STAFF
REPORTS

NO. 1106
MAY 2024

The Financial Consequences of Undiagnosed Memory Disorders

Carole Roan Gresenz | Jean M. Mitchell | Belicia Rodriguez | R. Scott Turner | Wilbert van der Klaauw

FEDERAL RESERVE BANK *of* NEW YORK

The Financial Consequences of Undiagnosed Memory Disorders

Carole Roan Gresenz, Jean M. Mitchell, Belicia Rodriguez, R. Scott Turner, and Wilbert van der Klaauw

Federal Reserve Bank of New York Staff Reports, no. 1106
May 2024
https://doi.org/10.59576/sr.1106

Abstract

We examine the effect of undiagnosed memory disorders on credit outcomes using nationally representative credit reporting data merged with Medicare data. Years prior to eventual diagnosis, average credit scores begin to weaken and payment delinquency begins to increase, overall and for mortgage and credit card accounts specifically. Credit outcomes consistently deteriorate over the quarters leading up to diagnosis. The harmful financial effects of undiagnosed memory disorders exacerbate the already substantial financial pressure households face upon diagnosis of a memory disorder. Our findings substantiate the possible utility of credit reporting data for facilitating early identification of those at risk for memory disorders.

JEL classification: I1, G41, G51
Key words: debt repayment, memory disorders, credit cards, mortgages

---

Rodriguez, van der Klaauw: Federal Reserve Bank of New York (emails: belicia.rodriguez@ny.frb.org, wilbert.vanderklaauw@ny.frb.org). Gresenz, Mitchell, Turner: Georgetown University (emails: crg70@georgetown.edu, mitchejm@georgetown.edu, turner@georgetown.edu). The authors thank Greg Lostoski at Georgetown University for programming support, Francis Mahoney at the Federal Reserve Bank of New York for help with developing the merged database and data management, and Rebecca Vanarsdall at the Georgetown University Massive Data Institute for project management. Research reported in this paper was supported by the National Institute on Aging of the National Institutes of Health under award numbers R56AGO53272 and R01AG080623.

For households with older adults, financial decisions are imbued with particular consequence, given increasing reliance with age on largely fixed assets (versus new income flows) and shifting resource demands for health-related needs (Jacobson et al. 2021; Machlin and Carper 2018). Among recent cohorts of older-adult households, declining defined retirement benefits, lengthening average periods of retirement, and increasing expected health and long-term care costs (Agarwal et al. 2009) have added to the consequential nature of financial decision-making.

The range and complexity of financial decisions in which households engage underscore the role of cognitive function in financial behavior. These include balancing consumption and savings over an uncertain time horizon, optimizing performance while mitigating risk in an asset investment strategy, and determining whether to initiate debt and the structure of such debt (Gomes, Haliassos, and Ramadorai 2021). Previous studies find cognitive ability is related to financial decisions regarding assets, including wealth and wealth composition (McArdle, Smith, and Willis 2011); investment performance (Kuo, Lin, and Zhao 2014); trading behavior and performance (Grinblatt, Keloharju, and Linnainmaa 2012); and stockholding (Christelis, Jappelli, and Padula 2010). With respect to liability, cognitive function has been linked to optimal credit card use (Agarwal and Mazumder 2013), the probability of mortgage default (Gerardi, Goette, and Meier 2013), and repayment behavior (Brown et al. 2016).

Despite the importance of financial decisions for older households and the importance of cognitive function to those decisions, older households are those most vulnerable to memory disorders such as Alzheimer's disease and related disorders (ADRD) which impair cognitive function (Alzheimer's Association 2023). In more than 90 percent of Alzheimer's disease cases, symptoms first occur after age 65 (National Institute on Aging (NIA) 2019). ADRD has a substantial and growing reach, affecting more than 11 percent of individuals age 65 and over in the U.S., and the size of the population affected is projected to more than double by 2050 as a result of epidemiologic and demographic trends (Alzheimer's Association 2023). Certain sub-populations are particularly at risk. For women, the estimated lifetime risk for Alzheimer's disease at age 45 is double that for men (Chêne et al. 2015), and the prevalence of ADRD is decidedly more pronounced among Black and Hispanic populations (Chen and Zissimopoulos 2018; Lines, Sherif, and Wiener 2014) and lower for Asian American populations compared to non-minority populations (Mayeda et al. 2017).

