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Killer Debt: The Impact of Debt on Mortality

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Abstract: This study analyzes the effect of individual finances (specifically creditworthiness and severely delinquent debt) on mortality risk. A large (approximately 170,000 individuals) subsample of a quarterly panel data set of individual credit reports is utilized in an instrumental variables design. The possibility of the reverse causality of bad health causing debt and death is removed by instrumenting for individual finances post 2011 using the exposure to the housing crisis based on their 2005 residence. Worsening creditworthiness and increases in severely delinquent debt are found to lead to increases in individual mortality risk. This result has implications for the benefit of policies such as the social safety net, which aims to protect individual finances, by adding reduced mortality to the benefit of any intervention.

JEL classification: I1, D14

Key words: debt, mortality, creditworthiness

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1. Introduction

Debt has increasingly become a central component of modern household and individual finance in the United States. Approximately 69 percent of all U.S. households held some form of debt, with a median household debt of $70,000 in 2011, up from $50,971 (in 2011 dollars) in the year 2000 (Vornovytskyy, Gottschlack and Smith, 2015). On one hand, this increase in indebtedness, in part due to changing credit standards, has been shown to dampen the effect of economic fluctuations by allowing households to better smooth out consumption over the life cycle, thus decreasing economic volatility (Dynan 2009). However, during the Great Recession, this increased debt became a major financial problem for households as the delinquency rate increased by more than 50 percent; households that had eased access to credit found themselves unable to meet their obligations (Athreya et al., 2015). The amount of delinquent debt (debt in arrears), in some ways, captures the nuance of an individual's financial situation better than an aggregate measure such as unemployment, as it reflects not only the current status of inability to meet financial obligations, but also the lowered ability to smooth consumption in the future due to less access to credit. This makes measures of debt and creditworthiness appealing for studies of the impact of economic well-being on health as different dimensions of debt and creditworthiness may be capable of detecting the subtleties of both an individual's current and expected future economic situation that influence an individual's health.

A number of studies have found a negative correlation between debt and health (Drentea and Lavrakas, 2000; Lyons and Yilmazer, 2005; Keese and Schmitz, 2010; Lau and Leung, 2011; Averett and Smith, 2014), but there are reasons to be concerned that these associations may not be causal. First, poor health, through a reduction in work and earnings and an accumulation of health care expenses, can cause debt (Lyons and Yilmazer, 2005). In addition, unobservable characteristics, such as a risk-taking personality or impulsivity, may be correlated with both debt and health (Grafova, 2007).

There are, however, plausible reasons to expect a causal relationship between debt (in particular delinquent debt), and poor health. High levels of delinquent debt could lead to an increase in stress and stress-related behaviors such as poor nutrition and substance use that can have negative health consequences. Stress has been linked to poor physical and mental health (Goldberger and Breznitz, 1993; McEwen 1998a, 1998b; Cooper, 2005; Schniederman, Ironson, and Siegel, 2005). In addition, financial insecurity may reduce health-care use and adherence to medical treatment plans leading to worsening health (Currie and Tekin 2014; Kalousova and Burgard, 2012).

Carrying delinquent debt brings with it the additional stressor of being contacted by debt collectors. The debt collection process is stress-inducing due to its adversarial nature, with a sample of debtors referring to collectors with terms such as, “inhuman” and “sadistic” (Hill 1994). Debt collection is the type of practice generating the most frequent complaints to the Consumer Financial Protection Bureau. Over half of the complaints for debt collection deal with poor communication tactics, threats, improper contact, or false representation (Consumer Financial Protection Bureau 2016). Carrying delinquent debt has been shown to increase the likelihood poor mental health, as measured by GHQ-12 scores, and the likelihood of reporting an anxiety-related illness (Gathergood 2012).

In this research, we explore the impact of delinquent debt and creditworthiness on mortality. To do this we take advantage of the individual panel component of the Federal Reserve’s Consumer Credit Panel (CCP). The CCP is a nationally representative 5% random sample of U.S. consumers and their household members with information in the consumer credit data system. The quarterly panel follows these individuals from 1999 to the present, with refreshing to account for attrition. The data contain credit balances and delinquencies for different categories of debt. In addition to age and geographic information, the CCP includes an indicator of the quarter of death for individuals who died while part of the panel. This individual-level, objective measure of health can be linked directly to objective measures of the individual’s financial well-being. The CCP allows us to follow financial well-being and mortality within the context of a single, individual panel data set.

