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# Exploring the Risks and Consequences of Elder Fraud Victimization: Evidence from the Health and Retirement Study

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## Abstract

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## Disciplines

Economics

## Comments


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Abstract

This is the first study to use longitudinal data to explore both the antecedents and consequences of fraud victimization in the older population. Because older persons are close to or past the peak of their wealth accumulation, they are often the targets of fraud. This paper reports on analysis of the *Leave Behind Questionnaires* (LBQs) fielded on Health and Retirement Study (HRS) respondents over three survey waves in 2008, 2010, and 2012. We evaluate the demographic determinants and risk factors of reporting financial fraud victimization in the survey, and explore whether there are demographic subgroups of older victims. In addition, we examine the financial, physical and psychological consequences of fraud. Overall results suggest that there is no single reliable predictor of fraud victimization across all three LBQ samples. When LBQ responses were pooled across survey years, we found that younger, male, better-educated, and depressed persons reported being defrauded significantly more often. Victimization was associated with lower non-housing wealth in the combined sample controlling for other factors, but had no measurable impact on cognitive, psychological, or physical health outcomes. Future research should examine predictors and outcomes based on the type of financial fraud experienced and the amount of money lost.

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The greying of the American population is certain to prompt greater demand for assistance with key financial decisions.[1] The consequences of poor financial capability for older adults can be numerous and serious, including being uninformed, making mistakes with credit, drawing down retirement assets too quickly, and being defrauded by financial predators. And because older persons are close to the peak of their wealth accumulation, they are an ideal target for fraud. Moreover, they may be unable to recoup financial losses, thereby becoming dependent on public assistance. Additional consequences for seniors include financial insecurity, loss of financial autonomy, emotional pain and suffering, and feelings of shame and depression (Button et al., 2010; Deem, 2000; FINRA Investor Education Foundation, 2015). In fact, a representative survey by the FINRA Investor Education Foundation (2013) found that more than 80% of adults of all ages had been solicited for potentially fraudulent offers; older Americans were particularly likely to be the targets and were more likely to lose money when targeted. Conservative estimates of fraud costs suggest annual losses of $50 billion among all U.S. adults (Deevy, Lucich, and Beals, 2012), with the older population at potentially greatest risk.

Despite the fact that media attention has increased regarding the threat of consumer fraud among the aging population, researchers have only made limited progress in identifying at-risk groups for targeted prevention and intervention (Deevy, Lucich, and Beals, 2012). One challenge has been inconsistent findings regarding how age, socioeconomic status, and financial sophistication shape the risk of fraud victimization. For example, financial literacy is thought to be a protective factor, yet in one study, investment fraud victims scored *higher* than non-victims on financial literacy questions (Consumer Fraud Research Group, 2006). Early survey research by

[1] See Agarwal et al (2009) and Karp and Wilson (2012). Span (2011) noted, “Impaired seniors are at risk not only because unscrupulous outsiders (or their own family members) can defraud them, but because they themselves make self-destructive decisions as shoppers or investors.”

Lee and Soberon-Ferrer (1997) reported that consumers were more vulnerable if they were older, less educated, single, and poor, but more recent national telephone surveys by the Federal Trade Commission (FTC) indicated that victimization rates were highest among middle aged Americans and lowest among older adults age 65+ (Anderson, 2013; 2007; 2004).

One potential explanation for these discrepancies is that prior studies have often been non-representative and cross-sectional, focused on specific types of fraud, and conducted in laboratories where fraud was measured using behavioral susceptibility questions rather than actual experiences of victimization. For this reason, the Financial Fraud Research Center at the Stanford Center on Longevity recommended that representative longitudinal data be used to differentiate the antecedents from the consequences of fraud (Deevy, Lucich, and Beals, 2012). Accordingly, the present study uses the Health and Retirement Study (HRS), a nationally representative sample of U.S. adults over age 50, to identify what demographic, socioeconomic, health and cognitive factors are associated with fraud, and how mental health, physical health, and financial status are affected by victimization. An additional advantage of the HRS is that it is a particularly rich survey, providing an extensive set of information about the older population.

In what follows, we first offer an overview of the literature regarding who tends to be victimized and what the consequences are of such patterns. Next we outline our research methods using the Leave Behind Questionnaires (LBQ) administered in the HRS, followed by a discussion of our findings. We conclude with some thoughts on limitations, paths for future research, and implications for policymakers.

## Prior Literature

**Profiling Fraud Victims.** It is well known that many older persons are financially unsophisticated, and financial illiteracy has been linked to a set of poor financial decisions. [2] Moreover, there is often a disconnect between actual financial knowledge and perceived financial knowledge, i.e., what people know versus what they think they know, and this disconnect is particularly large among the old (Lusardi and Tufano, 2015). Such disconnect can lead not only to poor retirement planning, but also to people falling for outright scams.

Prior research has further shown that many areas of financial decision-making decline with age (e.g., Plassman et al., 2008; Tymula et al., 2013), and these declines can precipitate fraud and financial abuse (e.g., Litchtenberg, 2016; Stiegal, 2012). Han and colleagues (2016) found that, compared to cognitively normal adults, those with mild cognitive impairment demonstrated greater susceptibility to scams. This built on their previous research showing that, even among cognitively healthy older adults, those who demonstrated subclinical problems in decision-making were more vulnerable (Boyle et al. 2012). In neuroscience research, Asp et al. (2012) reported that damage to parts of the ventromedial prefrontal cortex, an area involved in appraising whether information is true or false and that sometimes atrophies with age, did result in greater credulity toward misleading advertisements. These studies, however, did not measure fraud victimization directly; rather they inferred susceptibility based on responses to a questionnaire on risky financial decision-making or interest in purchasing items presented in hypothetical advertisements. Using brain imaging techniques, Spreng and colleagues (2017) found that elder financial exploitation victims had cortical thinning in brain regions associated with processing emotional and social information compared to a matched sample of targeted but non-victimized controls. Nevertheless, the

[2] For a recent literature review, see Lusardi and Mitchell (2014) and Lusardi, Mitchell, and Curto (2014).

exploitation had occurred months and sometimes years prior to the neuroimaging study, and they were unable to assess participants' functioning prior to or at the time they were exploited.

According to Ross, Grossmann, and Schryer (2014), the perception that older adults are more likely to be victims of consumer fraud has been driven by laboratory research on age-related declines in cognitive functioning, as well as negative stereotypes of older people as being lonely and overly trusting. For instance, one laboratory study found that older adults were less sensitive to and poorer at recognizing untrustworthy facial characteristics than were younger adults (Castle et al., 2012). Similarly, Ruffman, Murray, Halberstadt, and Vater (2012) found that older adults performed worse than young adults when asked to determine whether people were telling the truth or lying. In other words, though laboratory studies can provide insights on how information-processing changes with age, they may not necessarily translate to real-world behavior.

Perhaps as a result of this, consumer fraud surveys find that older adults report *lower* rates of victimization than younger and middle-aged adults. Only 7.3% of adults age 65-74 and 6.5% of adults age 75+ reported being victimized by fraud in the past year, or about half the 14.3% of adults age 45-54 who said they had been victimized over the same time period (in 2011) (Anderson, 2013). An early study using a national random probability sample of Americans 18 and older found that age was *negatively* associated with victimization (Titus, Heinzelmann, and Boyle, 1995). Similarly, three consecutive national telephone surveys by the FTC all supported the finding that older persons were less likely to be victims of most types of fraud relative to adults of other ages (Anderson, 2013, 2007, 2004), aside from bogus prize promotions (Anderson, 2013). Most recently, the Stanford Center on Longevity used an online survey panel that was demographically representative of the US adult population to pilot a fraud prevalence survey. The average age of victims was nine years younger than the average age of non-victims (age 41 compared to age 50) (DeLiema, Mottola, and Deevy, 2017).

A concern with consumer fraud surveys is that respondents may be reluctant or unwilling to report incidences of fraud. Another concern is that many either rely on a non-representative sample of confirmed victims identified by law enforcement or complaint agencies (e.g., Pak and Shadel, 2011; Consumer Fraud Research Group, 2006), or a random sample of adults who may have experienced fraud but who did not necessarily report it to authorities or decide to disclose victimization when interviewed for the survey (e.g., Anderson, 2013, 2007, 2004; Schoepfer and Piquero, 2009; Titus Heinzelmann, and Boyle, 1995; Investor Protection Trust, 2016). Other victim profiling studies used experimental manipulations and proxy questionnaires to assess vulnerability, but they did not measure how subjects responded when confronted with an attractive, yet bogus, opportunity. These methodological inconsistences make it challenging to compare risk factors across studies and draw reliable conclusions about which elderly groups are most vulnerable.

A major limitation of the aforementioned surveys is that they were cross-sectional and retrospective, so the analysts could not separate the antecedents from the consequences of experienced fraud. The FTC found that people who had experienced negative life events were also likely to report victimization by debt-related fraud and bogus prize promotion scams (Anderson, 2013), and the Consumer Fraud Research Group (2006) reported that victims were more likely than non-victims to have experienced difficulties maintaining their homes, have been in financial trouble, suffered from serious injury or illness, or have been unemployed prior to falling for a lottery or investment scam. Yet these findings were based on victims' retrospective reports, and in some cases may have immediately followed rather than preceded victimization. One research group (Lichtenberg, Stickney, and Paulson, 2015) tried to untangle these endogeneity issues using the HRS, and the team reported that the younger and better-educated were more likely to report fraud between 2008 and 2012. It also found that depression and low social needs fulfillment were significant predictors. The limitation of that study was that some of the respondents had already experienced fraud up to five years before 2008, which obscured the direction of the relationship between psychosocial vulnerability and victimization.

