expressed as the cumulative effect of treatment for the five years following diagnosis, relative to the probability of experiencing the outcome variable during the five years prior to diagnosis. Lines around the bars illustrate the 95% confidence interval. Panel A presents estimates by cancer staging and insurance status; panel B presents estimates by housing leverage.



Panel A: Full Sample – All Patients (Left), High CCLTV (Right)



Panel B: Medically Insured – All Patients (Left), High CCLTV (Right)

FIGURE VI: Comparison of Results Across Mortgage Equity Specifications

This figure plots yearly coefficients from specification 5, but adopts alternative strategies for constraining the variation in current CLTV. Specification (1) adds a control for loan age; specification (2) controls for region $\times$ cohort; specification (3) controls for cohort $\times$ time. Panel A shows all patients; Panel B subsets on the medically insured. Within each panel, we show estimates for the entire sample and for the subset of patients with CCLTV>80.

TABLE I: Summary Statistics

This table illustrates sample statistics for our two samples: the Full Sample and the Deeds Sample. The Full Sample contains information from the SEER Cancer dataset matched with bankruptcy information for all patients. The Deeds sample contains information on the subset of the data for which we were able to merge into Deeds records (using address). A full description of the merge process can be found in Appendix A.

	Full Sample		Deeds Sample	
	Mean	SD	Mean	SD
Age	60.926	12.8	58.086	12.8
Married	0.604	0.49	0.650	0.48
Marriage Missing	0.091	0.29	0.096	0.29
Male	0.505	0.50	0.497	0.50
Non-White	0.118	0.32	0.141	0.35
Synchronous Cancer	0.020	0.14	0.019	0.14
Occupation				
- Professional	0.184	0.39	0.211	0.41
- Clerical	0.169	0.37	0.186	0.39
- Laborer	0.256	0.44	0.236	0.42
- Other	0.064	0.25	0.056	0.23
- Not Employed	0.061	0.24	0.065	0.25
Insurance				
- Self-Pay	0.003	0.052	0.003	0.051
- Private Insured	0.095	0.29	0.147	0.35
- Medicare	0.449	0.50	0.341	0.47
- Medicaid	0.012	0.11	0.011	0.10
- Other	0.009	0.093	0.008	0.089
- Missing	0.432	0.50	0.491	0.50
Previous Cancer	0.059	0.24	0.058	0.23
Has Mortgage			0.221	0.41
Origination CLTV			94.127	48.9
Current CLTV			78.263	51.1
Sample Size	220117		64281	

TABLE II: Staging Frequency by Year

This table presents the count of cancer diagnoses by severity by year during our sample period. "Unstaged" cancers often represent cancers that are sufficiently advanced that physicians did not attempt to measure the staging. In subsequent analysis in this paper, we add the Unstaged cancers to the "Distant" category.

	Local	Regional	Distant	Unstaged	Total
1995	46	11	4	4	65
1996	1455	606	626	211	2898
1997	1661	675	697	220	3253
1998	1717	682	736	221	3356
1999	1878	775	787	204	3644
2000	2019	848	787	158	3812
2001	2185	1013	949	123	4270
2002	2364	1109	1044	95	4612
2003	2478	1151	1077	120	4826
2004	2605	1227	1100	108	5040
2005	2642	1182	1204	141	5169
2006	2782	1153	1199	149	5283
2007	2982	1380	1283	169	5814
2008	3113	1406	1251	131	5901
2009	3296	1420	1320	302	6338
Total	33223	14638	14064	2356	64281
Observations	64281				

TABLE III: Impact of Leverage on Treatment and Survival

This table examines how financial leverage impacts the progression of cancer diagnoses. Panel A runs a survival regression where the dependent variable is time to death and the key variables are measures of current CLTV at the time of diagnosis. Additional controls constrain the variation in home equity. Specification (1) controls for loan age; (2) adds controls for region $\times$ cohort, and (3) controls for cohort $\times$ time. Columns 4-6 repeat the specifications for the sample with high expected survival at the time of diagnosis. Panel B runs an OLS regression with the same independent variables, but the outcome variable measures the decision to refuse recommended treatment.

Panel A: Hazard of Mortality by Home Equity

	Full Sample			High Expected Survival			Insured		
Current CLTV $\leq$ 60					Omitted				
60 $<$ Current CLTV $\leq$ 80	0.073	0.069	0.072	0.044	0.20	0.11	-0.031	0.051	0.061
	(1.52)	(1.23)	(1.49)	(0.36)	(1.16)	(0.84)	(-0.51)	(0.59)	(0.96)
80 $<$ Current CLTV $\leq$ 100	0.100	0.12	0.10	0.077	0.34	0.16	-0.042	0.039	0.079
	(1.80)	(1.81)	(1.88)	(0.58)	(1.90)	(1.13)	(-0.61)	(0.38)	(1.05)
100 $<$ Current CLTV	0.17**	0.15*	0.18**	0.37*	0.37	0.36*	0.14	0.19	0.21**
	(3.01)	(2.36)	(3.10)	(2.56)	(1.87)	(2.45)	(1.79)	(1.82)	(2.72)
Specification:	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
N	14187			8363			7685		
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region · Cohort	No	Yes	No	No	Yes	No	No	Yes	No
Cohort · Time	No	No	Yes	No	No	Yes	No	No	Yes

Panel B: Refusal of Treatment against Leverage

	Full Sample			High Expected Survival			Insured		
Current CLTV $\leq$ 60				Omitted					
60 $<$ Current CLTV $\leq$ 80	0.0018	0.0027	0.0018	0.0058	0.0085	0.0057	0.0039	0.0056	0.0047
	(0.50)	(0.69)	(0.47)	(0.89)	(1.04)	(0.85)	(0.74)	(0.89)	(0.88)
80 $<$ Current CLTV $\leq$ 100	0.0040	0.0022	0.0039	0.010	0.0089	0.012	0.014*	0.0072	0.015*
	(0.91)	(0.48)	(0.89)	(1.33)	(1.01)	(1.49)	(2.10)	(0.94)	(2.13)
100 $<$ Current CLTV	0.0084	0.0086	0.0084	0.013	0.016	0.013	0.010	0.0084	0.0095
	(1.75)	(1.65)	(1.74)	(1.61)	(1.65)	(1.57)	(1.53)	(1.12)	(1.43)
Specification:	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Avg Refused Treatment	0.0386			0.0347			0.0319		
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region · Cohort	No	Yes	No	No	Yes	No	No	Yes	No
Cohort · Time	No	No	Yes	No	No	Yes	No	No	Yes

* $p<0.05$, ** $p<0.01$

TABLE IV: Instrumental Variable Analysis of Home Equity on Treatment Choices

This table examines the impact of home equity on individual treatment choices. The first column regresses change in (negative) home prices in the zipcode of residence during the 36 months prior to diagnosis on current CLTV (demeaned, and expressed in standard deviation). The second column regresses this measure of current CLTV against the decision to refuse treatment (the second stage). The third column examines whether changes in home prices directly impact the probability that the recommended treatment was refused ("reduced form"). The fourth column performs an IV regression: instrumenting current CLTV using the prior change in home prices and estimating the impact of housing equity on the refusal to perform treatment. Controls include the stage of the cancer interacted with its location, patient demographic characteristics, and zipcode fixed effects. Year fixed effects are not included. Panel B subsets on medically insured individuals.