To address the possibility of reverse causality (poor health leading to increased debt), we use geographic variation in financial distress related to the housing crisis and the Great Recession to identify the causal impact of personal debt on mortality. This is accomplished by identifying the impact of an adverse economic event that is plausibly exogenous to individual financial choices, in our case the housing crisis of 2006-2010, using mortgage delinquency data from the Residential Mortgage Servicing (RMS) Database from McDash Analytics. We use this information to construct an instrument for individual debt and creditworthiness later in life. To avoid conflating our results with the direct impact of the time-period of the financial crisis, the analysis of the impact of creditworthiness and debt on mortality is focused on the post-recession time-period of 2011-2016.

Even though there have been other estimates of the effect of debt on health, this study makes several leaps forward methodologically. This is one of the few studies in this literature to address the possibility of reverse causality through the use of an instrument. In addition, our analysis does not rely on self-reported health measures, utilizes individual-level panel data, and has finely detailed individual financial information. This is also the only study in this literature to remove the effect of endogenous migration: we calculate our instrument based on an individual's location before the housing crisis. To our knowledge, there is no previous study that has been this comprehensive.

Our results are consistent with those establishing a negative association between individual delinquent debt and health. We find that individuals with better credit risk and smaller amounts of delinquent debt have a lower probability of mortality. Addressing issues of reverse causality by use of an instrumental variable strengthens the claim that these findings as causal. Our results imply that policies aimed at improving individual financial solvency may have the additional benefit of promoting health.

2. Previous Literature and Contribution

There is a large literature on the impact of economic conditions on health outcomes. The original literature on the topic (Ruhm 2000, 2003, 2005a, 2005b; Dehejia and Lleras-Muney 2004) documented improvements in health outcomes and healthy behaviors when the U.S. economy worsens.[1] This early work

[1] This is not unique to the U.S., for example, similar results have been shown in Spain (Granados, 2009), Germany (Neumayer, 2004), and across 23 OECD countries (Gerdtham and Ruhm, 2006).

largely linked rising unemployment rates to better health measured in a variety of ways: death rates by cause, substance use, smoking, obesity, nutrition and exercise. The literature has since expanded greatly. For the purposes of placing the contribution of this study into context, we will split the literature into two branches of growth.

One branch of new work has further explored the relationship between economic well-being measured by unemployment and health by exploiting variation in health outcomes within different subsets of the population and over different time-periods. This literature has found that the positive impact of unemployment on health has attenuated and in some studies even reversed over time (McInerney and Mellor, 2012; Ruhm, 2015; Gordon and Sommers 2016) and that much of the improvement in health from poor economic conditions is concentrated among the elderly (Miller et al., 2009; Stevens et al, 2015). Additional work has found that, for the working-age population, unemployment is bad for health (Crost and Friedson, 2016), a result consistent with a parallel literature on job-loss and health outcomes (Elliason and Storrie, 2009; Rege et al., 2009; Strully, 2009; Sullivan and von Wachter, 2009).

The other branch of the recent literature expands on the idea of economic conditions influencing health by using finer measures of economic well-being. This literature has looked at the impact on health of dips in the stock market (McInerney, Mellor and Nicholas, 2013; Cotti, Dunn and Tefft, 2015; Angrisani, Kadiyala and Lee, 2015), changes in foreclosure rates (Currie and Tekin, 2015), and individual debt (Drentea and Lavrakas, 2000; Lyons and Yilmazer, 2005; Grafova, 2007; Keese and Schmitz, 2010; Lau and Leung, 2011; Averett and Smith, 2014).

Results are mixed in studies that address the endogeneity of health and debt. Grafova (2007) finds a negative association between reports of health and debt using data from the PSID, but these effects are not statistically significant after controlling for family-level fixed effects over time. Using German data, Keese and Schmidt (2010) find that a negative association between self-reported debt and health remains in models that include individual fixed effects and lagged debt measures. Averett and Smith (2014) analyze self-reported debt data (indicators of any credit card debt or reports of having trouble paying bills) to estimate propensity score matching, sibling fixed effects and instrumental variables models, and find little evidence of a causal relationship of debt on body mass index and obesity. Lau and Leung (2011) use Freddie Mac Housing Price Index data as an instrument and conclude that mortgage debt exacerbates the relationship between unemployment and obesity for individuals over the age of 50.