**Consequences of Victimization.** Relatively few clear research findings are available on the consequences of elder fraud. There have been efforts to estimate the total cost of consumer scams, with median losses ranging from $60 (Anderson, 2007) to $99 per victim (DeLiema, Mottola, and Deevy, 2017).[3] Results are heterogenous, however, with some people suffering much greater losses. For example, in a small sample of 24 older fraud victims whose cases were investigated by adult protective services, mean losses were approximately $619,000 per victim, and they ranged from $1,700 to $5,000,000; moreover, that was in addition to residential and commercial real estate properties taken by financial predators (DeLiema, 2017).

In addition to direct financial losses resulting from fraud, people may suffer other costs including legal fees and time off from work to report incidents, as well as emotional consequences such as shame, frustration, depression, and feelings of betrayal (Button et al. 2014; Deem 2000). The FINRA Investor Education Foundation (2015) assessed the non-traditional costs of financial fraud by surveying 600 victims (300 men and 300 women). Over half of them reported severe stress, 38% had difficulty sleeping, and 35% experienced depression as a direct result of the incident. Other reactions were anger (78%), regret (70%), and feeling betrayed (68%). Nearly half of the survey respondents paid $100-1,000 in additional costs associated with the incident such as

[3] An earlier study (Titus, Heinzelmann and Boyle 1995) reported mean losses of $216 per victim in a representative probability sample of 1,246 respondents.

late fees and bounced check fees, and 29% paid over $1,000 in indirect costs. The Stanford Center on Longevity reported similar emotional and financial consequences of fraud using an online panel (DeLiema, Mottola, and Deevy, 2017). Thirteen percent of victims reported that, as a direct result of the incident, they had difficulty meeting their monthly expenses or paying their bills, and over half (52%) stated that the incident was moderately or severely distressing. Eleven percent sought professional or medical help such as visiting a doctor or nurse, seeking counseling/therapy, and taking medication.

While these findings shed light on the short-term impact of fraud victimization, long-term outcomes are unclear. And as with most research profiling the experience of victims, existing studies to date have all been cross-sectional and retrospective. In the next section we outline our approach to analyzing the questions at hand.

## Research Methodology Using the Health and Retirement Study

**Sample**. The data used in the analysis below are drawn from the U.S. Health and Retirement Study (HRS), a nationally-representative longitudinal panel survey of about 22,000 individuals over the age of 50. The core survey, first administered in 1992, was divided into subject modules asking respondents about family structure, physical and cognitive functioning, health conditions, employment, finances, life experiences, attitudes, and behaviors. Subsequently, new cohorts have been added to the study every six years until their deaths. Additionally, African Americans and Hispanics are oversampled.[4]

[4] For additional information on the HRS, see Survey Research Center (ND). All results use baseline HRS sample weights.

Our research uses information from the 2008-2012 core HRS surveys, as well as the *Psychosocial Leave-Behind Participant Lifestyle Questionnaires* (the “LBQ”). The LBQs were delivered to half of the eligible HRS sample on a rotating schedule, so that each respondent received the questionnaire every other wave (every four years). It was designed to be completed by the respondents and returned by mail. The samples available for our analysis were 5,180 for 2008, 5,867 for 2010, and 414 for 2012; the pooled sample (with one observation per person) totaled 11,461.[5] Unlike the core HRS, the LBQs were not administered to proxy respondents, so any fraud that might have been experienced by those with severe cognitive or physical impairment or those living in institutional settings could not be captured.

***Variables***

**Measuring fraud victimization.** The 2008, 2010, and 2012 LBQ asked respondents if they had been the victims of fraud in the past five years, which is the main question we focus on in our analysis in this paper. Additionally, if the respondent indicated that he or she had been victimized, the survey asked which year the fraud occurred. Fifty-five respondents who reported victimization mentioned a year that was more than five years in the past, namely prior to 2003 for the 2008 LBQ respondents, 2005 for the 2010 respondents, and 2007 for the 2012 respondents. These individuals were excluded from the analyses.[6]

**Socio-demographic control variables.** Respondent characteristics included in all analyses below are a conventional set of controls including sex (male/female), age (in years), marital status (married/partnered versus single/divorced/separated/widowed), race (White/non-White), ethnicity (Hispanic/non-Hispanic), educational attainment (in years), number of children, total non-housing

[5] Overall response rates for the LBQ were 90% (2006), 85% (2008), 77% (2010), and 74% (2012), out of LBQ eligible participants.

[6] Only 55 respondents failed to report a valid fraud year, and they were excluded from the analysis below.

wealth and total housing wealth. Total non-housing wealth includes the net value of stocks, mutual funds, investment trusts, checking, savings, money market accounts, CDs, government savings bonds, and T-bills, bonds and bond funds, and all other savings minus the value of all debt. Total housing wealth includes the net value of the household's primary (and if relevant, secondary) residence. In the multivariate analyses, wealth variables were divided by 100,000. All wealth figures are in 2012 dollars.

**Cognitive functioning**. To measure cognitive functioning, HRS respondents were administered the Telephone Interview for Cognitive Status (TICS) at each survey wave (Folstein, Folstein, and McHugh, 1975). The TICS is a standardized assessment containing 35 items that measure word list memory, semantic knowledge, orientation, language, attention, mathematical skills, repetition, and nonverbal praxis. One point is given for each correct answer and higher scores indicate better cognitive performance. Epidemiological studies and clinical trials using the TICS have shown it to have high reliability and validity (e.g., Brandt, Spencer, Folstein, 1988; Welsh et al., 1993).

**Physical and mental health.** Depression was measured as the total number of symptoms of depression (yes/no) reported on the 8-item Center for Epidemiologic Studies Depression scale (CES-D; Radloff, 1977). Higher CES-D scores reflect more symptoms in the past week and include indicators such as feeling lonely, sad, and restless sleep. Self-rated health was dichotomized such that 1=Excellent/Very Good/Good health and 0=Fair/Poor health.

**Baseline characteristics (pre-fraud).** For time-varying characteristics such as wealth, cognitive functioning, and self-rated health, measures were drawn from the HRS survey administered six years before each respondent filled out the LBQ. For example, baseline data were drawn from the 2002 HRS wave for those who completed the LBQ in 2008. For this group of respondents, fraud could have occurred between 2003 and 2008 (i.e., within the previous five years). Similarly, for respondents who completed the LBQ in 2010, baseline data were drawn from 2004; and for those who completed the LBQ in 2012, baseline data were drawn from 2006. Twenty-six percent of the LBQ respondents were missing baseline data, and we dropped these cases from the analysis (more detail on sample construction is provided in Appendix Figure 1).

**Post-fraud outcomes.** Our measures of post-fraud outcomes include the variables identified above including cognitive functioning, depression, non-housing net wealth, and housing net wealth. All outcomes were measured in 2008, 2010, and 2012, respectively, corresponding to the year when the participant completed the LBQ. To measure differences pre-post, we control for respondents' baseline measures of each outcome as well as the self-report of whether he or she had been victimized. This represents a unique advantage of having longitudinal data.

***Methodology***

**Factors associated with being victimized.** Probit models were used to evaluate which factors were associated with people having reported being the subject of fraud victimization. We estimated separate models for each of the three cohorts (2008, 2010, and 2012) and also for a pooled sample. In addition, we used Latent Class Analysis (LCA) to categorize victims into subtypes based on their demographic characteristics. LCA tests the hypothesis that fraud victims differed from one another on key demographic and socioeconomic indicators, and it is a useful way to characterize heterogeneity across victims. LCA is similar to cluster analysis and uses a maximum likelihood approach to estimate the latent class structure based on the observed variables in the model, here, victim demographic and socioeconomic characteristics. These models do not rely on assumptions of linearity or normal distribution often violated in regression analysis, as this can lead to biased interpretations of the parameter estimates (Magidson and Vermunt, 2004).

All characteristics used to estimate the latent classes were categorical. The list includes age (less than 65 / age 65 or older), sex (male / female), race (white / non-white), marital status (married / divorced or separated / widowed / never married), education (less than college / some college or more), and total household wealth. Total household wealth was divided into quartiles based on the overall income distribution of the pooled victim sample: 1=less than $87,780; 2=$87,781-$309,824; 3=$309,825-$826,880; and 4=$826,881 or more). Figure 1 presents the latent class model.