Panel A: Full Sample

	$-\Delta$ HP $\rightarrow$ Current CLTV	Current CLTV $\rightarrow$ Refused Treatment	$-\Delta$ HP $\rightarrow$ Refused Treatment	$-\Delta$ HP $\rightarrow$ Extraction $\rightarrow$ Refused Treatment
$-\Delta$ HP	0.11^{**}		-0.0034^{*}	
	(14.38)		(-2.54)	
Current CLTV, SD		0.0026		-0.029^{*}
		(1.86)		(-2.50)
N	14141	14141	14141	14141
Specification:	First Stage	Second Stage	Reduced Form	IV
Controls	Yes	Yes	Yes	Yes
F-Stat				207

Panel B: Insured

	$-\Delta$ HP $\rightarrow$ Current CLTV	Current CLTV $\rightarrow$ Refused Treatment	$-\Delta$ HP $\rightarrow$ Refused Treatment	$-\Delta$ HP $\rightarrow$ Extraction $\rightarrow$ Refused Treatment
$-\Delta$ HP	0.10^{**}		-0.0035^{*}	
	(10.88)		(-2.14)	
Current CLTV, SD		0.0016		-0.034^{*}
		(0.82)		(-2.10)
N	7666	7666	7666	7666
Specification:	First Stage	Second Stage	Reduced Form	IV
Controls	Yes	Yes	Yes	Yes
F-Stat				118

* $p<0.05$, ** $p<0.01$

TABLE V: Financial Defaults on Mortgage Debt

This table analyzes the impact of cancer diagnoses on mortgage outcomes on the Deeds Sample, for which mortgage information is known. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where the outcome in columns 1–2 is notice of default, and foreclosure in Columns 3–4. Columns 1, 3, 5, and 7 subset on stage one cancers; columns 2, 4, 6, and 8 subset on cancers staged two and above. The "Treatment 5 Years" statistic measures the linear combination of the treatment effects for five calendar years after the initial diagnosis, inclusive of the year of diagnosis itself. The "Ref. Prob." measures the base rate of foreclosure or default for the year prior to diagnosis (which is excluded in the regression), or the five years prior to establish the baseline. Columns 5–8 replicate the analysis on an insured subset. Standard errors are clustered at the patient level.

Dep Var:	Notice of Default		Foreclosure		Notice of Default		Foreclosure	
	Stage 1	Stage 2+	Stage 1	Stage 2+	Stage 1	Stage 2+	Stage 1	Stage 2+
Year 5 Before Diagnosis	-0.00038	-0.0014**	-0.00013	-0.00021	-0.000067	-0.00044	0.00022	-0.0000068
	(-1.00)	(-3.05)	(-0.63)	(-0.96)	(-0.11)	(-0.74)	(0.71)	(-0.02)
Year 4 Before Diagnosis	-0.00021	-0.00072	-0.000093	0.000019	0.000022	0.00054	-0.00016	0.00025
	(-0.56)	(-1.56)	(-0.50)	(0.09)	(0.04)	(0.86)	(-0.76)	(0.93)
Year 3 Before Diagnosis	-0.000051	-0.00089*	-0.000092	0.00021	-0.00011	-0.00029	0.00014	0.00057*
	(-0.15)	(-2.10)	(-0.56)	(0.99)	(-0.21)	(-0.53)	(0.61)	(2.09)
Year 2 Before Diagnosis	0.00030	-0.00048	0.00017	0.000039	0.00013	-0.000040	0.00018	0.00030
	(0.85)	(-1.13)	(0.96)	(0.21)	(0.26)	(-0.07)	(0.81)	(1.32)
Year 1 After Diagnosis	0.00023	0.0011*	0.000100	0.00013	0.00039	0.0019**	-0.00016	0.00036
	(0.62)	(2.17)	(0.60)	(0.67)	(0.66)	(2.68)	(-0.83)	(1.33)
Year 2 After Diagnosis	0.0016**	0.0026**	0.00026	0.00085**	0.0025**	0.0031**	0.00021	0.00084*
	(3.59)	(4.02)	(1.39)	(3.16)	(3.16)	(3.23)	(0.80)	(2.29)
Year 3 After Diagnosis	0.0018**	0.0023**	0.00071**	0.00052*	0.0010	0.0018	0.00063	0.00036
	(3.75)	(3.19)	(2.88)	(2.12)	(1.59)	(1.83)	(1.72)	(1.19)
Year 4 After Diagnosis	0.0018**	0.0015*	0.00050*	0.00024	0.0018*	0.00047	-0.000065	-0.000070
	(3.56)	(2.00)	(2.21)	(1.03)	(2.28)	(0.51)	(-0.44)	(-0.41)
Year 5 After Diagnosis	0.0015**	0.00064	0.0012**	0.00050	0.0014	0.0012	0.00097*	0.000091
	(2.79)	(0.83)	(3.66)	(1.69)	(1.82)	(0.99)	(2.01)	(0.33)
Sample:	Deeds Sample				Deeds Sample – Insured			
Treatment 5 Years	0.0070	0.0081	0.0028	0.0022	0.0071	0.0086	0.0016	0.0016
S.E.	0.0016	0.0022	0.00076	0.00083	0.0024	0.0030	0.00097	0.00099
Ref. Prob. 1 Year	0.0020	0.0032	0.00040	0.00053	0.0020	0.0032	0.00040	0.00053
Ref. Prob. 5 Years	0.0070	0.0091	0.0018	0.0023	0.0077	0.0090	0.0020	0.0022
N	241301	202392	246495	227923	103672	99832	106436	113320

Marginal effects; t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$

TABLE VI: Bankruptcy Default Impacts

This table analyzes the impact of cancer diagnoses on bankruptcy filings. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where O_{it} is one if the individual files for bankruptcy in in the calendar year, measured in years from diagnosis. Columns 1, 3, 5, and 7 subset on stage one cancers; columns 2, 4, 6, and 8 subset on cancers staged two and above. Columns 1–2 and 5–6 focus on the whole sample, while columns 3–4 and 7–8 subset on the Deeds sample for which mortgage information is known. The "Treatment 5 Years" statistic measures the linear combination of the treatment effects for five calendar years after the initial diagnosis, inclusive of the year of diagnosis itself. The "Ref. Prob." measures the base rate of bankruptcy for the year prior to diagnosis (which is excluded in the regression), or the five years prior to establish the baseline. Columns 5–8 replicate the analysis on an insured subset. Standard errors are clustered at the patient level.