In studies using administrative data on debt and foreclosures, the evidence is also mixed. In their analyses of financial records reported in the Survey of Consumer Finances, Lyons and Yilmazer (2005) find little evidence of a causal link between self-reported health and measures of debt that include loan delinquency, asset-to-debt ratio and liquid asset to income ratio. In contrast, results from Currie and Tekin (2015), using data on total foreclosures and emergency room visits and hospitalizations linked by zip codes in four states hit hard by the recent mortgage crises, indicate that emergency room use and hospitalizations rise when there is a spike in foreclosures.

Our work adds to this literature in a number of important ways. First, the use of individual panel data that includes both observed explanatory and outcome measures is something that has been missing in the research to date; we do not have to rely on either self-reported data or variation in the explanatory variable from a higher level of aggregation. Second, due to the richness of the CCP data we are able to include a much more detailed debt measures than have been previously used. Third, we make use of an instrument to address reverse causality, something that, to our knowledge, has not been done in conjunction with the other contributions made by this paper. Finally, because we can track individuals over time, we are able to construct our instrument as an intent-to-treat variable (ITT) which removes the effect of endogenous migration.

The final contribution is non-trivial. It is possible that individuals with health-related characteristics and/or preferences selectively move either to or from places that were hard hit by the housing crisis. This would cause systematic migration that could bias the estimated effect of the crisis on health outcomes. For example, if healthy individuals selectively left places with bad shocks from the recession for places with less adverse shocks after the recession hit, it would appear as if the bad shocks from recession had a stronger negative impact on health than it truly did as the healthier individuals were selectively removed from the population of the hard hit area. The use of the ITT variable removes this effect, a correction that data in the literature has not previously made possible.

3. Data

Our data source is the individual panel component of the Federal Reserve Bank of New York Consumer Credit Panel (CCP), which is based on credit histories provided by Equifax. A thorough description of the CCP, its collection and components can be found in Lee and van der Klaauw (2010). Here we describe the features of the CCP pertinent to our analysis and provide descriptions of the relevant variables used in our models.

The CCP is a nationally representative 5 percent random sample of the U.S. population with Equifax credit reports (all data in the CCP comes from Equifax) collected from 1999 to the present. The consumer records are anonymous. The sample is structured in a quarterly panel, so that once selected for inclusion an individual stays in the panel until they no longer have a credit history.[2] New individuals are added to the panel each quarter to maintain the 5 percent sample; this constantly repopulates the panel to account for both attrition and population growth. Each quarter, the CCP reports all of the information available on a credit report: credit rating (credit risk) as well as account balances and delinquencies across a wide range of categories. There is also information on the birth year of the individuals as well as geographic location of each individual down to the census tract level. We restrict our sample to individuals with a credit report who were age 25 or older in 2005 and alive in the 4th quarter of 2010. We also restricted our sample to only include individuals for which Equifax had enough information to calculate credit risk (Equifax's equivalent of a FICO score). The CCP also identifies the type of mailing address for the individual: a detached home, a high rise, a post office box or a military installation.

Most important for our analysis is the indicator that captures individual mortality. When an individual dies, their credit history is not immediately wiped out. In many cases the debts of a decedent may continue on for some time. The maximum length of time for which a decedent remains in the CCP is 15 quarters after death. However, in this analysis, once an individual is deceased, we remove their data from the sample for

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[2] No longer having a credit history occurs when an individual ceases generating information collected by a credit risk company, and their old information is gradually deleted. This most commonly occurs with death which is identified in the data, but can also happen is an individual chooses to completely eschew debt or moves out of the country.

subsequent periods to prevent observations that involve the paying down of their debts by their survivors (or writing off debt if there are no survivors) from biasing the estimation.

The final sample includes individuals in the age range of 25 to 90 in 2005 that are observed in the CCP sample in both the fourth quarter of 2005 and the first quarter of 2011 in order to capture pre-financial crisis zip code data. In addition, everyone in the panel is alive in the first quarter of 2011. Given the low frequency of death, which occurs for approximately 0.4 to 0.7 percent of the sample in any given year, we construct a sample that includes all individuals who die after quarter one of 2011 through the first quarter of 2016, the last quarter of available data. Given that a sample size of 40 to 50 million observations is available in each year of the CCP, a one percent random sample of individuals who do not die, and have no missing observations, is included in our analytical sample. The final data set has 2,493,484 person-quarter observations. There are 94,442 unique individuals who die within the time-period and 73,462 unique individuals that do not die during the time-period of analysis. Weighting adjustments recommended by Solon, Haider, and Wooldridge (2015) are used when reporting descriptive statistics and conducting the analyses.