Previous studies suggest financial decision-making deficits are often among the first functional changes attributable to early-stage cognitive impairment and that effects on financial behavior are magnified as symptoms progress (Marson et al. 2000; Martin et al. 2008; Triebel et al. 2009). Cognitive changes associated with early-stage disease, including episodic memory and perceptual speed,

may not only make individuals more susceptible to compromised financial decision-making on their own (Han et al. 2015a), but also render individuals more susceptible to financial exploitation by others (Han et al. 2015b; Wood and Lichtenberg 2017). The potential financial vulnerability created by cognitive deficits associated with early-stage Alzheimer's is compounded by the challenges of detecting and diagnosing mild cognitive impairment (Sabbagh et al. 2020) and the years-long time span of the prodomal stage (Vermunt et al. 2019). Moreover, some evidence points to personality changes during early stages of Alzheimer's disease, such as a reduction in conscientiousness and increase in neuroticism (Robins Wahlin and Byrne 2011), and previous research finds such traits are related to financial distress (Parise and Peijnenburg 2019).

Recent empirical studies have begun to examine the vulnerability of those in the early stages of the disease to poor financial outcomes. Gresenz et al. (2019) find that early stage ADRD places households at significant risk for large adverse changes in liquid assets, regardless of who in the household is afflicted, and reduces net wealth, with a more pronounced effect when the financial head of household is affected. In a study of seniors living alone, Nicholas et al (2021) find an increased risk of missing bill payments and developing a subprime credit score in the several years prior to ADRD diagnosis.

This paper extends research on ADRD and household financial behavior among older adults in several key ways. First, we examine the effect of ADRD on credit outcomes in the years preceding diagnosis using a very large, nationally representative, longitudinal data set. The data set includes credit data from Equifax merged at the individual level using Social Security number (SSN) with Medicare claims and enrollment data from the Center for Medicare and Medicaid Services (CMS). Second, we investigate a broad range of outcomes, including credit score, payment delinquency, and delinquency by credit type (mortgage and credit card). Third, we examine the effect of ADRD prior to diagnosis on financial outcomes among seniors regardless of their household structure and inclusive of those who live alone as well as those living with a spouse or partner or other household members. This is important because only 27% of adults ages 60 and older live alone in the U.S. (Ausubel 2020) and previous research shows effects of early stage ADRD on financial outcomes across single- and multi-person households (Gresenz et al. 2019) as well as effects of cognitive decline on financial wealth among two-person (coupled) households (Angrisani and Lee 2019). Fourth, we implement a difference-in-differences event study model where we control for selection effects by applying propensity score weighting (Abadie 2005; Hirano, Imbens, and Ridder 2003) and including individual fixed effects. Fifth, we examine potential heterogeneity associated with gender and race in the effect of ADRD prior to diagnosis on credit outcomes.

We find, on average, deterioration in credit scores and a heightened probability of payment

delinquency in the five years prior to an eventual diagnosis of ADRD. Considering the typical progression of the disease, these findings point to financial consequences of the disease in its earliest stages, when symptoms are typically mild and not widely apparent. The financial consequences of ADRD prior to diagnosis steadily increase over time. Credit scores weaken and the probability of delinquency rises as individuals approach diagnosis. These patterns correspond to the increasing symptomatology that is typical with the disease given its progressive nature. We also find effects of ADRD prior to diagnosis on payment delinquency associated specifically with mortgages and credit card accounts which are the largest components of debt for older adults. The probability of delinquency among credit card account holders is consistently worse in the five years prior to diagnosis and for mortgage borrowers is worse in the three years prior to diagnosis. The magnitude of payment delinquency is particularly concerning: Two years prior to diagnosis, the probability of credit card delinquency among account holders is 21 percent higher and the probability of mortgage delinquency among mortgage borrowers is 11 percent higher compared to baseline. Black adults are particularly susceptible to poor financial outcomes from early stage ADRD compared to White adults. For women, the effects of ADRD prior to diagnosis are similar to those among men, but the effects after diagnosis are more pronounced for some financial outcomes. Our findings are important because the adverse effects of undiagnosed ADRD on credit scores and payment delinquency increase immediate pecuniary costs such as late fees and interest charges. These changes also reduce access to credit and affect credit limits and interest rates on credit cards and personal loans—all at a time when the demand for household financial resources is likely to increase to pay for the substantial caregiving and related costs associated with later stages of memory disorders (Hurd et al. 2013). Further, our findings substantiate the possible utility of credit data for facilitating early identification of those at risk for ADRD. Additional work is required to explore the application of machine learning to credit reporting data in support of algorithm development.