Sample:	Full Sample		Deeds Sample		Full Sample – Insured		Deeds Sample – Insured	
	Stage 1	Stage 2+	Stage 1	Stage 2+	Stage 1	Stage 2+	Stage 1	Stage 2+
Year 5 Before Diagnosis	0.00035	0.00049	-0.00014	-0.00024	0.0013**	0.00077	0.00039	-0.00067
	(1.00)	(1.26)	(-0.22)	(-0.34)	(3.28)	(1.79)	(0.55)	(-0.79)
Year 4 Before Diagnosis	-0.00022	-0.00024	-0.00060	-0.00099	0.00032	0.00020	0.00020	-0.0013
	(-0.65)	(-0.64)	(-1.00)	(-1.49)	(0.84)	(0.48)	(0.28)	(-1.58)
Year 3 Before Diagnosis	0.000069	0.00057	-0.0013*	0.00022	0.00026	0.00080*	-0.00070	0.00034
	(0.21)	(1.54)	(-2.51)	(0.34)	(0.73)	(2.02)	(-1.23)	(0.44)
Year 2 Before Diagnosis	0.00014	-0.00032	-0.00070	-0.00088	0.00031	-0.000084	0.00051	-0.0010
	(0.46)	(-0.94)	(-1.34)	(-1.48)	(0.95)	(-0.24)	(0.90)	(-1.56)
Year 1 After Diagnosis	0.00076*	-0.000055	0.00088	0.000025	0.00061	0.000030	0.0017**	-0.00031
	(2.40)	(-0.16)	(1.57)	(0.04)	(1.85)	(0.08)	(2.60)	(-0.44)
Year 2 After Diagnosis	0.00077*	0.00020	0.0014*	0.00088	0.000020	0.00011	0.0016*	0.000091
	(2.32)	(0.51)	(2.24)	(1.21)	(0.06)	(0.27)	(2.28)	(0.11)
Year 3 After Diagnosis	0.00028	0.000069	0.0013*	-0.00038	0.00014	-0.00013	0.00079	0.000066
	(0.83)	(0.16)	(2.06)	(-0.48)	(0.39)	(-0.28)	(1.15)	(0.06)
Year 4 After Diagnosis	-0.00010	-0.00057	0.00071	0.000086	-0.00012	-0.0010*	0.0016*	-0.00088
	(-0.30)	(-1.21)	(1.09)	(0.10)	(-0.33)	(-2.14)	(2.11)	(-0.89)
Year 5 After Diagnosis	0.000090	-0.00090	0.00069	-0.000036	-0.000041	-0.0015**	0.0013	-0.00088
	(0.25)	(-1.81)	(1.01)	(-0.04)	(-0.10)	(-2.98)	(1.69)	(-0.86)
Treatment 5 Years	0.0018	-0.0013	0.0050	0.00058	0.00061	-0.0025	0.0070	-0.0019
S.E.	0.0013	0.0015	0.0023	0.0028	0.0013	0.0015	0.0023	0.0032
Ref. Prob. 1 Year	0.0045	0.0056	0.0046	0.0057	0.0045	0.0056	0.0046	0.0057
Ref. Prob. 5 Years	0.022	0.027	0.021	0.027	0.015	0.020	0.012	0.021
N	857745	747067	264973	221465	438598	409441	113041	108972

Marginal effects; t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$

TABLE VII: Panel Regression, OLS, By Mortgage Equity Among Insured

This table analyzes the impact of cancer diagnoses among medically insured individuals along three measures of financial default, cutting by pre-existing mortgage leverage. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where the outcome is notice of default in Panel A, foreclosure in Panel B, bankruptcy in Panel C, and accessing mortgage credit in Panel D (through a refinancing or adding a second lien). All specifications restrict on the Deeds subsample. All specifications restrict on the Deeds subsample. The "5-Year Effect" statistic measures the linear combination of treatment effects during the five calendar years following initial diagnosis, inclusive of the year of diagnosis itself. Column (1) restricts on patients having a measured combine loan-to-value (CLTV), (2) subsets on patients with origination CLTV less than 100, and (3) subsets on those with origination CLTV greater than 100. Columns (4) and (5) focus on current CLTV (CCLTV), cutting the sample between patients above and below 80. The "Ref. 5-Year" probability measures the base rate of foreclosure, default, or bankruptcy during the five years prior to diagnosis. Standard errors are clustered at the patient level.

	Has CLTV	CLTV $<$ 100	CLTV $>=$ 100	CCLTV $<$ 80	CCLTV $>=$ 80
			Panel A: Notice of Default		
Notice of Default 5-Year Effect	0.015	-0.0045	0.077**	0.0098	0.046*
S.E.	0.0082	0.0071	0.027	0.0059	0.022
Ref. 5-Year Default Probability	0.020	0.013	0.032	0.012	0.034
N	37360	23960	13400	25547	11784
			Panel B: Foreclosure		
Foreclosure 5-Year Effect	0.0038	-0.0024	0.020*	0.0058	0.0052
S.E.	0.0033	0.0031	0.0098	0.0031	0.0079
Ref. 5-Year Foreclosure Probability	0.0069	0.0051	0.010	0.0054	0.0092
N	39008	25068	13940	26575	12404
			Panel C: Bankruptcy		
Bankruptcy 5-Year Effect	0.0090	0.00014	0.0346*	0.0088	0.0099
S.E.	0.0059	0.0058	0.01	0.0061	0.012
Ref. 5-Year Bankruptcy Probability	0.030	0.022	0.044	0.022	0.043
N	49756	32664	17092	31548	18173
			Panel D: New Credit		
New Credit 5-Year Effect	-0.0090	0.17**	-0.28**	0.093	-0.28**
S.E.	0.043	0.050	0.088	0.050	0.078
Ref. 5-Year New Credit Probability	0.67	0.57	0.84	0.65	0.70
N	38013	24204	13809	25890	12094

* $p < 0.05$, ** $p < 0.01$

TABLE VIII: Mortgage-Credit Bureau Panel

This Table focuses on outcomes measured in the BlackBox-Equifax panel. This dataset comprises private-label securitized mortgages, and associated credit bureau information from Equifax, that are linked to Deeds records. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where time here is measured monthly relative to diagnosis, and effects are combined for the three years before and after diagnosis. Panel A examines delinquency outcomes, including measures of financial default, where 90 DPD refers to missing three or more payments on a mortgage (taken from BlackBox), Installment Delinquency refers to missing two or more payments on installment accounts (including student loans, auto loans, etc.) and Revolving Delinquency identifies defaults on revolving lines of credit (such as credit cards and other store cards). Panel B examines access to credit. "Has Auto" refers to the presence of automobile-related debt (as a proxy for car ownership), Credit Score refers to the Vantage Score, Card Balance is the cumulative total of all credit card debt, and Credit Limit combines the available credit on all lines of credit cards.

Panel A: Measures of Financial Default

	90 DPD+	Installment Delinquency	Revolving Delinquency
Year -3	0.0025	0.019	0.016
	(0.51)	(1.58)	(1.09)
Year -2	-0.00014	0.014	0.015
	(-0.04)	(1.63)	(1.49)
Year +1	0.0062	-0.0092	0.012
	(1.27)	(-1.14)	(1.26)
Year +2	0.024^{**}	0.010	0.020
	(3.67)	(1.05)	(1.90)
Year +3	0.020^{**}	0.013	0.025^{*}
	(2.87)	(1.26)	(2.15)
N	1339760		

Panel B: Other Measures from Credit Bureau Data

	Has Auto	Credit Score	Card Balance	Credit Limit	# Revolving Accounts
Year -3	-0.0023	-3.07	400.8	209.3	-0.073
	(-0.18)	(-0.98)	(0.73)	(0.08)	(-0.18)
Year -2	-0.0099	0.76	-209.7	189.3	0.14
	(-1.12)	(0.37)	(-0.68)	(0.11)	(0.53)
Year +1	-0.0069	-3.01	152.6	1149.1	0.54^{**}
	(-0.89)	(-1.69)	(0.55)	(0.72)	(2.62)
Year +2	-0.016	-11.7^{**}	10.0	1497.0	0.53
	(-1.56)	(-4.36)	(0.03)	(0.73)	(1.93)
Year +3	-0.0099	-13.9^{**}	388.4	1663.6	0.15
	(-0.84)	(-4.55)	(0.98)	(0.71)	(0.50)
N	1339760				

* $p<0.05$, ** $p<0.01$

Appendix A

For Online Publication: Data Construction

Data Sources

SEER Data Our data are a subset of the National Cancer Institute's Surveillance Epidemiology and End Results (SEER) program, and comprise the Cancer Surveillance System of Western Washington. The data are intended to be a comprehensive catalog of cancer diagnoses occurring between 1996–2009, totaling over 270,000 cases overall. A unique patient id links records together: patients re-enter the dataset for each separate diagnosis.