The CCP data include a rich set of measures of debt levels and account delinquency, which capture individual-level economic distress. The first variable of interest is an individual's credit risk. Credit risk is the Equifax equivalent to a FICO score. Like the FICO score, credit risk is used to predict the individual risk of becoming seriously delinquent (having debt that is 90 days past due or more), in the next 24 months; it is simply calculated by a different algorithm than the FICO score. The credit risk ranges from 280 to 850, with higher scores denoting individuals with better risk from the perspective of a creditor. For most of our analyses, we include a one-quarter lag of the credit risk as a continuous variable, given that no credit risk is reported in quarter of death. We also allow for non-linearities in the effect of credit risk on mortality by stratifying individuals into credit risk categories based upon the rate-setting strategy of Fannie Mae. These categories exist to assess different interest rates based upon the level of credit risk. The distribution of these categories and their range of credit risk in the first quarter of 2011 are shown in Table 1. The largest groups are at either end of the credit risk distribution. The least credit-worthy, in Risk Category 1 (R1), make up over 22 percent of the sample, while approximately 52% of the sample falls into the least risky category, R5.

The CCP also includes information on the dollar amount of debt in each account and indicators of whether the account is or is not in good standing. We aggregate across debt accounts to create three different measures of debt that is not in good standing. In order to be consistent with the methodology behind the credit risk variable and the FICO score, we categorize accounts that are 90 days past due or more as severely delinquent. These three variables include an indicator of being severely delinquent on payments for at least one account, the dollar amount of debt that is severely delinquent (in quarter one, 2011 dollars), and the number of accounts that are severely delinquent.

To account for possible reverse causality between debt and health, we estimate an instrumental variables model. To generate our instrument we turn to another source of debt data. RMS data is comprised of the servicing portfolios of the top ten largest mortgage servicers in the United States (this number has shrunk over time due to mergers). It contains detailed information on loan characteristics and status for approximately 151 million loans dating back to 1992. Loans in the RMS can be tied geographically to zip codes and we use these data to construct a measure of mortgage default during the housing crisis of 2006-2010 which preceded/coincided with the great recession. Our instrument is the percent of mortgages within a zip code that were severely delinquent during the period of 2006-2010, and we refer to this measure as the Mortgage Delinquency Rate (MDR). To remove the effect of endogenous migration on this measure, we assign each individual the MDR during the crisis of the zip code of his or her residence in 4th quarter of 2005 (which is before the housing crisis was underway).

This variable identifies the share of mortgages in the individual's pre-housing crisis zip code of residence that were delinquent or in default in any quarter during the housing crisis and is intended to capture the extent to which changes in local housing markets would negatively affect an individual's wealth and debt. It passes the exclusion restriction for an instrumental variable since the only way that the financial distress of the housing crisis could be affecting current health is through channels related to individual financial well-being. Further, the wave of bad economic outcomes from the housing crisis can be seen as plausibly exogenous to individual financial decisions, and is certainly exogenous to individual health shocks that are debt-inducing. We use the MDR to identify clean variation in individual economic conditions post-2011 while eliminating the possibility that zip code location for the instrument reflects endogenous migration in response to the financial crisis.

Summary statistics for the main variables of interest are reported in Table 2. The mortality rate in the analysis sample is 3.12% per quarter, which represents the oversampling of the population that died. Reflecting our 1% sampling strategy this corresponds to a nationally weighted annual rate of approximately 12 deaths per 1,000. The average amount of severely delinquent debt per person is \$5,489, which represents 7.9 percent of the average individual's total debt. However, for those that have any debt that is severely delinquent, the average amount of debt past due is over \$47,938.40, which represents almost 60% of their total debt, and the average number of accounts overdue is two, which represents half of the total number of accounts.

4. Methods

To investigate the impact of debt on mortality, our initial analyses use person-quarter observations from the CCP data from quarter two (Q2) of 2011 to Q1 of 2016. That is, each individual contributes up to 20 quarters of data totaling 2,493,484 observations.