1 Data and Methods

1.1 Data Sources

We use data from the Federal Reserve Bank of New York's (FRBNY) Consumer Credit Panel (CCP) spanning 2000-2017 merged at the individual level using a unique common identifier (Social Security number) with data from the Base, Cost & Use, and Chronic Conditions segments of the Medicare Beneficiary Summary File (Centers for Medicare & Medicaid Services 2023a) covering the same time period.

The CCP was designed to provide an anonymized, nationally representative sample of U.S.

residents with a credit history and an SSN associated with their credit file (Lee and Klaauw 2010). The CCP derives from credit data collected and stored by Equifax, one of three primary credit bureaus to collect such information in the U.S. These agencies compile and maintain credit histories for all U.S. residents who have applied for or taken out a loan—an estimated 89 percent of all U.S. adults (Brevoort, Grimm, and Kambara 2016; Lee and Klaauw 2010). The credit data are highly granular, including an overall derived credit score as well as detailed information on loan origination, amount, balance, term, credit limit and payment status/delinquencies for, separately, mortgages, home equity loans and revolving accounts, auto loans, credit card accounts, consumer finance and retail loans, and other loan accounts. These variables are updated continuously, and, for most adults, over the time span from early adulthood forward. Avery et al. (2003) provide a comprehensive overview and additional detail on consumer credit reports content. A key advantage of the CCP for this research is that it tracks financial outcomes from administrative as opposed to self-reported data. This feature of the data is important because the primary population of interest in the research includes individuals with increasing cognitive impairments whose ability to self-report outcomes may be compromised.

To create the CCP, a first stage random sample of 5 percent of all individuals with a credit history and SSN was selected, based on the last four (random) digits of SSN. For each primary sample member in the CCP, information is then collected on other individuals living at the exact same address (secondary sample members). The first stage 5 percent sample includes approximately 12 million individuals. The total sample, after second stage sampling, includes approximately 38.1 million individuals representing 11.2 million households. The sampling scheme was repeated for every quarter beginning with quarter 1 of 1999 through the present day in order to create a longitudinal panel. New individuals are added (e.g., adults who establish a credit history for the first time) and others are dropped (e.g., deaths) in each quarter so that the sample is representative of the target population in each quarter, while at the same time comprising a representative panel over time. Our data comprise 72 quarters (18 years) of CCP panel data (2000-2017). More details regarding the CCP sample design can be found in Lee and van der Klaauw (2010).

We use multiple segments of the Master Beneficiary Summary File (MBSF) from 2000-2017, which contain data on all Medicare enrollees for a given calendar year (Centers for Medicare & Medicaid Services 2023b). The MBSF Base Segment contains socio-demographic and enrollment data for all enrollees, including state/county/zip code of residence; date of birth; date of death (if applicable); gender; race/ethnicity; dual Medicaid-Medicare enrollment status; and plan enrollment type (traditional Medicare vs. Medicare Advantage). The MBSF Chronic Conditions and Cost & Use segments are based on claims data and are for traditional Medicare enrollees only, as health

care utilization among managed care (known as Medicare Advantage) enrollees does not generate claims. The MBSF Chronic Conditions segment, known as the Chronic Conditions Warehouse, includes indicators of the presence or absence of various clinical conditions and the date of diagnosis of each. The MBSF Cost & Use segment contains a measure of out-of-pocket health care spending.