The data include a rich set of fields detailing the demographic characteristics of the patient (such as race, age, listed occupation, marital status), the nature of the cancer (its type and staging), as well as select treatment decisions taken by the patient.

Bankruptcy Data Our bankruptcy data comprise all federal bankruptcy records from Western Washington state including chapters 7, 11, and 13. These data are readily accessible through PACER and have been frequently used in prior academic scholarship on bankruptcy.

Deeds Data Our Deeds dataset is provided by DataQuick, a vendor which collects public-use transactions information. The data are organized at a property level and are comprehensive in covering all mortgage transactions between 2000–2011 (foreclosure transactions typically go back further in time). The data list each transaction—including sales, transfers, new mortgages (first and second liens), and refinancing—related to a given property. We use the timing of the sales information to infer when a cancer patient resided in a property, and follow foreclosures for the duration of the residence. We additionally use mortgage information at origination (the date when the patient obtained the mortgage, often the same date as the beginning of the residence period) to calculate our key leverage statistics.

BlackBox Data BlackBox LLC is a private vendor that has collected individual mortgage records related to private-label securitized bonds (i.e., mortgages that are not securitized by a government-sponsored entity such as Fannie Mae or Freddie Mac). Although private label securitization made up only a fraction of total mortgage origination, even at its peak before the crisis; our data contain more than 20 million mortgages in total. These mortgages are typically subprime, Alt-A, or jumbo-prime in credit risk.

The BlackBox data contain static information taken at the time of origination, such as origination balance, credit score (FICO score), interest rate, and contract terms. The data are also updated monthly with dynamic information on fields such as interest rates, mortgage payments, and mortgage balances. The mortgage payment field is most critical for our analysis, as it allows us to calculate the precise number of payments the household has made, not just whether or not the household has entered foreclosure.

Equifax Data Equifax is a major credit bureau that maintains detailed dynamic monthly credit information on households concerning their balances on mortgage and other debt, as well as credit scores (Vantage score).

Data Merges

A key innovation in our of analysis is the use multiple sources of data on individual behavior to track financial outcomes around cancer diagnoses. This requires us to implement complex merges between many datasets that were not originally intended to be linked. Due to privacy restrictions, we are unable to make these data publicly available. However, the code used for all analysis is available upon request. Below we document the merge process and identify the linking variables that enabled us to construct our dataset.

SEER-Bankruptcy The linkage between the SEER and Bankruptcy datasets was performed by the Fred Hutchinson Cancer Research Center via a probabilistic algorithm based on the patient's name, sex, address, and last four Social Security Number digits (Ramsey et al. 2013).

SEER-Deeds Data Three match criteria were used to link SEER and Deeds data based on common text address fields:

- A *tight* match was based on full address, street directional (ie, NW), zip or city, and census tract.
- An *intermediate* match was based on house number, the first three letters of the street name, street end (ie, lane or drive), end number (any number in the last position of the address, such as an apartment number), street direction, zip or city, and census tract.
- A *loose* match was based on house number, the first three letters of the street name, street end, end number, zip or city, and census tract. These are all of the match criteria used in the intermediate match, with the exception of street direction.

The match was conducted by first prioritizing tight matches. Intermediate matches not found using the tight match were added next, and finally any loose matches not found using either of the two other methods were added. The vast majority of matches were achieved using the tight match: 63,661 records were matched using the tight match, 7,970 using the intermediate match; and 2,065 using the loose match. In total, 73,696 SEER records matched a record in the Deeds data.

Deeds Data-BlackBox Although Deeds and BlackBox data were not designed to be linked, they are both administrative datasets containing reliable information on a variety of mortgage fields. We developed a novel match method to link the two datasets using a training dataset (for which we knew matches exactly) to develop the algorithm. The merge relies on the following common fields:

1. Exact date matches between origination dates of the mortgage are reported in the two datasets (this dimension was not used if the origination date was likely imputed, i.e., if the date in BlackBox was the first or end of the month).
2. Zip code matches between the two datasets.

3. Matches based on mortgage purpose (i.e., refinancing or purchase).

4. Matches based on mortgage type (i.e., adjustable-rate or fixed-rate).

5. Matches based on mortgage origination amount (rounded down to the hundred)

We used a *backward* window of 31 days, which meant that the mortgage origination date in BlackBox was at most 31 days after the date of the mortgage reflected in Deeds. We used a *forward* window of 20 days.

The match algorithm worked by first focusing on 1) zip matches and 2) origination amount matches within the backward window (or the forward window if no matches existed in the backward window).

If only one match was found using those criteria, it was kept. If there were multiple matches, we restricted further by iteratively applying the following the following criteria. We first employed a "tight" match which required that the loan match uniquely on day, or (if there were multiple day matches) uniquely on mortgage purpose or type among those that matched on day.

If this did not uniquely identify a match, we next restricted to "looser" matches where there was (1) only one match uniquely on mortgage type and purpose. If no mortgage matched, we moved on to cases where there was (2) one unique match of either mortgage type or purpose with the other field missing; (3) one unique match on mortgage type, and (4) one unique match on mortgage purpose. The merge algorithm proceeded among all matching cases in the order specified above—if a high quality match was found, the mortgage was kept and the procedure only moved on to the other match cases in the order specified if no match was found.

BlackBox-Equifax BlackBox, a mortgage-level dataset, was linked by Equifax to borrower-level information on a variety of debts, including mortgages. The merge algorithm relied on a proprietary code that we cannot access. The vast majority of accounts in BlackBox were linked to a credit account.

To verify the accuracy of the merge, we imposed a restriction on samples that make use of Equifax variables. Specifically, we require that the two entries match either on (1) zip code of the borrower (at least once over the life of the loan) or (2) have a "match confidence" of at least .85. The zip code restriction compares the zip code of the property as listed in BlackBox matches with the address of the borrower as listed in Equifax. A mismatched zip code is not necessarily indicative of a mismatch in loans—it could also suggest the presence of an investor who does not live in the property in question. In addition to the zip code measure, Equifax provided a measure of match confidence ranging from 0–0.9. Loans at the top end of the confidence score reflect extremely well-matched loans, and we allow for a mismatch in zip code so long as it is accompanied by a match confidence score of at least 0.85. Robustness checking based on other common attributes between the two datasets (such as common measures of default) suggests that the two measures of match accuracy that we employ are effective in correctly identifying well-matched loans. For further details on the BlackBox-Equifax merge algorithm, see Piskorski, Seru and Witkin (2015).

Variable Definitions

Occupation The SEER data provide a numerical occupation coding. Using the occupation coding derived from Washington State Department of Health (Ossiander and Milham (2006)), we classified the following occupation fields: Professional, Clerical, Laborer, Other Occupation, and Occupation Missing.

We impute "Unemployed" individuals as those who (1) are listed as "Occupation Missing" and (2) have a marital status at diagnosis that is not missing or listed as "Unknown." We assume that the occupation non-response of such individuals, since it is paired with a response on the martial status form, is indicative of a genuine non-response for occupation (which would have been recorded by the reporting hospital as an occupation had the individual reported an occupation). We interpret a genuine non-response as evidence that the person is unemployed.

Mortgage Equity For the Property Database, we measure housing equity by estimating the total mortgage amount (of both first and second liens) at origination and comparing it with an estimate of house price.