Direct Effect of Debt on Mortality

The first set of analyses utilizes four measures of financial wellbeing: the credit risk, the probability of having a severely delinquent account, the total amount of debt that is severely delinquent, and the number of accounts that are severely delinquent. In the first model we conduct the following simple discrete-time hazard model of death per quarter:

$$M_{ijt} = \alpha_0 + \beta_1 C_{ijt-1} + \delta X_{ijt} + \rho_{jt} + \epsilon_{ijt} \qquad (1)$$

where M_{ijt} is a binary variable indicating whether individual *i* in zip code *j* died during quarter t. C_{ijt} is the debt variable of interest. This variable is always lagged at least one quarter because credit information is typically unavailable in the quarter of death. X_{ijt} is a vector of individual characteristics which includes dummy variables for each type of mailing address and for each value of age. ρ_{jt} is a vector of state-by-quarter fixed effect. All of the models are estimated as linear probability models via ordinary least squares (OLS), and weighted as recommended by Solon, Haider and Wooldridge (2015) to correct for the sampling procedure. Standard errors are robust (White 1980), and corrected for clustering within the zip code.

We also investigate the relationship between debt that is further removed temporally from the time-period at risk of mortality. This is done by estimating the following equations:

$$M_{ijt} = \alpha_0 + \beta_1 C_{ijt-4} + +\delta X_{ijt} + \rho_{jt} + \epsilon_{ijt} \qquad (2)$$

and

$$M_{ijt} = \alpha_0 + \beta_1 C_{ijt-8} + +\delta X_{ijt} + \rho_{jt} + \epsilon_{ijt} \qquad (3)$$

where C_{ijt-4} and C_{ijt-8} are measures of delinquency lagged one year and two years respectively.

Credit Risk Threshholds

Estimates from model 1 will indicate a relationship between debt measures such as credit risk and mortality, but will not provide insight as to what segment of the debt distribution is driving any result. For example, if there is a negative relationship estimated between credit risk and mortality it is not possible to tell from this estimate alone if it is good credit risk that causes lower mortality or if it is bad credit risk that causes higher mortality or some combination of the two. Re-estimating model 1with a series of binary credit risk grouping variables (Fannie Mae's risk categories) rather than a continuous variable will reveal if the relationship between credit risk and mortality is non-linear.

Two-Stage Estimation

We are concerned about the possibility of reverse causality, where accumulation of bad debt could be caused by poor health. A prolonged hospital stay could lead to considerable debt as well as death, which could cause the model specified in equation (1) to overestimate the impact of bad debt on mortality. We address this by estimating equation (1) using the MDR as an instrument for the individual's delinquency measure. This strategy explicitly removes the impact of reverse causality of mortality on debt conditional on the appropriateness of the instrument. This estimation strategy requires MDR to affect mortality solely through its effect on individual finances (which we measure with delinquent debt and credit risk) and to have a strong correlation with the debt variable.

Because more financially resilient individuals may move from economically hard-hit neighborhoods, post-recession residential location may be endogenous. Assigning the MDR to each individual based on the location they were living in 2005 (before the housing crisis), creates an ITT estimate, which removes the impact of endogenous migration.

Age of the Individual

It is possible that the effects of creditworthiness and delinquency on mortality are different at different points in the lifecycle. To examine this possibility, we repeat the estimation of equation (1) and the associated instrumental variables analysis for two sub-populations: individuals who were under the age of 44 as of the fourth quarter of 2005 (and thus 55 in 2016), and individuals who were over the age of 55 as of the fourth quarter of 2005. Any differences in the results for these two sub-populations will be a mix of the effect of being at different parts of the lifecycle in addition to any generational differences that may exist between the cohorts.

5. Results

One of the strengths of the CCP data is the wide range of measures of debt and credit-worthiness available. This variety of measures allows us to understand nuances in the link between financial strain and health. Table 3 reports estimates of the models represented by Equations 1-3 in four columns and in three different panels. Each column reports estimates from models that include a different measure of credit-worthiness or financial distress. These measures include the credit risk (Column 1), the probability of being severely delinquent (Column 2), the total dollar amount of debt that is severely delinquent (Column 3), and the number of credit accounts that are severely delinquent (Column 4), the different panels correspond to different time lags for the credit risk and the respective delinquency measures. Panel A lags delinquency or credit risk a single quarter, Panel B lags the measures a year, and Panel C lags the measures two years.