*Figure 1 here*

We used *SAS V9.4* to identify the number of distinct victim subtypes (classes, $k$) in the pooled sample of victims who reported fraud in the 2008, 2010, and 2012 LBQs (the number of observation is 5,362, 6,043, and 438 for 2008, 2010 and 2012, respectively, for a total sample of 11,843 observations. This analysis also estimates the relative size of each subtype (proportion of victims within each subtype, $\gamma$,), and the distribution of characteristics within each subtype (probability of each characteristic based on subtype membership, $\rho$). Using stepwise addition, $k$+1 classes were added until the best solution for the data was reached (Lanza and Rhoades, 2013). The optimal value of $k$ was determined based on an assessment of which model, e.g., four classes versus five classes, offered the most parsimonious grouping of individuals into subtypes and on four indicators of model fit: the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), relative entropy, and the Likelihood Ratio Statistic ($G^2$). Lower AIC, BIC, and $G^2$ values are preferred.[7] The optimal class solution has high relative entropy, low AIC and BIC

[7] Relative entropy is a measure from 0 to 1 of how well individuals are assigned to their latent classes. A value of 1 means that respondents are perfectly assigned to into one and only one latent class, indicating excellent class differentiation. Values close to 0 indicate uncertainty in classification. The bootstrap likelihood ratio test (BLRT) assesses the relative improvement in fit between nested models such as a model with $k$ classes (e.g., four victim subtypes) versus a smaller model with $k$-1 classes (e.g., three victim subtypes).

values, and a $G^2$ value that is significantly smaller than the $G^2$ value of the $k$-1 model based on the BLRT results. As important, the characteristics of victims within a subtype should be distinct from the characteristics of victims assigned to other subtypes. In other words, the subtypes must be qualitatively and conceptually distinct.

**Outcomes from fraud victimization.** Ordinary least squares (OLS) regression models were used to determine the effects of victimization on cognitive functioning, depression, non-housing wealth, and net housing wealth, controlling for baseline status. Because self-rated health was coded dichotomously (poor/fair = 0; good/very good/excellent = 1), fraud's impact on self-rated health was estimated using Probit regression. All outcome (post-fraud) variables were measured in 2008, 2010, and 2012 as part of the core HRS, and these corresponded to when the participant completed the LBQ. As mentioned earlier, all baseline data were drawn from the corresponding HRS core survey administered six years before (i.e., 2002, 2004, or 2006). A dichotomous fraud victimization indicator is included as an independent variable in each of these models. As with the Probit models for fraud victimization, OLS models were weighted and estimated separately for the 2008, 2010, and 2012 LBQ samples, as well as the pooled sample.

## Results

### *Descriptive statistics*

Table 1 presents the characteristics of the 2008, 2010, and 2012 respondent samples and the pooled sample. Over half (54%) of respondents completed the LBQ in 2010, followed by 2008 (41%). Only 5% of respondents in the sample completed the 2012 LBQ. The latter individuals were either new to the HRS or did not complete the LBQ in 2008 or 2010. The fraction of persons reporting they had been the victims of fraud within the five-year retrospective window was 4% (in

2008), 5% (in 2010), and 7% (in 2012). The overall rate for the pooled sample was 5%. These figures are less than half the national prevalence rate for all U.S. adults that was estimated for 2011 (Anderson, 2013), but similar to AARP's finding that 4% of adults ages 45 years and older were victims of a major consumer swindle in the past year (AARP, 2003). Both the AARP survey and the HRS used a single item to estimate fraud prevalence, whereas studies that report higher prevalence rates use multiple items to ask about specific subtypes.

*Table 1 here*

Respondents for all three survey years combined (pooled sample) were 63.2 years old (SD= 9.6), on average, at baseline; 45% were male, 71% were married, 88% were White, and 6% reported that they were Hispanic or Latino. On average, respondents had 12.9 years of education (SD = 3.0) and 3 children (SD=2.0). At baseline, respondents scored an average of 1.4 (SD = 1.9) on the CES-D, with average cognitive functioning of 24.0 (SD = 4.5). Mean household net wealth was $569,209 (SD = $1,210,342), net housing wealth $376,051 (SD = $1,041,735), and non-housing net wealth $376,051 (SD = $1,041,735).

Follow-up was measured from the close of the five-year fraud reporting window. At that point, the average CES-D score for the pooled sample was 1.4 (SD = 2.0), cognitive functioning averaged 22.9 (SD = 4.9), total household net wealth was $507,679 (SD = $1,181,200), net housing wealth was $173,511 (SD = $411,076), and non-housing net wealth was $334,167 (SD = $934,145). Eighty percent of the sample reported good/excellent health at baseline, while 74% reported having this health status at follow-up.

***Predictors of fraud***

Results from the Probit models of fraud victimization appear in Table 2. Our results indicate that there is considerable variability in risk factors by survey year. For instance, in 2008, 2010, and the pooled samples, age was negatively associated with fraud victimization. As age increased, the likelihood of reporting fraud occurring between one and six years after baseline decreased ($\beta_{pooled}$= -.001, $p$ < .001). Males were more likely to report victimization than females, but only among the 2012 respondents ($\beta_{2012}$= .026, $p$ < .01) and the pooled sample ($\beta_{pooled}$= .009, $p$ < .05). Educational attainment was significant in the 2010 sample and the pooled sample, such that as years of education increase the likelihood of reporting fraud increases ($\beta_{pooled}$= .004, $p$ < .001). Experiencing more symptoms of depression was also a significant predictor of fraud among the 2010 respondents ($\beta_{2010}$= .004, $p$ < .01) and the pooled sample ($\beta_{pooled}$= .003, $p$ < .01). Number of children and net housing wealth were the only significant predictors of fraud among respondents in the 2012 sample: $\beta_{2012}$= .003, $p$ < .01 and $\beta_{2012}$= .002, $p$ < .01, respectively. In the 2010 sample, good/excellent self-rated health was negatively associated with fraud occurring between one and six years after baseline ($\beta_{pooled}$= -.017, $p$ < .05). While in specific sub-samples some of the factors were associated with reporting fraud victimization, overall results suggest that there is no single reliable predictor of fraud victimization using longitudinal data from the HRS. The most robust predictor of fraud was younger age, consistent with cross-sectional survey research (Anderson, 2013; Schoepfer and Piquero, 2009; Titus Heinzelmann and Boyle, 1995).

*Table 2 here*

***Results from latent class analysis***

**Model selection:** Fit statistics for latent class solutions one through five are presented in Table 3. Overall, none of the class solutions offered excellent differentiation of the fraud victims. Classification certainly (relative entropy) was also low, suggesting that fraud victims did not fall into clear demographic subtypes. Still, the four-class solution offered the best delineation of fraud victims into groups.

*Table 3 here*

From the one- to five-class solutions, $G^2$ values decreased and the BLRT results showed a statistically significant improvement in model fit ($p$ < .001). The AIC value was lower in the four-class solution compared to the two-class solution (269 versus 304), and the three-class solution (277). There was little decrease in the AIC value in the five-class model (266), suggesting that this was not a better fit for the data. The BIC value in the four-class solution was 454, higher than the two-class (395) and three-class (415) solutions, but BIC penalizes models having more parameters. Because of this penalization, the BIC statistic provides a useful "upper bound" indicator for selecting the optimal class solution (Lanza and Rhoades, 2013). Relative entropy values were higher for the three- and four-class solutions (both 0.71) compared to the two-class (0.62) and the five-class (0.65) solutions.

An equally important criterion for determining the optimal number of latent classes is the interpretability, or plausibility, of the subtypes within a latent class solution. This assessment is based on the conditional probabilities *($\rho$)* within each subtype. Conditional probabilities represent the likelihood that a person assigned to a given subtype has a particular characteristic, such as the probability that a person in subtype 1 is male, or the probability that a person in subtype 3 is married. It is desirable to have $\rho$ values that are close to 0 (low probability that a person possess that characteristic) or 1 (high probability that a person possess that characteristic). If $\rho$ values are near 0.5, the probability of having that characteristic is near random chance and that subtype is poorly differentiated on that characteristic. Thus, high homogeneity on the $\rho$ estimates suggests that each subtype is comprised of individuals well-differentiated by the characteristics selected to estimate the latent class model. In this analysis, item homogeneity was greater in the four-class solution than the three-class solution, and the distribution of $\rho$ values in the four-class solution was more plausible than the five-class solution.

**Victim subtypes:** The results of the four-class solution appear in Figures 2 and 3. First we report the relative size of each of the four classes *($\gamma$)*, or the proportion of the victims within each subtype. Second, we present the distribution of probabilities for each socioeconomic/ demographic characteristic according to victim subtype.

*Figures 2 and 3 here*

We assigned the four victim subtypes descriptive labels based on the distribution of conditional probabilities. Subtype 1, labeled *Low-education White married couples*, have a high probability of being White ($\rho$=.96) and married ($\rho$=.91), and a low probability of having a college education or more ($\rho$=.03). This group is the largest subtype and comprises 40% of all fraud victims in the HRS sample. They were not well-differentiated on age, gender, or wealth. Subtype 2, *Low-income young widows,* is the smallest subtype with only 12% of victims. The probability that a person in Subtype 2 was younger than age 65 is $\rho$=.78, and the probability that this person was a widow is $\rho$=.79. Subtype 3, *Low-income older adults*, comprised one-quarter of the victims (24%). This group was likely to be age 65 and older ($\rho$=.85), and in the lowest wealth quartile ($\rho_{Q1}$ = .58 versus $\rho_{Q4}$ = 0.002). Subtype 4, *High education older White married couples,* also made up 24% of the victims. These individuals had the highest probability of attaining a college education ($\rho$ = .94) and being White ($\rho$ = .95). The majority of them were in the two highest wealth quartiles ($\rho_{Q4}$ = .49 and $\rho_{Q3}$ = .31).[8]

As we can see from these four subtypes, most fraud (~75%) is perpetrated against vulnerable groups, such as widows and older couples who do not necessarily have a lot of financial

[8] Conditional probabilities for the three-class and five-class solutions are available on request from the authors.

resources or education. Although these targets do not offer the same financial returns as wealthier targets, they nevertheless suffer financially or emotionally and may be easier to manipulate because of their more fragile social and economic status.