To estimate the house price, we begin with the purchase price, if available. Unfortunately, sometimes we lack information on sale prices (but do have data on mortgages if the mortgage was refinanced). In that case, we impute the house price based on other sales on the same property at a different time (including by other owners), and infer the original house price using a zip-level house price index from Zillow.

For the Credit Report Dataset, we use the exact mortgage balances. We combine data on both first liens (derived from BlackBox) and second liens (from Equifax). We use an estimate of origination house value derived from the reported origination loan-to-value, and we adjust the house price at the time of diagnosis using the Zillow index to compute a current loan to value ratio.

Data Cleaning

From the base SEER data, the following cuts were made:

- Benign cancers were dropped.
- Among cancers reported multiple times within the same day, only one cancer entry was kept.
- Synchronous cancers were identified in which multiple cancers presented within a three month interval. Only the first instance of the synchronous cancer was kept. If the stages of the two cancers differed, the maximum stage was taken. If the sites of the two cancers differed, the cancer was classified as "Other."
- In the case of multiple, non-synchronous cancers, a cancer was included if its diagnosis was not followed by another cancer diagnosis during the next three years. If another cancer diagnosis did occur during the next three years, only the second cancer would be included (provided that there were no subsequent diagnosis in the three years subsequent to that diagnosis), with a dummy variable indicating the presence of a prior cancer.
- We keep patients aged 21–80 at the time of diagnosis.

To connect the SEER data to the DataQuick records, the DataQuick data were separated on the basis of sale records. If a cancer diagnosis was associated with a property prior to any recorded sale, we assumed that a real estate transaction took place prior to when the DataQuick records began (the year 2000).

The data were organized in a panel structure based on diagnosis-calendar year. It is possible for the same patient to have multiple cancers and so be repeated in the data for the years surrounding each diagnosis (subject, however, to the three year window discussed above). The panel includes the five calendar years subsequent to diagnosis (counting the year of diagnosis); and five calendar years prior to diagnosis.

Three forms of censoring were applied to the panel data:

- Censoring based on property information. Calendar years prior to the individual moving into the property, as reflected in a sale record, were excluded. So were calendar years after the person moved out (again, as reflected in a sale record).
- Censoring based on mortality. Our data record the death date of individuals. We censor all calendar years subsequent to death.
- Censoring due to previous episode of financial distress. Given the property-centric nature of our dataset, we can only follow one foreclosure per patient. We therefore censor all observations in calendar years subsequent to the first foreclosure. We adopt an identical censoring strategy with respect to bankruptcies (it is possible for patients to file multiple bankruptcies, but the law imposes constraints on a patient's ability to do this).

In addition to the other cuts, the Credit Panel Data made the following additional restrictions:

1. We require that the diagnosis take place subsequent to origination.
2. We require sufficient data from our datasets in order to estimate effects. If a borrower's data is missing for an entire year, the year is dropped.

3. If more than two BlackBox entries matched a given borrower in the Property Dataset, we dropped the entries. Two were permitted as these frequently coincided with a refinanced mortgage (in which both original and refinanced mortgage were present in the dataset), or a first and second lien.

4. Among entries with two BlackBox entries, entries were dropped if:

   (a) The two BlackBox entries did not share a common id as reported in Equifax. These entries may reflect mismatched loans, rather than different borrowing by the same consumer.

   (b) If the two BlackBox entries were non-overlapping in date (i.e., as frequently happens in the case of refinancing), they were kept. If they were overlapping, the entry with the smaller mortgage amount was dropped (frequently, this was a second lien).

Appendix B

For Online Publication: A Model of Mortality Risk and Financial Management

How does a sudden increase in mortality risk—triggered by a cancer diagnosis—affect a household's choice between different legal and economic responses to a health shock? This question arises naturally from the vast literature on life-cycle models, which considers the effect of uncertain horizons, health shocks, and mortality risks on investment and consumption (see, e.g., Stoler and Meltzer (2012)). An unanticipated contraction in an individual's time horizon will reduce incentives to invest and increase consumption. Individuals diagnosed with Huntington's Disease, for example, are substantially less likely to invest in education, undertake costly behaviors that reduce other health risks (cancer screening, avoiding smoking), or make other human capital investments, as Oster, Shoulson and Dorsey (2013) show.

A contraction in an individual's time horizon can also affect financial management decisions, such as default, foreclosure, and bankruptcy. Because debt absorbs cash flow available for consumption, a sudden increase in mortality risk can reduce incentives to repay debt. Of course, there are significant costs to default: Creditors can seize assets and the individual's access to capital markets will decline, both of which will be costly if the individual is uncertain about longevity or wants to leave wealth to others (family) after death. This trade-off could, for some individuals, weigh in favor of default, particularly default on a home mortgage. The gains from default can be substantial: Mortgage payments typically consume a large fraction of monthly income, the lender will not pursue foreclosure until the homeowner has missed multiple payments, and the foreclosure process often takes a year to complete. The costs of default can be low, particularly for individuals who have no home equity and whose non-housing wealth is largely protected by state exemption laws. Moreover, many households view their homes as a combination of an investment and a consumption good. The mortgage, therefore, is partly funding future investment. When an individual experiences a contraction in time horizon, the incentive to invest declines.

By defaulting on the mortgage, the individual can curtail investment and, due to long delays in foreclosure, not reduce consumption of housing services for a substantial period, perhaps more than a year.

These observations imply that the incentive to default and experience foreclosure will be strongest when (a) the individual expects to die within the next few years, (b) default will not put other assets at risk because the individual has no assets or they are shielded by exemption laws, and (c) the individual is either unconcerned about leaving bequests or has already set aside funds for bequests and these funds will be unaffected by default and foreclosure.

Health shocks could have a very different effect on the incentive to file for bankruptcy. A core function of a bankruptcy filing is to discharge debt and either (i) protect future income or (ii) protect assets from creditor collection efforts. The first function is served by a Chapter 7 filing: The filer gives up some assets today in exchange for a discharge of unsecured debts that could be applied against future income. The latter is served by a Chapter 13 filing: The filer agrees to a tax on future income in exchange for a discharge of debts that could be applied against assets in the future. In either case, therefore, a bankruptcy filer uses bankruptcy to conserve future cash flow (or utility) derived from human capital or physical assets. A Chapter 13 filing, for example, is an important device for households to retain their homes, cars, or other assets when faced with foreclosure, as White and Zhu (2010) and Morrison and Uettwiller (2017) show. Chapter 7 is also used to renegotiate with mortgage lenders while discharging unsecured debt (Morrison (2014)).

Seen this way, a bankruptcy filing is analogous to an investment decision: An individual renegotiates or discharges debt by exchanging value today (income or assets) for value (income or assets) in the future. Because a contraction in an individual's time horizon will reduce the incentive to invest, it will also reduce the incentive to file for bankruptcy. Similar logic can be applied to refinancing, which is equivalent to renegotiating current debt in order to increase future cash flows. A refinancing is an investment decision, which will be less attractive to individuals with relatively high mortality risk.

A simple model can formalize most of these intuitions. Consider a two-period model of a risk-neutral patient who receives a cancer diagnosis in period 1 and learns that she will survive with probability p to period 2. She incurs medical costs equal to M in period 1 only. Her income in each period is $y < M$. She has one asset, a house, which has market value A and delivers housing services equal to γA per period. The home is subject to a mortgage that has face value D and requires periodic payments equal to δD. Assume, for simplicity, that D is sufficiently large relative to A that the patient cannot borrow additional funds to pay her medical expenses (i.e., she cannot access credit markets to smooth consumption). The discount rate is zero.