Direct Effect of Debt on Mortality

The results in Table 3 paint a remarkably similar picture of the relationship between debt and mortality regardless of the timing or specific measure of credit risk or delinquent debt. Specifically, as credit risk scores improve, mortality rates fall. As shown in column 1, when an individual's credit risk improved by 100 points in the previous quarter, his mortality risk for the next quarter declines by

0.00028 (0.028 percentage points), a 4.38 percent decline in mortality risk from a baseline level of 0.06. Without exception, as severely delinquent debt increases, by any of our measures reported in columns 2-4 the risk of mortality rises. For example, moving from having no severely delinquent accounts to any severely delinquent accounts causes an increase in mortality risk for the next quarter of 0.003 percentage points, or approximately a 5 percent increase in mortality risk. These patterns are evident regardless of whether debt is measured with a one-quarter lag in panel one, or whether it is lagged one or two years (in panels two and three, respectively). The magnitude of the impact is attenuated as the lag length increases. This suggests that if one survives the short-term impact of a delinquency then the probability of dying in any single quarter declines.

Credit Risk Threshholds

Results from the threshold (non-linear) version of Models 1 are presented in Table 4. In this model, the pattern of results is as one would expect. As credit risk (creditworthiness) improves, mortality risk declines. Across the distribution, the groups with the best scores have a lower probability of death, whereas poor scores are associated with higher mortality relative to the reference group. The coefficients are larger in magnitude as the credit risk moves further from the reference group (risk category 3, or the middle category). This monotonic progression suggests that there are no significant non-linearities in the relationship between credit risk and mortality, and statistical significance for each category suggests that the relationship is not driven by either the low or high end of the credit risk distribution.

Two-Stage Estimation

One may be concerned that the models presented in Tables 3 and 4, rather than capturing the impact of financial strain on health are picking up the accumulation of debt and reduction in creditworthiness as health declined prior to death. To address this concern about reverse causality, we use an exogenous measure of debt, the 2006-2010 MDR in an individual's location in 2005, as an instrument for individuals' current debt as measured by each of the personal risk and delinquent debt measures. The results from this two-stage estimation are shown in Table 5. The first-stage results shown in the upper panel suggest that MDR is a very strong predictor of an individual's personal credit risk in the current period. That is, individuals who, in 2005 before the beginning of the housing crisis, lived in a location that was hard-hit during the recession (as evidenced by a higher neighborhood MDR) have a significantly lower individual credit risk, and higher values of all of the delinquent debt measures. The instrument has a high F-statistic for all of the measures except for the total amount severely delinquent, although even this F-statistic exceeds the commonly used threshold of 10 (Sock and Yogo 2005; Stock and Watson 2007).

The second-stage results indicate that this exogenous measure of credit risk significantly reduces mortality. Each 100-point improvement in the credit risk lowers the quarterly risk of death by .036 percentage points. The magnitude is similar to that estimated in Table 3 suggesting that the use of the individual credit risk measure, despite concerns about possible reverse causality and endogenous migration, closely captures the exogenous impact of debt on mortality. The second-stage IV estimates for the other delinquent debt measures also indicate a significant exogenous effect of debt on mortality. The estimates in the two-stage model are an order of magnitude larger than those reported in the previous models. This suggests that while credit risk may be a measure that is robust to reverse causality, account balances are not. The difference in the changes between the two sets of estimates is perhaps because credit risk can be slow to adjust to new debt information, whereas account balances immediately reflect new financial situations.

Age of the Individual

Results stratified by the age of the individual are reported in Table 6a for the simple model and Table 6b for the two-stage model (only the second stage is reported).[3] In both tables, the top panel reports results for the population that was 44 or younger in the fourth quarter of 2005 and the bottom panel reports results for individuals that were 55 or older in the fourth quarter of 2005 (younger than 50 or older than 61 in the fourth

[3] The First state is available upon request.

quarter of 2011). In both tables the same pattern of result emerges: individuals who are at later parts of the life-cycle illustrate a larger impact of financial well-being on mortality.

There are multiple potential explanations for this outcome. It is possible that due to their lower stock of health capital, older individuals are more responsive to any shocks that could influence health outcomes. It is also possible that individual finances are less volatile later in the lifecycle, and a shock to credit risk or delinquent debt carries a larger weight as the expectation of financial volatility is lower. It could also be the case that the lifecycle has no relevance, and we are simply detecting generational differences.