***Impact of fraud victimization on physical and mental health and wealth status***

Table 4 presents a summary of the impact of fraud victimization on health and wealth measures controlling for baseline status. Fraud had no consistent effect on any of these outcomes across all survey years, but was significant in some samples. For example, fraud victims in the 2008 LBQ sample (who experienced fraud between 2003 and 2008) had poorer cognitive functioning at follow-up compared to non-victims ($\beta_{2008}$= -0.623, $p$ <.05) controlling on baseline characteristics in 2002, yet fraud was not associated with cognitive functioning for either the 2010 or 2012 waves, nor in the pooled sample. Fraud victimization was also not significantly associated with declines in self-rated health or increase in symptoms of depression in any sub-sample or the pooled sample after controlling for baseline physical and mental health status and demographic characteristics.

In both 2008 and the pooled sample, those who reported being victimized had less non-housing wealth, controlling for other factors ($\beta_{2008}$= -0.881, $p$ <.05 and $\beta_{pooled}$ = -0.827, $p$ <.01). Fraud victimization occurring sometime between 2005 and 2010 was negatively associated with net housing wealth measured in 2010, after controlling for baseline wealth and other characteristics ($\beta_{2010}$ = -0.396, $p$ <.01), but did not have a significant impact on housing wealth in the 2008, 2012, or in the pooled LBQ samples ($\beta_{pooled}$= -0.157).[9]

*Table 4 here*

[9] Detailed results of OLS and probit regression models estimating the impact of fraud on each outcome measure are presented in Appendix Tables 1 through 5.

## Discussion

Though media reports (e.g., Lewis, 2012; Lloyd, 2012) have stated that older people are more susceptible than younger persons to fraud, our research provides a more nuanced set of conclusions. In particular, we see variability in the demographic, economic, and health characteristics associated with fraud victimization in the older population across survey years. For example, the risk associated with being male, in fair/poor health, and having more housing wealth differed across the 2008, 2010, and 2012 LBQ samples. Results of the latent class analysis using the pooled sample also suggest that victims cannot be classified precisely into distinct subtypes. Entropy was 71% for the four-class model and many of the demographic traits within subtypes were not well-differentiated: conditional probabilities were often close to 0.50 instead of 0 or 1.

Taken together, our results suggest that there are no unique risk profiles that characterize older fraud victims in the U.S. A probable explanation for these findings is that fraud susceptibility, in general, is not specific to a particular demographic group. A variety of fraud schemes target different individuals who face particular life circumstances or engage in consumer behaviors that make them either more accessible to perpetrators or more susceptible to persuasion. In other words, anyone may become a victim under the right circumstances and incentives.

While there has been considerable research exploring potential risk factors for fraud, no studies have previously used longitudinal data to understand the consequences of victimization, while controlling for baseline status. Most outcome studies are retrospective: that is, victims are asked to recall how the fraud incident affected their sense of well-being and their financial status (e.g., FINRA Investor Education Foundation, 2015; DeLiema, Mottola, Deevy, 2017). Our study is unique in using panel data to control for baseline characteristics, and it shows that there is no single unique outcome associated with reporting being defrauded.

Previous authors who profiled victims according to the type of fraud experienced tend to agree that people victimized by different scams have different social and demographic characteristics. For example, the Consumer Fraud Research Group (2006) and Pak and Shadel (2011) reported that not only do victims of investment fraud and bogus lotteries differ demographically and socioeconomically from non-victims, they also differ from one another. Compared to the general adult population, prize promotion victims are more likely to be single, female, less educated, and have an annual income of less than $50,000; by contrast, investment fraud victims are more likely to be male, better educated, and have an annual income of over $50,000 (Pak and Shadel, 2011). These victim profiles partially overlap with two of the victim subtypes identified in our study using LCA: Subtype 4—*High education older White married couples*, and Subtype 2—*Low-education young widows*.

The notion that people's life circumstances and behaviors can impact scam susceptibility is consistent with *routine activity theory* (Cohen and Felson, 1979). Applied to the context of financial fraud (DeLiema, 2017; Holtfreter, Reisig, and Pratt, 2008), routine activity theory proposes that day-to-day behaviors/routines affect the likelihood that motivated offenders will intersect in space and time with suitable targets in the absence of capable guardianship (or measures of protection). For example, consumers who engage in risky behaviors such as responding to telemarketers, opening spam mail, and making frequent online purchases, are more likely to be exposed to scams (AARP, 1996; Reisig and Holtfreter, 2013; Van Wyk and Benson, 1997).

Routine activity theory also posits that the "attractiveness" of a potential victim will influence the likelihood that someone is targeted by a motivated offender. Older adults with physical or mental health problems, along with those who are cognitively impaired, may be seen as attractive targets because of their presumed functional and psychological vulnerability. In the HRS, baseline health and cognitive functioning were *not* associated with victimization, but depression symptoms were statistically significant. Lichtenberg, Stickney, and Paulson (2013) also found that depression measured in the HRS in 2002 was a significant predictor of fraud occurring sometime between 2003 and 2008. This is consistent with our findings using the 2010 LBQ respondents (baseline = 2004 survey) and in the pooled sample. Lichtenberg et al. (2013) speculated that self-reported symptoms of depression reflect disappointment over discrepancies between a person's expectations for her life and the realities of her current situation. Based on this interpretation, a scam artist's promise to transform financial status or improve emotional well-being may hold greater appeal for those in a depressed psychological state, causing them to be more open to accepting a fraudulent offer.

A potential victim's perceived wealth or economic status is another factor that may increase his or her attractiveness to financial predators. Although we found no consistent relationship between wealth variables and fraud across survey years, prior analysis by the FTC (Anderson, 2013) found that there was roughly a U-shaped association between income and fraud, such that rates of victimization were highest at both upper and lower levels of household income. Adults living in middle income households ($40,000-$60,000 per year) reported the lowest rates of victimization (Anderson, 2013). Perhaps the types of fraud targeting low-income persons differ from those focusing on the high-income. For instance, people facing financial hardship may consider prize promotions and debt consolidation services as opportunities to improve their financial situation, whereas wealthy socialites might purchase bogus weight-loss products or anti-aging remedies.

Further evidence that different types of fraud appeal to different types of people was found by Schoepfer and Piquero (2009) in a telephone survey of US adults. They reported that being unemployed was associated with victimization by free prize and 800/900-number phone fraud, but not auto-repair or investment fraud. The only consistent demographic factor associated with nearly all scam types was being younger, a conclusion we also support in the present study (where most respondents were middle-aged and older).

Another postulate of routine activity theory is that criminal activity is more likely to occur when targets lack appropriate guardianship or protective oversight. Shafer and Koltai (2014) found that older people with dense social networks were less likely to experience elder mistreatment, perhaps because network members deterred each other from exerting power and undue influence over vulnerable older persons. Network density was not measured in the HRS, but two proxy variables for social oversight, being married and the respondent's number of children, were not significantly associated with lower rates of reporting fraud in the overall sample.

In our research using the HRS, few characteristics were systematically and significantly associated with fraud across survey years, consistent with other surveys that rely on self-report (Anderson, 2013; Policastro and Payne, 2014; Schoepfer and Piquero 2009; Titus, Heinzelmann, and Boyle, 1995; Van Wyk and Mason, 2001). Yet being older was negatively associated with fraud in 2008, 2010, and in the overall sample, findings that contradict the common assumption that vulnerability increases with age, perhaps due to cognitive decline or detrimental changes in information processing (e.g., Castle et al., 2012; James, Boyle, and Bennett, 2014; Han et al., 2015). Moreover, we find that cognitive functioning at baseline was unrelated to fraud victimization in the HRS, while victimization risk rose for the better educated. It may be, as suggested by routine activity theory, that middle-aged adults and the better-off experience the highest rates of fraud because consumption peaks in middle-age. These groups participate most actively in the consumer marketplace providing opportunities for fraud exposure (Attanasio, Banks, Meghir, and Weber, 1999; Van Wyk and Mason, 2001).

An alternative explanation is that older adults may actually experience higher rates of fraud but fail to report victimization to complaint agencies, law enforcement, and in surveys such as the HRS. Underreporting could be prevalent if older people's subjective memory of past events declines with age (Craik, 1994). Also, older adults have a greater tendency to minimize emotionally negative experiences, and to remember autobiographical events more positively than do younger adults (Charles and Carstensen, 2010). They may also choose to hide victimization because of shame, embarrassment, or a belief that they are partially to blame for being complaisant in the scam (Deem, 2000; Ganzini, McFarland, and Bloom, 1990), and disclosure of victimization could lead to a loss of financial independence. Thus, analysis that relies on victim self-report may underestimate the frequency of fraud among older adults.

**Limitations of the study**

Victimization may have a serious impact on well-being that could only be measured imprecisely in this study, due to the infrequency with which HRS participants were surveyed and the long interval between baseline and follow-up. This study used baseline data from the core survey administered *six* years before respondents completed the LBQ regardless of when fraud may have happened during that time frame. Moreover, we did not model differences in outcomes based on when fraud occurred. Compared to respondents who were victimized soon after baseline, those who experienced fraud nearer to follow-up may still be recovering from the incident. In these cases, the psychological and financial effects of fraud may be more pronounced.