Because M exceeds the patient's income y in period 1, she will choose between foreclosure and bankruptcy. If the patient chooses bankruptcy, she must pay costs equal to f. Although she will discharge her medical debt (M), she will continue to service her housing debt (mortgage debts are not dischargeable in bankruptcy unless a homeowner abandons her home). Period 1 consumption will therefore equal income (y) plus housing services (γA) minus debt service (αD): $y + \gamma A - \alpha D$. At the end of period 1, she will survive to the next period with probability p. If she survives, she will receive income y and housing services δA and pay debt service (δD). Because it is the final period, she will also consume her net wealth, $max[\Delta, 0]$, where $\Delta = A - D$. For convenience, we assume the mortgage is non-recourse. That is, if $A < D$, the lender cannot sue the patient for the difference. Conditional on survival, then, period 2 consumption is $y + \gamma A + max[\Delta, 0]$. Because the discount rate is zero, expected consumption from bankruptcy is:

$$C_B = y + \gamma A - \delta D - f + p(y + \gamma A - \delta D + max[\Delta, 0]) \tag{6}$$

If the patient instead chooses foreclosure in period 1, she will default on her mortgage, not pay her medical expenses, and consume her income and housing services. Total period 1 consumption will therefore be $y + \gamma A$. If she survives to period 2, her home will be liquidated in foreclosure. The net recovery to the patient from foreclosure is $max[\Delta, 0]$. She will lose her home, but her debt will be satisfied. The patient will still owe medical expenses M, which exceed her income. She can therefore file for bankruptcy in period 2. By paying costs f, she will keep her income y and the net value from foreclosure (which I assume is protected by state exemption laws). Her expected consumption from foreclosure is therefore:

$$C_F = y + \gamma A + p(y - f + max[\Delta, 0]) \tag{7}$$

The patient will choose foreclosure if $C_F > C_B$, which will be true when:

$$(1 + p)\delta D > p\gamma A - (1 - p)f \tag{8}$$

The left-hand side of the inequality captures the gains from foreclosure relative to bankruptcy: Foreclosure allows the patient to avoid debt service (δD) in periods 1 and 2. The right-hand side captures the net costs of foreclosure relative to bankruptcy: Foreclosure forces the patient to give up consumption services (γA) in period 2. Under either choice, bankruptcy costs (f) will be incurred, but they occur only probabilistically when the patient submits to foreclosure. Thus, the net costs of foreclosure are reduced by the lower expected costs of bankruptcy.

This inequality captures the idea that foreclosure is more attractive as mortality risk increases: When the patient is certain to die during period 1 ($p = 0$), the inequality is always satisfied. Additionally, foreclosure becomes more attractive as debt (D) increases and as bankruptcy filing costs (f) rise.

This simple model illustrates how mortality risk can affect financial policy. The issue is important to public policy because it points to a strategic element in financial management among individuals who experience health shocks. Because of these shocks, the individuals are financially stressed, but can respond to the stress in various ways. Strategic considerations may explain why some people choose foreclosure while others choose bankruptcy.

Appendix C

For Online Publication: Heterogeneity by Occupation, Cancer, and Expected Survival

Our cancer data include information about the individual's occupation, cancer type, and treatment. This information is useful because we can determine whether our results vary with the socioeconomic status of the individual as well as whether particular cancers or treatments are more likely to produce financial stress. We can also use this information to test whether the buffering effect of home equity varies by cancer severity. This test is important because our findings in his paper—that home equity is an important buffer against health shocks—could be confounded by a correlation between leverage and cancer severity (a proxy for health human capital).

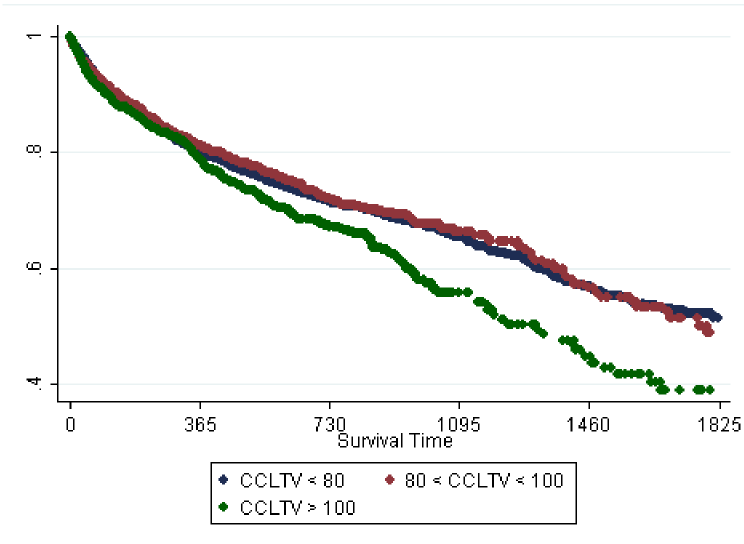
Table A.II explores the effect of cancer diagnoses on default, foreclosure, and bankruptcy by professional occupation. As discussed above, every cancer patient is asked about his or her "usual occupation." We code occupational status based on responses to this question. Table A.II shows that, after controlling for leverage, cancer diagnosis increases default rates only for individuals with "clerical" or "laborer" occupations. This is unsurprising in light of a long literature showing a correlation between socioeconomic status (proxied here by occupation) and health outcomes. We find a similar pattern among foreclosures (Panel B). The magnitudes of the effects here are comparable to those we observe among households with CLTV greater than 100. We find a different pattern among bankruptcies (Panel C), where only laborers exhibit a meaningful (but imprecisely measured) response to cancer diagnoses.

Table A.III and Table A.IV examine heterogeneity in response to cancer diagnosis by (a) cancer site and (b) recommended treatment. Because the baseline five-year rates of default, foreclosure, and bankruptcy are very low (around one percent for default and foreclosure, and two percent for bankruptcies), cutting the sample into site-based and treatment-based categories yields relatively small subsamples with low statistical power. Nonetheless, the magnitudes of the coefficients for default and foreclosure are quite large relative to the baseline rates, especially for lung and thyroid cancers and for radiation-based treatment (which is commonly recommended for thyroid cancer). The effects for bankruptcy are also very large for thyroid cancer and radiation-based treatments. Our results for lung cancer are consistent with prior work, such as Boscoe et al. (2014), showing that lung cancer is strongly positively correlated with poverty. The results for thyroid cancer (and radiation-based treatment) is more puzzling because the incidence of this type of cancer is negatively correlated with income. Recent evidence indicates that the incidence of thyroid cancer is highest among younger women (median age of 49).[18]

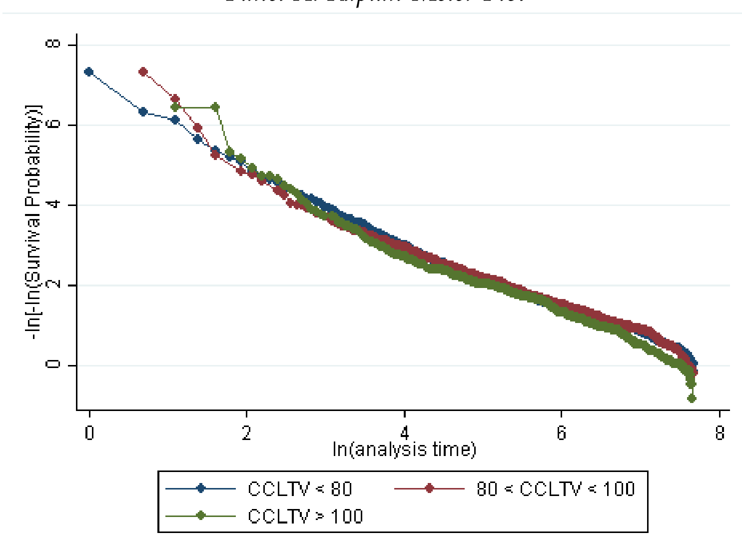
We next explore whether our primary finding thus far—that home equity mitigates the effect of cancer diagnoses on financial outcomes—varies with cancer severity. In Table A.V, we separate individuals based on their expected survival after cancer diagnosis, placing those with above-average life expectancies in the "High Survival" category and the others in the "Low Survival" category. The first two columns test whether the effect of cancer on financial outcomes varies by expected survival. We find much larger effects on default and foreclosure for low survival individuals, but larger effects on bankruptcy for those with high expected survival. This finding is consistent with our theory, expressed in equation 8, which predicts that foreclosure becomes more attractive as mortality risk increases.