6. Summary and Conclusions

As the debt burden of Americans has increased in recent decades, and the depth of recessions and involvement of financial and real estate markets in these economic downturns has intensified, this paper sheds light on the extent to which macroeconomic fluctuations that increased household debt may have adversely influenced individual health. Using nationally representative longitudinal data comprised of 5% of all credit records in the US, we examine the link between increased debt and mortality.

Our estimates using individual-level debt support a negative association between delinquent debt and health, as measured by mortality (and a positive association between credit-worthiness and health). We use longitudinal data with large samples sizes and fine geographic indicators to address concerns about possible endogeneity of health and personal debt by estimating models that use neighborhood rates of mortgage delinquency during the housing crisis between 2006 and 2010 as an instrument. Results from these models reinforce the results found in the simple estimations.

Taken as a whole, it seems clear that debt resulting from a financial crisis has lasting effects on health that are substantial enough to increase mortality rates. This suggests that not only are macroeconomic policies during economic downturns important to improve short-term economic well-being, but that these policies may also have important long-term public health consequences. This extends to micro-oriented policies as well, in particular any program that improves individual finances, such as components of the social safety net. For example, recent studies have shown that public health insurance expansions include sizable improvements in the financial well-being of those affected (Gross and Notowidigdo 2011; Baicker et al. 2013; Barcellos and Jacobson 2015; Mazumder and Miller 2016; Hu et al. 2016). Results from these studies thus also imply an indirect mortality improvement though the improvement in financial well-being. A 10% exposure to the 2006 health insurance expansion in Massachusetts as estimated by Mazumder and Miller (2016), improved credit scores by 3.4 points. This would imply a corresponding decrease in mortality risk of 0.001 percentage points (or a decrease in the base probability of dying in the next quarter of about 2 percent) based on our estimates.

Taken as a whole, our results imply that financial policies are health policies: the effect of individual finances on mortality is non-trivial.

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Table 1. Risk Categories

Riskscore Category	Riskscore (R) Range	Share of Sample
R1	<620	22.16%
R2	620<=R< 660	8.46%
R3	660<= R< 700	8.12%
R4	700<=R< 740	9.31%
R5	R>=740	51.94%

Note: Means are taken in the first quarter of 2011, before any individuals in the panel have died. Proportions are weighted to reflect population totals.

Table 2: Weighted Sample Means

	Whole Sample	Dies During Panel	Does Not Die During Panel
Credit Risk	716.9324	721.4235	711.1587
	(103.6969)	(102.1665)	(105.3515)
Any Severe Delinquency	0.14207	0.13812	0.14213
	(0.34913)	(0.34502)	(0.34918)
Total Amount Severely Delinquent	5,488.841	4,497.753	6,762.974
	(44,354.33)	(37,697.13)	(51,639.91)
Number of Accounts Severely Delinquent	0.2821	0.2792	0.2858
	(0.9332)	(0.9301)	(0.9373)
Age	63.1801	70.2615	54.0780
	(16.1804)	(13.5834)	(14.6242)
Death during Sample Period	0.01269		
	(0.11194)		
Number of Individuals	167,904	94,442	73,462

Note: Means are taken in the first quarter of 2011, before any individuals in the panel have died. Means are weighted to produce population averages. The number of unweighted individuals in the sample is reported.

Table 3: Determinants of the Quarterly Probability of Death – 2011-2015

	Credit Risk (100s)	Any Severe Delinquency	Total Amount Severely Delinquent (100,000s)	Number of Accounts Severely Delinquent
Panel A: Lagged One Quarter				
Effect on Mortality	-0.00028***	0.00030***	0.00003***	0.00018***
	(0.00000)	(0.00001)	(0.00001)	(0.00001)
N	2,493,484	2,493,484	2,493,484	2,493,484
Panel B: Lagged One Year				
Effect on Mortality	-0.00021***	0.00026***	0.00001***	0.00010***
	(0.00001)	(0.00001)	(0.00001)	(0.00000)
N	2,493,484	2,493,484	2,493,484	2,493,484
Panel C: Lagged Two Years				
Effect on Mortality	-0.00018***	0.00012***	0.00001***	0.00007***
	(0.00000)	(0.000009)	(0.000004)	(0.00000)
N	2,493,484	2,493,484	2,493,484	2,493,484

Note: All regressions include age fixed effects, dwelling type fixed effects, and state-by-quarter fixed effects. Regressions weighted as recommended by Solon, Haider, and Wooldridge (2015). Robust standard errors clustered by zipcode. Total past due is in Quarter 1, 2011 dollars.