In other words, a five-year retrospective window may be too long for some older respondents to remember victimization, and one might expect higher rates of underreporting especially among participants with memory problems. Future surveys should ask respondents to report fraud that happened in just the last year, in addition to their experiences with fraud over longer spells. Despite the frustration, embarrassment, and loss of confidence that fraud inflicts (Deem, 2000), the financial and emotional aftermath of victimization may feel like a momentary dip in well-being over a multi-year period. These short-term effects and life disruptions may not be well-captured using a longer measurement period, and a narrower observation window would help us understand the immediate impact of victimization (though we may end up with a small number of respondents who experienced fraud).

Financial fraud is defined very broadly across legal, consumer, and academic contexts. Individual conceptualizations/interpretations of fraud victimization vary across consumers (DeLiema, Mottola, and Deevy, 2017). Some respondents may have reported fraud victimization when they were targeted by a scam but experienced little to no financial consequences, whereas others who suffered large losses may not label the experience as fraud. A major limitation of the LBQ was that victims were not asked to report how much money they lost or the type of fraud they experienced, so it is not possible to distinguish serious incidents, such as loss of retirement assets in a Ponzi scheme, from minor incidents, such as being billed a reoccurring fee for a bogus magazine subscription. Having data on the amount of money lost allows for an assessment of how losses, relative to current wealth, impact the victim's financial, mental, and physical well-being.

Previous research has shown that victim profiles vary by scam type. More details on the type of fraud would allow for a more refined analysis of risk factors. This issue will be resolved in a future study using data from the 2016 HRS module on fraud that we designed and that was administered to randomly selected HRS respondents. We will conduct separate analyses to identify whether risk factors differ according to fraud type (e.g., investment scams versus bogus sweepstakes). Another limitation of the present study is that the LBQ survey did not ask respondents about their lifetime experiences with fraud. As a result, those who were defrauded more than five years in the past are categorized as non-victims in the analysis, even if they might share some of the same risk profiles as recent victims. And finally, the LBQs are not administered to people living in institutions or to those who are too cognitively or physically impaired to complete the survey. For this reason, the analysis excludes potentially the most vulnerable adults who may be explicitly targeted by financial predators.

**Conclusions and Outstanding Research Questions**

A major advantage of the present study over prior telephone or internet surveys is that it relies on prospective longitudinal data to explore the antecedents and consequences of fraud victimization. Aside from a consistent negative association between age and risk of fraud victimization, we found considerable variability in the predictors and outcomes of fraud across survey years. There appears to be no simple set of “vulnerability traits” that can inform targeted prevention and intervention programs. Moreover, our results indicate that using a single item to measure fraud is insufficient to evaluate victimization more broadly. For this reason, more specific questions such as those included in the 2016 HRS fraud module, will be useful in estimating risk correlates for a wider variety of fraud schemes targeting older Americans.

Meanwhile, our findings will be of interest to the financial services industry as well as regulators concerned with protecting older Americans’ financial wellbeing (e.g., the Securities and Exchange Commission, the Financial Industry Regulatory Authority, the Consumer Financial

Protection Bureau, the Social Security Administration, and the National Association of Insurance Commissioners, among others). Many of these entities have expressed growing concern about how advisors, investment counsellors, and employers are managing workers' and retirees' difficulties with making financial decisions at older ages.[10] Older persons' vulnerability to financial mismanagement is also particularly important as they decide when to claim Social Security benefits, spend down company pensions, downsize their homes, purchase health and longevity insurance, and undertake other financial transactions, all decisions which are consequential and can affect the financial security of older Americans. Our research indicates there is large variability among the characteristics of those who experienced fraud and that not just the wealthy and oldest adults can suffer from fraud. Thus, it is very important for regulatory authorities to be vigilant for large strata of the population and to equip and educate individuals, even the younger ones in the adult population, to protect themselves against fraud.

[10]For instance see FINRA, SEC, and NASAA (2008, updated 2010).

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**Table 1. Characteristics of the HRS analysis sample**

| | 2008 | | 2010 | | 2012 | | Pooled | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Sd.Dev.** | **Mean** | **Sd.Dev.** | **Mean** | **Sd.Dev.** | **Mean** | **Sd.Dev.** |
| Fraud victim | 0.04 | 0.21 | 0.05 | 0.22 | 0.07 | 0.25 | 0.05 | 0.22 |
| self-reported good health | 0.71 | 0.45 | 0.75 | 0.43 | 0.70 | 0.46 | 0.73 | 0.44 |
| Cognition score | 22.27 | 5.20 | 22.72 | 4.90 | 21.21 | 6.08 | 22.47 | 5.10 |
| CESD score | 1.34 | 1.87 | 1.29 | 1.89 | 1.56 | 2.20 | 1.33 | 1.90 |
| Nonhousing wealth (/100K, 2012$) | 3.94 | 10.73 | 3.80 | 9.02 | 3.61 | 9.32 | 3.85 | 9.77 |
| Housing wealth (/100K, 2012$) | 2.22 | 6.50 | 1.79 | 3.26 | 1.57 | 2.68 | 1.96 | 4.85 |
| Age | 64.86 | 9.07 | 62.06 | 9.87 | 62.48 | 9.35 | 63.23 | 9.62 |
| Male | 0.42 | 0.49 | 0.43 | 0.50 | 0.50 | 0.50 | 0.43 | 0.50 |
| White | 0.88 | 0.32 | 0.88 | 0.33 | 0.77 | 0.42 | 0.88 | 0.33 |
| Hispanic | 0.06 | 0.24 | 0.06 | 0.24 | 0.10 | 0.30 | 0.06 | 0.25 |
| Education year | 12.67 | 3.06 | 13.12 | 2.90 | 12.73 | 3.46 | 12.91 | 3.00 |
| Married | 0.68 | 0.47 | 0.73 | 0.44 | 0.70 | 0.46 | 0.71 | 0.45 |
| Nkids | 3.20 | 2.11 | 2.89 | 1.91 | 3.17 | 2.03 | 3.03 | 2.00 |
| Cognition score | 24.06 | 4.61 | 24.11 | 4.34 | 22.46 | 5.45 | 24.01 | 4.52 |
| CESD score | 1.38 | 1.90 | 1.30 | 1.88 | 1.72 | 2.04 | 1.35 | 1.90 |
| Good health | 0.79 | 0.40 | 0.80 | 0.40 | 0.74 | 0.44 | 0.80 | 0.40 |
| Nonhousing wealth (/100K, 2012$) | 3.45 | 9.19 | 3.94 | 10.83 | 4.39 | 14.79 | 3.76 | 10.42 |
| Housing wealth (/100K, 2012$) | 1.75 | 2.57 | 2.05 | 3.70 | 2.24 | 3.86 | 1.93 | 3.30 |
| LBQ08 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.41 | 0.49 |
| LBQ10 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.54 | 0.50 |
| LBQ12 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.05 | 0.21 |
| N | 5,180 | | 5,867 | | 414 | | 11,461 | |

Note: This table reports means and standard deviations of the variables used in our empirical work using several waves of the HRS.

**Table 2. Probit models of fraud victimization**

| | 2008 | 2010 | 2012 | Pooled |
|---|---|---|---|---|
| Age | -0.001 ** | -0.001 *** | -0.001 | -0.001 *** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Male | 0.004 | 0.006 | 0.026 ** | 0.009 * |
| | (0.007) | (0.006) | (0.010) | (0.005) |
| White | 0.002 | 0.007 | -0.003 | 0.005 |
| | (0.010) | (0.010) | (0.009) | (0.007) |
| Hispanic | 0.008 | 0.004 | 0.016 | 0.008 |
| | (0.017) | (0.017) | (0.023) | (0.012) |
| Education year | 0.002 | 0.005 *** | 0.001 | 0.004 *** |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| Married | -0.004 | 0.002 | -0.006 | -0.002 |
| | (0.009) | (0.008) | (0.009) | (0.006) |
| Nkids | 0.000 | -0.001 | 0.003 ** | 0.000 |
| | (0.002) | (0.002) | (0.002) | (0.001) |
| Cognition score | 0.000 | 0.001 | -0.001 | 0.000 |
| | (0.001) | (0.001) | (0.001) | -0.001 |
| CESD score | 0.002 | 0.004 ** | 0.002 | 0.003 ** |
| | (0.002) | (0.002) | (0.002) | (0.001) |
| Good health | -0.001 | -0.017 * | 0.009 | -0.006 |
| | (0.009) | (0.010) | (0.008) | (0.007) |
| Nonhousing wealth (/100K, 2012$) | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Housing wealth (/100K, 2012$) | 0.001 | 0.000 | 0.002 ** | 0.001 |
| | (0.002) | (0.001) | (0.001) | -0.001 |
| LBQ10 | | | | 0.002 |
| | | | | (0.005) |
| LBQ12 | | | | 0.012 |
| | | | | (0.015) |
| N | 5,180 | 5,867 | 414 | 11,461 |
| R-square | 0.017 | 0.035 | 0.200 | 0.026 |
| Mean of dep var | 0.045 | 0.053 | 0.065 | 0.050 |
| St.dev of dep var | 0.207 | 0.225 | 0.247 | 0.219 |

Note: * p<0.10, ** p<0.05, *** p<0.01

Controlled with missing dummies, clustered on household

**Table 3. Indicators of model fit for latent class solutions two through five**

| | Number of classes (*k*) | | | |
|---|---|---|---|---|
| **Indicators of model fit** | **2** | **3** | **4** | **5** |
| G-squared | 262.95 | 213.36 | 183.18 | 159.5 |
| AIC | 304.95 | 277.36 | 269.18 | 267.5 |
| BIC | 395.07 | 414.69 | 453.72 | 499.24 |
| Entropy | 0.62 | 0.71 | 0.71 | 0.65 |
| Log-likelihood | -2416.18 | -2391.39 | -2376.3 | -2364.46 |
| Degrees of freedom | 234 | 223 | 212 | 201 |

Note: Lower values of AIC, BIC, and G-squared are preferred.