The next two columns of Table A.V rerun the analysis, but subset on individuals between ages 26 and 60, who are less likely to benefit from public health insurance (such as Medicare) and may therefore be more financially fragile. We find an even starker contrast between high and low survival individuals, with the latter substantially more likely to enter default or foreclosure during the five years following a cancer diagnosis, and the former more likely to file for bankruptcy. The final columns of Table A.V test whether these patterns change when we subset on households with no home equity. We obtain substantially larger coefficients, indicating again that the observed effect of cancer diagnoses on financial outcomes is largely driven by households without home equity, confirming that home equity plays an important role in mitigating the financial impact of cancer. These findings are important, we believe, because they provide further evidence to rule out potential confounds, such as a correlation between leverage and cancer severity.

[18] See Kitahara and Sosa (2016) for a literature review.



Panel A: Kaplan-Meier Plot



Panel B: Cox regression

FIGURE A.I: Survival Analysis and Housing Equity — Insured Sample

This figure replicates the analysis in Figure II, but subsets on the medically insured.

TABLE A.I: Impact of Leverage on Performed Treatment

This table examines how financial leverage impacts the outcome of recommended treatment performed for cancer patients. Specification (1) controls for loan age; specification (2) also controls for region $\times$ cohort, and specification (3) also controls for cohort $\times$ time. Columns 4-6 repeat the specifications for the sample with high expected survival at the time of diagnosis.

Performed Treatment against Leverage

	Full Sample			High Expected Survival			Insured		
Current CLTV $\leq$ 60	Omitted								
60 $<$ Current CLTV $\leq$ 80	-0.017*	-0.018*	-0.018*	-0.021	-0.019	-0.026*	-0.028*	-0.024	-0.027*
	(-2.80)	(-2.68)	(-2.84)	(-1.71)	(-1.26)	(-2.06)	(-2.81)	(-1.90)	(-2.65)
80 $<$ Current CLTV $\leq$ 100	-0.016*	-0.016*	-0.017*	-0.020	-0.016	-0.024	-0.018	-0.011	-0.021
	(-2.30)	(-2.22)	(-2.50)	(-1.42)	(-1.03)	(-1.69)	(-1.62)	(-0.75)	(-1.81)
100 $<$ Current CLTV	-0.022*	-0.017*	-0.024*	-0.022	-0.014	-0.022	-0.047**	-0.046*	-0.053**
	(-2.88)	(-2.04)	(-3.03)	(-1.50)	(-0.83)	(-1.52)	(-3.69)	(-2.70)	(-4.07)
Specification:	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region · Cohort	No	Yes	No	No	Yes	No	No	Yes	No
Cohort · Time	No	No	Yes	No	No	Yes	No	No	Yes
N	14199			5820			3858		
Avg. Performed	0.896			0.948			0.872		

* p<0.05, ** p<0.01

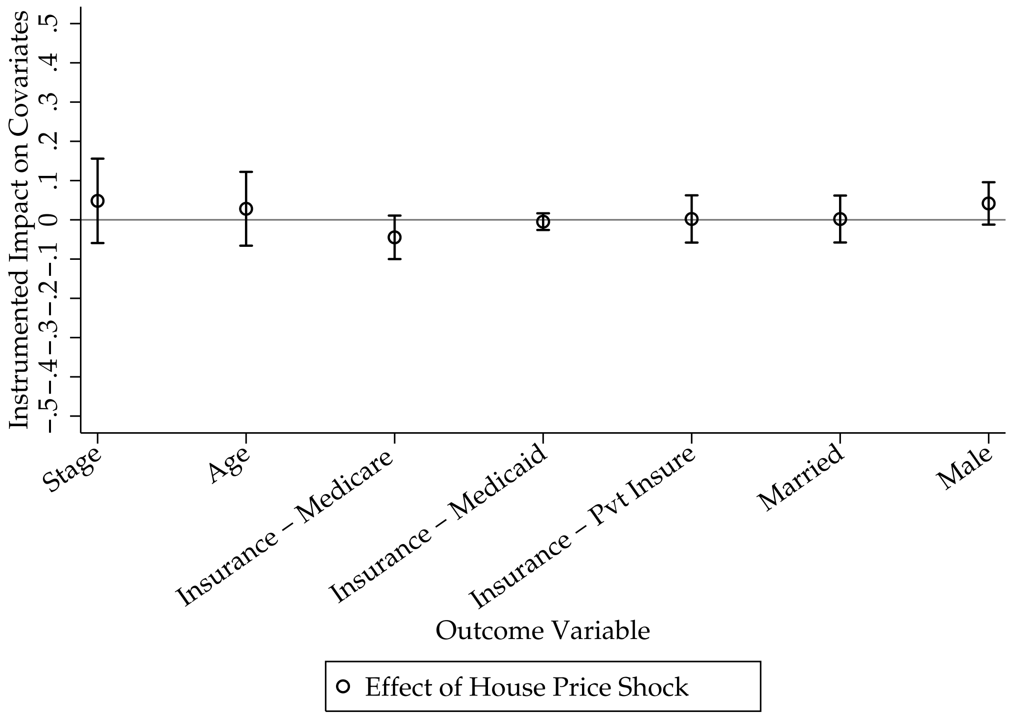


FIGURE A.II: Exogeneity Test of House Price Instrument

This figure tests the exogeneity of the house price instrument described in section IV. For each variable, the IV specification is run with that variable as the outcome variable. The first two variables included are normalized by subtracting the mean and dividing by the standard deviation to produce a coefficient of variation; the remainder dummy variables. The scale for Stage is increasing in medical severity.

TABLE A.II: Panel Regression, OLS, By Occupation, Aged 26–60

This table analyzes the impact of cancer diagnoses on three measures of financial default cutting by stated Occupation among individuals aged 26–60. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where the outcome is notice of default in Panel A, foreclosure in Panel B, and bankruptcy in Panel C. Panels A and B subset on the Deeds subsample; Panel C uses the Full sample. Occupation status was computed using written occupations matched with coding derived from the Washington State Department of Health (details in Appendix A). Non-employment was imputed for individuals without a written response. The "5-Year Effect" statistic measures the linear combination of treatment effects during the five calendar years following initial diagnosis, inclusive of the year of diagnosis itself. The "Ref. 5-Year" probability measures the base rate of foreclosure, default, or bankruptcy during the five years prior to diagnosis. Standard errors are clustered at the patient level.