Clinical indicators in the Chronic Conditions Warehouse are based on algorithms CMS has established for each chronic condition (Chronic Conditions Data Warehouse 2023). Conditions identified in the Chronic Conditions segment include Alzheimer's Disease, ADRD and 25 other chronic conditions.[1] For each condition, the date of first occurrence is measured, and flags earmark mid- and end-of year presence of the condition.[2] Previous research has employed a claims-based approach to identifying ADRD (Mucha et al. 2008; Joyce et al. 2007; Gresenz et al. 2019) and examined the sensitivity and specificity of claims data for identifying ADRD (Taylor et al. 2009). Sensitivity represents the probability that a person who has ADRD is identified as having ADRD from claims data whereas specificity represents the probability that a person who does not have ADRD is accurately identified as cognitively healthy. Thus, a high sensitivity rate indicates few false negatives and a high specificity rate indicates few false positives. Taylor et al. (2009) report sensitivity and specificity of 0.85 and 0.89, respectively, for identifying ADRD using claims data and Grodstein et al. (2022) report sensitivity and specificity of 0.79 and 0.88.

1.2 Data Construction

We select a target sample from the CCP that includes individuals age 65 or over during the 2000-2017 timeframe. This sample comprises a "finder file" for searching MBSF data for SSN matches. Figure 1 profiles information on the data construction process.

The CCP finder file, prepared by Equifax, consists of 12,456,009 SSNs. 91.8% of SSNs (n=11,436,425) in the finder file uniquely match to an SSN in the MBSF Base file. A non-match may occur if the individual is not eligible for or not enrolled in Medicare or if the SSN is not legitimate (6.9% of individuals in the finder file, n=860,101). Additionally, 1.3% of SSNs in the finder file (n=159,483) have a non-unique match, which may occur when multiple individuals claim Medicare benefits under the same SSN or an individual changes the SSN under which they claim

[1] We use the 27 CCW Chronic Conditions version of the file that spans 1999–2021. The conditions include acute myocardial infarction; cataract; rheumatoid/osteoarthritis; chronic obstructive pulmonary disease (COPD); atrial fibrillation; heart failure; diabetes; depression; glaucoma; osteoporosis; stroke/transient ischemic attack; chronic kidney disease; hip/pelvic fracture; ischemic heart disease; various cancers (breast, colorectal, endometrial, lung, prostate); anemia; asthma; hyperplasia (benign prostatic), hyperlipidemia; hypertension; and hyperthyroidism (acquired).

[2] The ICD9-CM diagnosis codes for ADRD are: 331.0, 331.11, 331.19, 331.2, 331.7, 290.0, 290.10, 290.12, 290.13, 290.20, 290.21, 290.3, 290.4, 290.41, 290.42, 290.43, 294.0, 294.10, 294.11, 294.8, and 797. Beneficiaries must have at least one inpatient, skilled nursing facility, home health, Part B institutional, or Part B non-institutional claim with specified diagnosis code in any position.

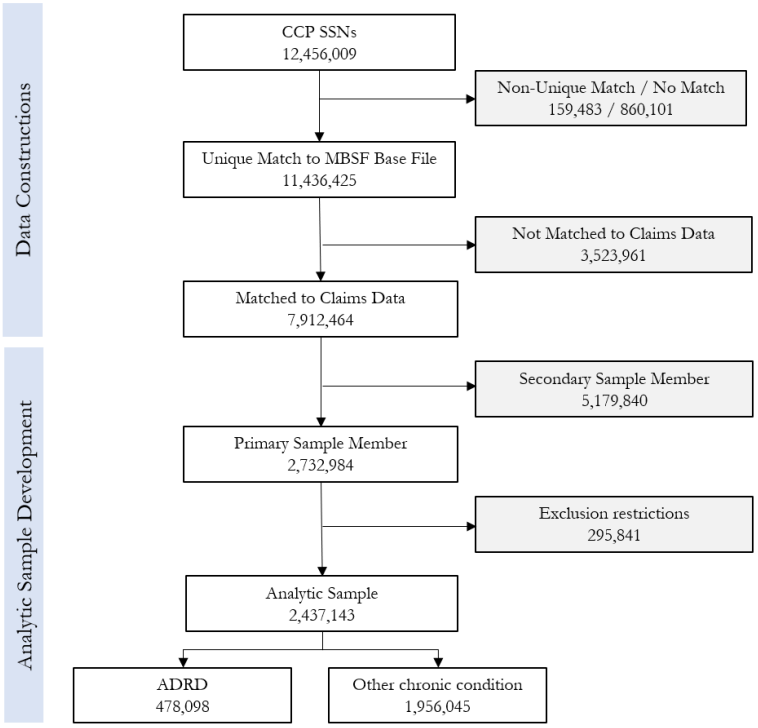

Figure 1: Construction of Data and Development of Analytic Sample

benefits (Virnig 2023).