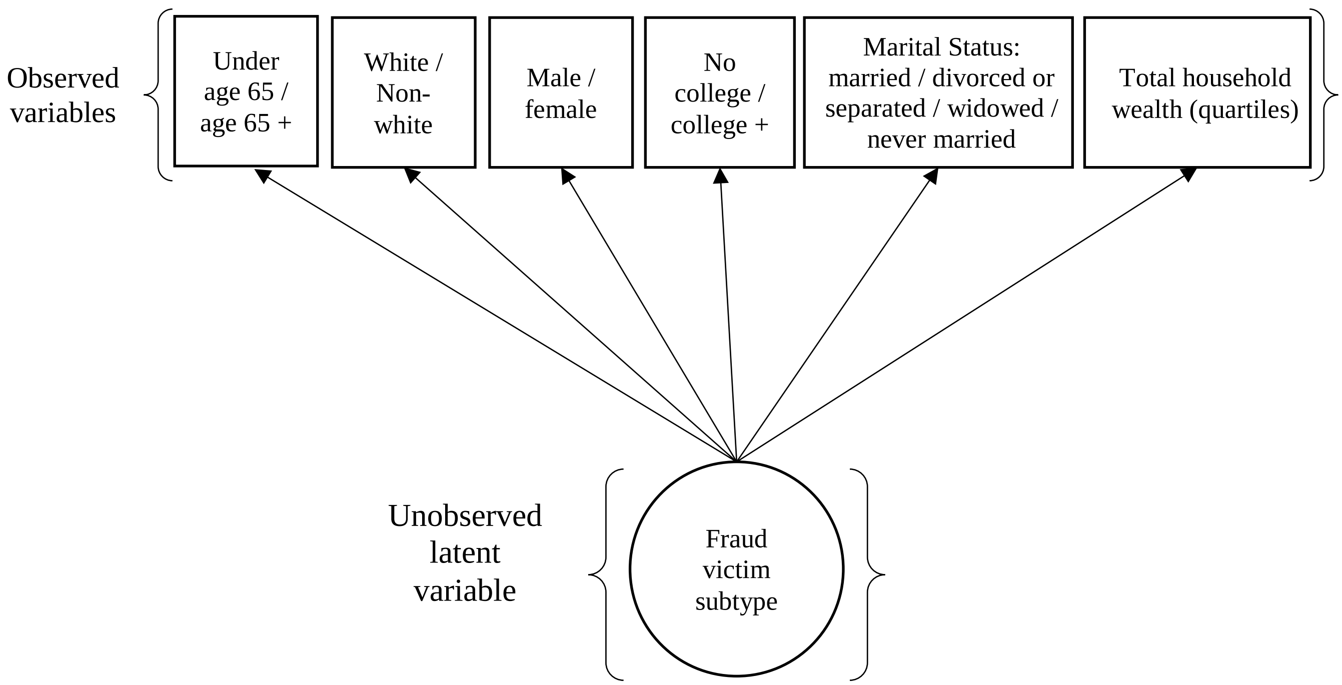
**Table 4. Summary of health and wealth measures regressed on self-reported fraud victimization**

| | **Impact of fraud victimization on outcome measure (victim=1)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent (outcome) measure | 2008 | | 2010 | | 2012 | | Pooled | |
| Self-rated good/excellent health | 0.045 | | -0.029 | | 0.040 | | 0.003 | |
| | (0.037) | | (0.032) | | (0.116) | | (0.024) | |
| Cognitive functioning | -0.623 | * | 0.120 | | 1.524 | | -0.041 | |
| | (0.333) | | (0.173) | | (1.069) | | (0.172) | |
| CESD score | -0.066 | | 0.181 | | -0.414 | | 0.056 | |
| | (0.117) | | (0.144) | | (0.295) | | (0.095) | |
| Net housing wealth (/100K, 2012$) | 0.270 | | -0.396 | ** | -0.052 | | -0.157 | |
| | (0.299) | | (0.187) | | (0.451) | | (0.182) | |
| Non-housing wealth (/100K, 2012$) | -0.881 | * | -0.743 | | -1.335 | | -0.827 | ** |
| | (0.525) | | (0.505) | | (1.963) | | (0.362) | |
| N | 5,180 | | 5,867 | | 414 | | 11,461 | |

Note: * p<0.10, ** p<0.05, *** p<0.01

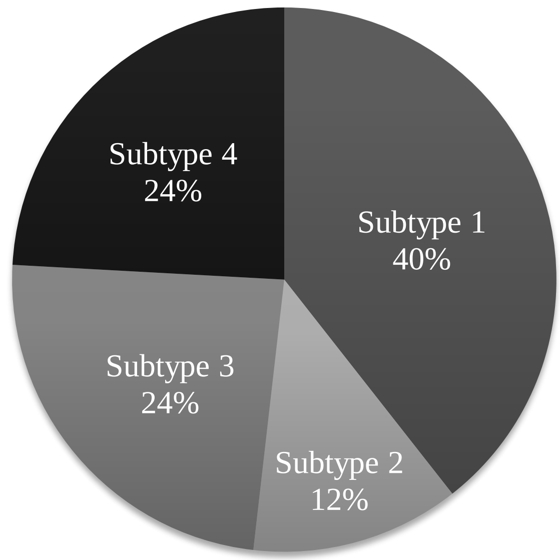
The impact of fraud victimization on health and wealth status was assessed in separate OLS or probit regression models for each of these measures. All models control for health and wealth status at baseline (survey administered six years before the LBQ), sex, age, race (White/non-White), ethnicity (Hispanic/non-Hispanic), education, marital status (married/not married), and number of children.

**Figure 1. Latent class analysis model estimating fraud victim subtypes**



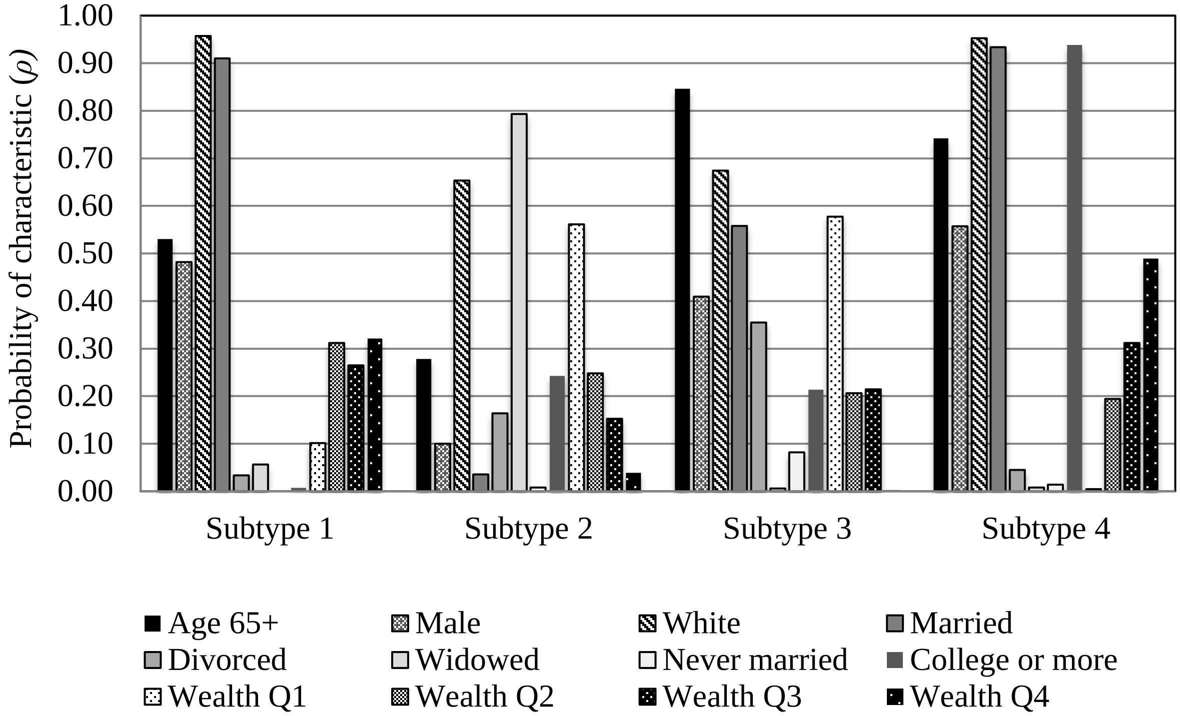

Source: Authors' latent class analysis framework using the HRS.