*, **, and *** denote p<0.1, 0.05, and 0.01 respectively.

Table 4: Determinants of the Quarterly Probability of Death – 2011- 2015, Threshold Analysis

Risk Category 1 (R1)	0.00029***
	(0.00001)
Risk Category 2 (R2)	0.00006***
	(0.00001)
Risk Category 4 (R4)	-0.00008***
	(0.00001)
Risk Category 5 (R5)	-0.00041***
	(0.00001)
N	2,493,484

Note: All regressions include age fixed effects, dwelling type fixed effects, and state by quarter fixed effects. Regressions weighted as recommended by Solon, Haider, and Wooldridge (2015). Robust standard errors clustered by zipcode.

*, **, and *** denote p<0.1, 0.05, and 0.01 respectively.

Table 5: Two-Stage Least Squares Model

	Credit Risk (100s)	Any Severely Delinquent	Total Severely Delinquent (100,000s)	Number of Accounts Severely Delinquent
Panel A: First Stage				
Mortgage Delinquency Rate – 2005 Location	-5.5472***	0.9837***	0.3739***	1.79606***
	(0.0014)	(0.0312)	(0.0354)	(0.08156)
F – Statistic	255.13	86.15	17.56	55.57
N	2,493,484	2,493,484	2,493,484	2,493,484
Panel B: Second Stage				
Instrumented effect of debt measure	-.000359***	0.00202***	0.00532***	0.00111***
	(0.000023)	(0.00013)	(0.00035)	(0.00007)
N	2,493,484	2,493,484	2,493,484	2,493,484

Note: All regressions include age fixed effects, dwelling type fixed effects, and state by quarter fixed effects. Regressions weighted as recommended by Solon, Haider, and Wooldridge (2015). Robust standard errors clustered by zipcode. Total past due is in Quarter 1, 2011 dollars

*, **, and *** denote $p<0.1$, 0.05, and 0.01 respectively.

Table 6a: Younger vs Older Populations

	Credit Risk (100s)	Total Severely Delinquent (100,000s)	Share of total past due	Accounts past due	Share of accounts past due
Panel A: Younger than 44 in 2005					
Effect on Mortality	-0.00007***	0.00003***	0.00016***	0.00004***	0.00023*
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00012)
N	747,090	747,090	747,090	747,090	747,090
Panel B: Older than 55 in 2005					
Effect on Mortality	-0.00090***	0.00014***	0.00278***	0.00093***	0.00730***
	(0.00002)	(0.00001)	(0.00012)	(0.00005)	(0.00238)
N	1,239,918	1,239,918	1,239,918	1,239,918	1,239,918

Note: All regressions include age fixed effects, dwelling type fixed effects, and state by quarter fixed effects. Regressions weighted as recommended by Solon, Haider, and Wooldridge (2015). Robust standard errors clustered by zipcode.

*, **, and *** denote p<0.1, 0.05, and 0.01 respectively.

Table 6b: Younger vs Older Populations (IV Model, second stage)

	Credit Risk (100s)	Total past due (100,000s)	Share of total past due	Accounts past due	Share of accounts past due
Panel A: Younger than 44 in 2005					
Effect on Mortality	-0.00007***	0.00152***	0.00059***	0.00020***	0.06614*
	(0.00001)	(0.00016)	(0.00006)	(0.00002)	(0.00012)
N	747,090	747,090	747,090	747,090	747,090
Panel B: Older than 55 in 2005					
Effect on Mortality	-0.00103***	0.03020***	0.01049***	0.00400***	1.8794***
	(0.00010)	(0.00304)	(0.00106)	(0.00040)	(0.1891)
N	1,239,918	1,239,918	1,239,918	1,239,918	1,239,918

Note: All regressions include age fixed effects, dwelling type fixed effects, and state by quarter fixed effects. Regressions weighted as recommended by Solon, Haider, and Wooldridge (2015). Only the second stage of the IV is reported. Robust standard errors clustered by zipcode.

*, **, and *** denote p<0.1, 0.05, and 0.01 respectively.