	Professional	Clerical	Laborer	Non-employed	Other
			Panel A: Notice of Default		
Notice of Default 5-Year Effect	0.0057	0.015**	0.014**	-0.0047	-0.00087
S.E.	0.0030	0.0042	0.0051	0.0082	0.0048
Ref. 5-Year Default Probability	0.0017	0.0036	0.0042	0.0049	0.0042
N	61903	53369	56450	16963	57737
			Panel B: Foreclosure		
Foreclosure 5-Year Effect	-0.0013	0.0054**	0.0065**	0.00060	0.0038*
S.E.	0.0021	0.0018	0.0020	0.0044	0.0018
Ref. 5-Year Foreclosure Probability	0.00087	0.00078	0.00088	0.0017	0.00094
N	64056	55897	60623	17236	60659
			Panel C: Bankruptcy		
Bankruptcy 5-Year Effect	0.0050	-0.00089	0.0080*	0.0081	-0.00086
S.E.	0.0031	0.0043	0.0040	0.0055	0.0036
Ref. 5-Year Bankruptcy Probability	0.022	0.037	0.045	0.032	0.035
N	160084	147277	183786	47541	183381

TABLE A.III: Panel Regression, OLS, By Cancer Site

This table analyzes the impact of cancer diagnoses on three measures of financial default, cutting by the category of cancer. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where the outcome is notice of default in Panel A, foreclosure in Panel B, and bankruptcy in Panel C. All specifications restrict on the Deeds subsample. The “5-Year Effect” statistic measures the linear combination of treatment effects during the five calendar years following initial diagnosis, inclusive of the year of diagnosis itself. The “Ref. 5-Year" probability measures the base rate of foreclosure, default, or bankruptcy during the five years prior to diagnosis. Standard errors are clustered at the patient level.

	Breast	Colon	Lymphoma/Leukemia	Lung	Prostate	Skin	Thyroid	Uterine	Other
				Panel A: Notice of Default					
Notice of Default 5-Year Effect	0.0060*	0.0012	0.0061	0.014**	0.0041	-0.00012	0.016*	0.0055	0.013**
S.E.	0.0030	0.0051	0.0044	0.0050	0.0022	0.0046	0.0074	0.0058	0.0033
Ref. 5-Year Default Probability	0.0087	0.0076	0.0078	0.0098	0.0051	0.0079	0.010	0.0099	0.0082
N	87199	35732	42101	42029	77442	29926	14262	13157	101845
				Panel B: Foreclosure					
Foreclosure 5-Year Effect	0.0018	0.0022	0.0031	0.0029*	0.00030	0.0023	0.0034	0.0025	0.0044**
S.E.	0.0014	0.0024	0.0019	0.0013	0.0014	0.0021	0.0034	0.0020	0.0011
Ref. 5-Year Foreclosure Probability	0.0019	0.0025	0.0021	0.0023	0.0012	0.0029	0.0019	0.0016	0.0022
N	88829	38015	45150	51876	78442	30415	14414	13584	113693
				Panel C: Bankruptcy					
Bankruptcy 5-Year Effect	0.0086	-0.0039	0.0061	0.00040	0.00034	-0.0059	0.030*	0.015	-0.0014
S.E.	0.0038	0.0062	0.0060	0.0066	0.0037	0.0066	0.012	0.0093	0.0042
Ref. 5-Year Bankruptcy Probability	0.022	0.022	0.026	0.028	0.016	0.023	0.024	0.026	0.028
N	95583	38894	46372	45164	83662	33569	16292	14368	112534

TABLE A.IV: Treatment Choices and Financial Defaults

This Table measures the role of different cancer treatments on default choices. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where time here is measured monthly relative to diagnosis, and effects are combined for the three years before and after diagnosis. Each column subsets on patients recommended a particular type of cancer treatment. The last column identifies patients for whom a treatment was not performed. The sample selection effectively compares individuals receiving a particular treatment at different points in time, both before and after their diagnosis.

	Surgery	Radiation	Chemo	Hormone	Transplant Endo	Other	Not Performed
				Panel A: Notice of Default			
5-Year Effect	0.0049^{*}	0.013^{**}	0.0094^{*}	0.0072^{**}	-0.015	0.025	0.0086
S.E.	0.0023	0.0031	0.0031	0.0026	0.019	0.013	0.0051
Ref. Prob.	0.0078	0.0069	0.0089	0.0079	0.0091	0.0087	0.0073
				Panel B: Foreclosure			
5-Year Effect	0.0026^{**}	0.0034^{**}	0.0023	0.0045^{**}	-0.017	-0.0013	0.0012
S.E.	0.0011	0.0013	0.0012	0.0011	0.012	0.0023	0.0018
Ref. Prob.	0.0022	0.0013	0.0024	0.0015	0.0036	0.0044	0.0019
				Panel C: Bankruptcy			
5-Year Effect	0.000094	0.010^{*}	0.00056	0.0065	0.0018	0.011	0.0011
S.E.	0.0032	0.0050	0.0039	0.0038	0.021	0.013	0.0056
Ref. Prob.	0.024	0.021	0.028	0.021	0.024	0.028	0.024
N	151308	54132	124595	101656	4100	5069	45133

* p<0.05, ** p<0.01

TABLE A.V: Panel Regression, OLS, By Survival Status

This table analyzes the impact of cancer diagnoses on three measures of financial default divided by duration of survival. The specification is the standard event-study diff-in-diff: $O_{it} = \alpha + \sum_{k=-s}^{s-1} \mu_k \cdot 1[(t - T_i) = k] + X_{it} + \theta_t + \varepsilon_{it}$, where the outcome is notice of default in Panel A, foreclosure in Panel B, and bankruptcy in Panel C. Survival duration is predicted using a survival analysis using all covariates (including age, cancer type, and stage) as well as an interaction of cancer type with cancer stage. The sample is divided in half into "High Survival" and "Low Survival" subpopulations. The "5-Year Effect" statistic measures the linear combination of treatment effects during the five calendar years following initial diagnosis, inclusive of the year of diagnosis itself. The "Ref. 5-Year" probability measures the base rate of foreclosure, default, or bankruptcy during the five years prior to diagnosis. Standard errors are clustered at the patient level.

	Full Sample		Aged 26–60		CLTV > 100	
	High Survival	Low Survival	High Survival	Low Survival	High Survival	Low Survival
			Panel A: Notice of Default			
Notice of Default 5-Year Effect	0.0057**	0.010**	0.0052*	0.013**	0.032	0.085**
S.E.	0.0016	0.0023	0.0023	0.0047	0.017	0.025
Ref. 5-Year Default Probability	0.0074	0.0087	0.0084	0.012	0.030	0.034
N	264181	179433	176216	70158	14502	9475
			Panel B: Foreclosure			
Foreclosure 5-Year Effect	0.0022**	0.0031**	0.0019	0.0064**	0.020**	0.033**
S.E.	0.00078	0.00082	0.0012	0.0017	0.0076	0.011
Ref. 5-Year Foreclosure Probability	0.0019	0.0022	0.0023	0.0028	0.011	0.012
N	268339	205997	179073	79347	14744	10305
			Panel C: Bankruptcy			
Bankruptcy 5-Year Effect	0.0046*	0.000083	0.0058	-0.0014	0.029*	-0.011
S.E.	0.0023	0.0028	0.0033	0.0062	0.014	0.018
Ref. 5-Year Bankruptcy Probability	0.022	0.026	0.027	0.039	0.043	0.061
N	291260	195083	196038	77446	19475	12592