**Figure 2. Relative proportion of respondents in each fraud victim subtype (*γ*)**




Note: Subtype 1= "*Low-education White married couples"*; Subtype 2= "*Low-income young widows"*; Subtype 3= "*Low-income older adults"*; Subtype 4= *"High education older White married couples"*

**Figure 3. Conditional probabilities ($\rho$) of demographic characteristics based on fraud victim subtype**




Note: $Wealth_{Q1}$=less than \$87,780; $Wealth_{Q2}$=\$87,781-\$309,824; $Wealth_{Q3}$=\$309,825-\$826,880; $Wealth_{Q4}$=\$826,881 or more

**Appendix Table 1. Probit models of self-reported good health**

| | 2008 | 2010 | 2012 | Pooled |
|---|---|---|---|---|
| Fraud victim | 0.045 | -0.029 | 0.040 | 0.003 |
| | (0.037) | (0.032) | (0.116) | (0.024) |
| Age | -0.002 * | -0.002 *** | -0.002 | -0.002 *** |
| | (0.001) | (0.001) | (0.003) | (0.001) |
| Male | -0.036 ** | -0.020 | -0.042 | -0.029 *** |
| | (0.017) | (0.014) | (0.059) | (0.011) |
| White | 0.017 | 0.006 | 0.031 | 0.012 |
| | (0.025) | (0.020) | (0.062) | (0.015) |
| Hispanic | -0.054 | -0.016 | 0.016 | -0.027 |
| | (0.035) | (0.030) | (0.083) | (0.022) |
| Education year | 0.018 *** | 0.009 *** | 0.018 * | 0.013 *** |
| | (0.003) | (0.003) | (0.010) | (0.002) |
| Married | 0.017 | 0.032 * | 0.046 | 0.025 * |
| | (0.019) | (0.017) | (0.061) | (0.013) |
| Nkids | -0.001 | -0.005 | 0.009 | -0.003 |
| | (0.004) | (0.003) | (0.014) | (0.003) |
| Cognition score | 0.009 *** | 0.007 *** | -0.009 | 0.007 *** |
| | (0.002) | (0.002) | (0.006) | (0.001) |
| CESD score | -0.032 *** | -0.028 *** | -0.025 * | -0.030 *** |
| | (0.004) | (0.004) | (0.015) | (0.003) |
| Good health | 0.424 *** | 0.405 *** | 0.376 *** | 0.410 *** |
| | (0.021) | (0.021) | (0.072) | (0.015) |
| Nonhousing wealth (/100K, 2012$) | 0.001 | 0.000 | 0.007 | 0.001 |
| | (0.001) | (0.001) | (0.007) | (0.001) |
| Housing wealth (/100K, 2012$) | 0.011 ** | 0.009 | 0.013 | 0.010 ** |
| | (0.005) | (0.005) | (0.012) | (0.004) |
| LBQ10 | | | | 0.028 *** |
| | | | | (0.011) |
| LBQ12 | | | | 0.025 |
| | | | | (0.027) |
| N | 5,180 | 5,867 | 414 | 11,461 |
| R-square | 0.235 | 0.233 | 0.214 | 0.231 |
| Mean of dep var | 0.708 | 0.753 | 0.700 | 0.733 |
| St.dev of dep var | 0.455 | 0.431 | 0.459 | 0.443 |

Note: * p<0.10, ** p<0.05, *** p<0.01

Controlled with missing dummies, clustered on household

**Appendix Table 2. OLS models of cognition score**

| | 2008 | 2010 | 2012 | Pooled |
|---|---|---|---|---|
| Fraud victim | -0.623 * | 0.120 | 1.524 | -0.041 |
| | (0.333) | (0.173) | (1.069) | (0.172) |
| Age | -0.118 *** | -0.117 *** | -0.171 *** | -0.120 *** |
| | (0.009) | (0.005) | (0.032) | (0.005) |
| Male | -0.557 *** | -0.031 | 0.172 | -0.214 *** |
| | (0.129) | (0.091) | (0.503) | (0.077) |
| White | 1.439 *** | 0.722 *** | 0.989 * | 1.071 *** |
| | (0.203) | (0.140) | (0.565) | (0.119) |
| Hispanic | 0.053 | 0.143 | 1.453 | 0.207 |
| | (0.277) | (0.216) | (0.893) | (0.173) |
| Education year | 0.326 *** | 0.200 *** | 0.274 *** | 0.258 *** |
| | (0.026) | (0.020) | (0.084) | (0.016) |
| Married | 0.002 | -0.027 | -0.449 | -0.069 |
| | (0.154) | (0.116) | (0.588) | (0.094) |
| Nkids | 0.076 ** | -0.023 | 0.156 | 0.029 |
| | (0.033) | (0.025) | (0.119) | (0.020) |
| Cognition score | 0.497 *** | 0.649 *** | 0.551 *** | 0.576 *** |
| | (0.017) | (0.015) | (0.053) | (0.011) |
| CESD score | -0.093 ** | -0.131 *** | -0.065 | -0.116 *** |
| | (0.039) | (0.028) | (0.120) | (0.023) |
| Good health | 0.755 *** | 0.281 ** | 1.242 ** | 0.540 *** |
| | (0.184) | (0.130) | (0.622) | (0.110) |
| Nonhousing wealth (/100K, 2012$) | -0.006 | -0.002 | 0.015 | -0.001 |
| | (0.007) | (0.004) | (0.010) | (0.004) |
| Housing wealth (/100K, 2012$) | 0.046 * | 0.010 | 0.099 | 0.021 |
| | (0.028) | (0.014) | (0.060) | (0.014) |
| LBQ10 | | | | -0.090 |
| | | | | (0.082) |
| LBQ12 | | | | -0.374 |
| | | | | (0.238) |
| Intercept | 12.050 *** | 11.070 *** | 13.132 *** | 11.732 *** |
| | (0.817) | (0.545) | (2.645) | (0.472) |
| N | 5,180 | 5,867 | 414 | 11,461 |
| R-square | 0.493 | 0.613 | 0.622 | 0.557 |
| Mean of dep var | 22.269 | 22.724 | 21.214 | 22.467 |
| St.dev of dep var | 5.202 | 4.899 | 6.078 | 5.097 |

Note: * p<0.10, ** p<0.05, *** p<0.01

Controlled with missing dummies, clustered on household

**Appendix Table 3. OLS models of depression (CESD) score**

| | 2008 | 2010 | 2012 | Pooled |
|---|---|---|---|---|
| Fraud victim | -0.066 | 0.181 | -0.414 | 0.056 |
| | (0.117) | (0.144) | (0.295) | (0.095) |
| Age | 0.007 ** | 0.006 ** | 0.012 | 0.007 *** |
| | (0.003) | (0.003) | (0.015) | (0.002) |
| Male | -0.112 ** | -0.134 *** | 0.082 | -0.112 *** |
| | (0.056) | (0.051) | (0.266) | (0.038) |
| White | -0.062 | 0.076 | -0.530 * | -0.020 |
| | (0.098) | (0.080) | (0.291) | (0.062) |
| Hispanic | -0.019 | -0.151 | 0.058 | -0.098 |
| | (0.140) | (0.108) | (0.378) | (0.085) |
| Education year | -0.023 ** | -0.029 *** | -0.003 | -0.025 *** |
| | (0.012) | (0.011) | (0.039) | (0.008) |
| Married | 0.005 | -0.045 | -0.596 * | -0.045 |
| | (0.066) | (0.066) | (0.359) | (0.048) |
| Nkids | -0.002 | -0.017 | -0.067 | -0.011 |
| | (0.013) | (0.013) | (0.056) | (0.009) |
| Cognition score | -0.018 ** | -0.020 *** | 0.015 | -0.018 *** |
| | (0.007) | (0.007) | (0.025) | (0.005) |
| CESD score | 0.420 *** | 0.446 *** | 0.454 *** | 0.436 *** |
| | (0.021) | (0.020) | (0.076) | (0.015) |
| Good health | -0.573 *** | -0.690 *** | -0.485 | -0.625 *** |
| | (0.088) | (0.085) | (0.343) | (0.061) |
| Nonhousing wealth (/100K, 2012$) | -0.007 *** | -0.003 * | 0.005 | -0.004 *** |
| | (0.002) | (0.002) | (0.006) | (0.001) |
| Housing wealth (/100K, 2012$) | -0.019 ** | -0.005 | -0.032 * | -0.010 ** |
| | (0.008) | (0.004) | (0.019) | (0.004) |
| LBQ10 | | | | 0.025 |
| | | | | (0.038) |
| LBQ12 | | | | 0.054 |
| | | | | (0.120) |
| Intercept | 1.644 *** | 1.846 *** | 1.234 | 1.715 *** |
| | (0.331) | (0.295) | (1.445) | (0.224) |
| N | 5,180 | 5,867 | 414 | 11,461 |
| R-square | 0.285 | 0.314 | 0.291 | 0.298 |
| Mean of dep var | 1.345 | 1.292 | 1.561 | 1.326 |
| St.dev of dep var | 1.873 | 1.887 | 2.198 | 1.897 |

Note: * p<0.10, ** p<0.05, *** p<0.01

Controlled with missing dummies, clustered on household

**Appendix Table 4. OLS models of non-housing wealth**

| | Nonhousing wealth (/100K, 2012$) | | | |
|---|---|---|---|---|
| | 2008 | 2010 | 2012 | Pooled |
| Fraud victim | -0.881 * | -0.743 | -1.335 | -0.827 ** |
| | (0.525) | (0.505) | (1.963) | (0.362) |
| Age | 0.011 | -0.025 | -0.026 | -0.012 |
| | (0.016) | (0.018) | (0.034) | (0.012) |
| Male | 0.211 | 0.088 | -0.456 | 0.078 |
| | (0.147) | (0.159) | (0.693) | (0.115) |
| White | -0.067 | 0.917 *** | 0.181 | 0.498 ** |
| | (0.379) | (0.264) | (0.814) | (0.231) |
| Hispanic | 0.537 * | -0.454 * | 0.389 | -0.075 |
| | (0.278) | (0.235) | (0.564) | (0.174) |
| Education year | 0.225 *** | 0.185 *** | 0.247 ** | 0.216 *** |
| | (0.073) | (0.051) | (0.125) | (0.041) |
| Married | 0.160 | 0.491 | 0.391 | 0.412 |
| | (0.390) | (0.305) | (0.739) | (0.254) |
| Nkids | -0.093 * | -0.013 | 0.021 | -0.061 |
| | (0.055) | (0.067) | (0.134) | (0.042) |
| Cognition score | 0.018 | 0.015 | -0.038 | 0.016 |
| | (0.028) | (0.028) | (0.086) | (0.020) |
| CESD score | 0.016 | -0.133 *** | -0.003 | -0.078 ** |
| | (0.051) | (0.052) | (0.144) | (0.036) |
| Good health | 0.519 * | 0.177 | 0.439 | 0.250 |
| | (0.290) | (0.211) | (0.489) | (0.158) |
| Nonhousing wealth (/100K, 2012$) | 0.628 *** | 0.395 *** | 0.201 * | 0.453 *** |
| | (0.229) | (0.076) | (0.118) | (0.079) |
| Housing wealth (/100K, 2012$) | 0.656 ** | 0.496 ** | 1.263 *** | 0.588 *** |
| | (0.313) | (0.222) | (0.459) | (0.191) |
| LBQ10 | | | | -0.729 *** |
| | | | | -0.199 |
| LBQ12 | | | | -0.992 ** |
| | | | | -0.47 |
| Intercept | -3.621 ** | -1.099 | -1.088 | -1.580 |
| | (1.804) | (1.570) | (3.339) | (1.180) |
| N | 5,180 | 5,867 | 414 | 11,461 |
| R-square | 0.425 | 0.381 | 0.558 | 0.388 |
| Mean of dep var | 3.943 | 3.797 | 3.613 | 3.848 |
| St.dev of dep var | 10.730 | 9.023 | 9.319 | 9.774 |

Note: * p<0.10, ** p<0.05, *** p<0.01

Controlled with missing dummies, clustered on household

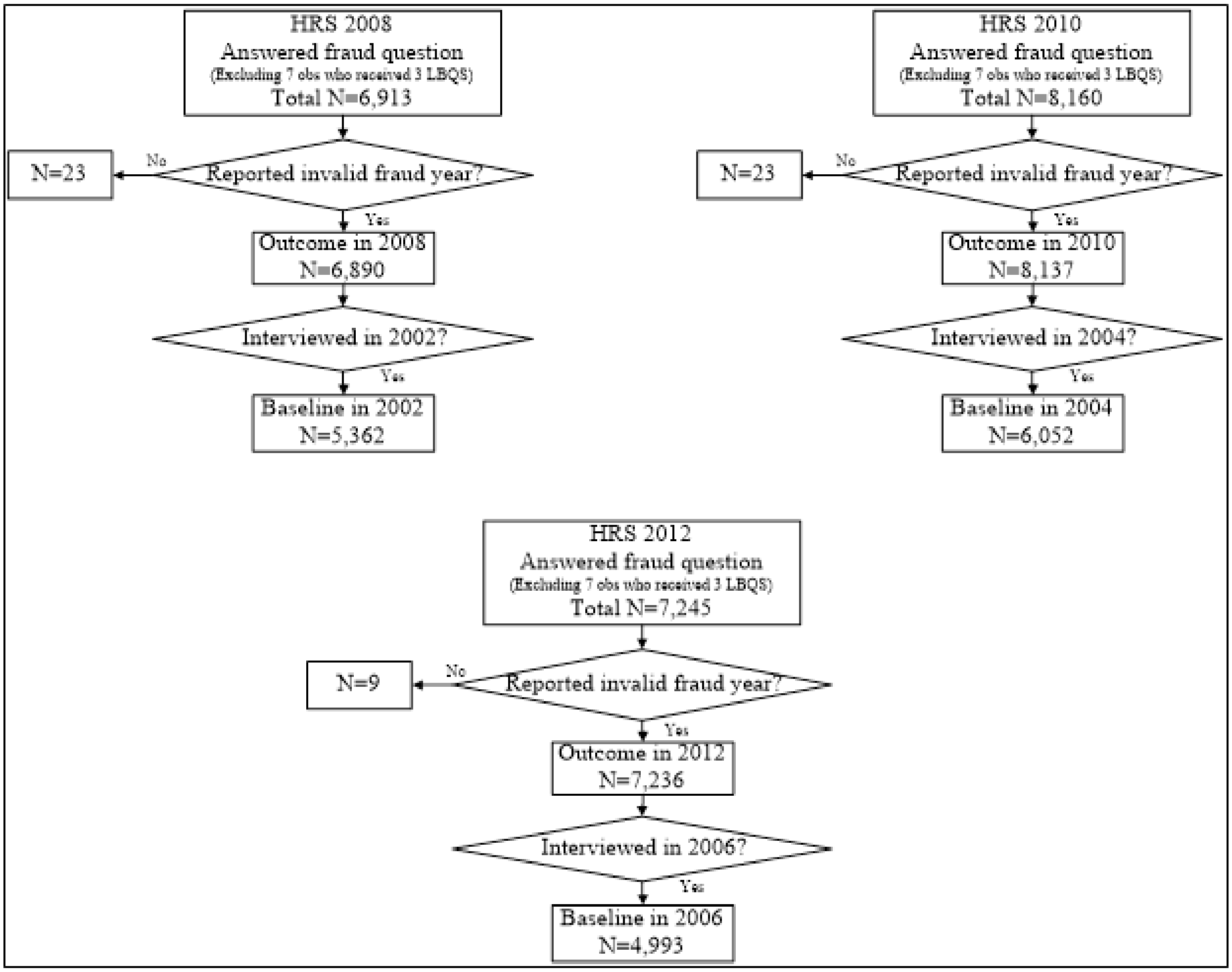
**Appendix Table 5. OLS models of net housing wealth**

| | Housing wealth (/100K, 2012$) | | | |
|---|---|---|---|---|
| | 2008 | 2010 | 2012 | Pooled |
| Fraud victim | 0.270 | -0.396 ** | -0.052 | -0.157 |
| | (0.299) | (0.187) | (0.451) | (0.182) |
| Age | -0.018 ** | -0.003 | -0.006 | -0.009 * |
| | (0.008) | (0.005) | (0.009) | (0.005) |
| Male | 0.058 | -0.031 | 0.100 | 0.011 |
| | (0.053) | (0.061) | (0.163) | (0.039) |
| White | -0.069 | 0.160 | -0.292 | 0.032 |
| | (0.173) | (0.102) | (0.186) | (0.088) |
| Hispanic | 0.543 ** | 0.055 | 0.543 * | 0.261 ** |
| | (0.251) | (0.110) | (0.307) | (0.121) |
| Education year | 0.041 | 0.062 ** | 0.032 | 0.062 *** |
| | (0.032) | (0.025) | (0.033) | (0.021) |
| Married | 0.050 | 0.157 | 0.098 | 0.195 |
| | (0.171) | (0.163) | (0.159) | (0.125) |
| Nkids | 0.030 | -0.016 | -0.020 | 0.003 |
| | (0.044) | (0.017) | (0.038) | (0.022) |
| Cognition score | 0.006 | 0.002 | 0.014 | 0.009 |
| | (0.015) | (0.010) | (0.019) | (0.009) |
| CESD score | -0.020 | -0.036 ** | -0.047 | -0.032 ** |
| | (0.020) | (0.017) | (0.044) | (0.014) |
| Good health | 0.119 | 0.160 ** | (0.070) | 0.118 * |
| | (0.079) | (0.080) | (0.202) | (0.067) |
| Nonhousing wealth (/100K, 2012$) | 0.124 | 0.049 *** | 0.003 | 0.074 *** |
| | (0.081) | (0.017) | (0.006) | (0.029) |
| Housing wealth (/100K, 2012$) | 0.929 *** | 0.444 *** | 0.575 *** | 0.566 *** |
| | (0.143) | (0.161) | (0.075) | (0.149) |
| LBQ10 | | | | -0.715 *** |
| | | | | (0.144) |
| LBQ12 | | | | -1.054 *** |
| | | | | (0.196) |
| Intercept | 0.455 | -0.280 | 0.155 | 0.286 |
| | (0.679) | (0.647) | (0.895) | (0.506) |
| N | 5,180 | 5,867 | 414 | 11,461 |
| R-square | 0.235 | 0.381 | 0.739 | 0.243 |
| Mean of dep var | 2.217 | 1.793 | 1.570 | 1.957 |
| St.dev of dep var | 6.503 | 3.256 | 2.684 | 4.851 |

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Controlled with missing dummies, clustered on household

**Appendix Figure 1: Sample construction**




Source: Authors' analysis using the HRS.