We obtained Medicare Chronic Conditions and Cost & Use data for enrollees in the matched sample who were ever diagnosed with ADRD or any of the other 25 chronic conditions tracked in the Chronic Conditions Warehouse. Because diagnoses are based on fee-for-service claims, they are available only for individuals enrolled in traditional Medicare, and not for individuals enrolled in Medicare Advantage (MA). During the time frame of our data, between 65 and 83 percent of Medicare enrollees were enrolled in traditional Medicare each year (Freed et al. 2021). Correspondingly, we are able to merge Chronic Conditions and Cost & Use data to 69 percent of the enrollees in our matched sample of 11.4M (n=7,912,464).[3]

1.3 Analytic Sample

Our sample includes primary sample members in the CCP (n=2,732,984). These individuals are consistently tracked over time in the CCP, whereas secondary sample members enter or leave the sample depending on whether they remain in the same household as the primary sample member. However, we use information on secondary sample members to characterize the household structure

[3]Those not matched to claims data also include some individuals enrolled in fee-for-service who were never diagnosed with one of the 27 chronic conditions in the Chronic Conditions Warehouse. However, the vast majority of individuals 65 and over have at least one chronic condition, as (85.6%) have one or more of six chronic conditions (diabetes, asthma, COPD, cancer, arthritis, or cardiovascular disease) (National Center for Health Statistics 2015).

of the primary sample member. We exclude primary sample members who have no credit report data during the study time period or if they only have credit data following their death; individuals who reside in U.S. territories; individuals who are never observed in a household setting (defined as always living in a setting with 100 or more individuals); individuals diagnosed with ADRD prior to age 65, and individuals with ADRD who have an observed date of diagnosis that is immediately preceded by either ineligibility for Medicare due to age or MA enrollment, to avoid potential measurement error in date of diagnosis (specifically, a measured date of onset that is later than in actuality). Our resulting analytic sample includes 2,437,143 individuals. Of these, 478,098 are diagnosed with ADRD during the study time frame (2000-2017) and the remainder have one or more of the other 25 chronic conditions measured in the Chronic Conditions segment, but are never observed with a diagnosis of ADRD. For each sample member, the observation window spans at most 72 quarters (from 2000-2017), but some individuals have shorter windows of observation. We exclude from analysis quarters after death and, for individuals who switch from traditional Medicare to MA, quarters after that transition because we do not observe whether individuals are diagnosed with ADRD while enrolled in MA.[4]

1.4 Outcome Variables

We examine an individual's credit score and the existence of any payment delinquency for all types of debt as well variables capturing any delinquency and delinquent balance for mortgages and credit card debt specifically. The credit score measure, Equifax Risk Score 3.0, was developed by Equifax and assesses the likelihood of a consumer becoming seriously delinquent (90+ days past due) over the next 12 months. It is a multi-dimensional construct that can be viewed as important indicator of an individual's overall creditworthiness. The score not only captures behavior regarding paying bills (including whether any payment is delinquent as well as the number, length and amount of delinquencies), but also reflects new account origination, debt balance relative to credit available (credit utilization ratio), and credit mix (type of accounts). The score ranges from 280-850, with higher scores representing better credit risk. Generally, credit scores are classified as super-prime (above 720), prime (660-719), near-prime (620-659) and subprime (below 620).

We measure delinquency status according to whether the individual is current (paid as agreed) on all accounts or has at least one account that is at least 30 or more days late. Additionally, we analyze two specific types of delinquency—mortgage and credit card—with a measure of any

[4]Individuals who transition from MA to traditional Medicare during the observation window are included in analysis unless they have a diagnosis of ADRD in their first quarter in traditional Medicare (because their true date of diagnosis may have been earlier). We incorporate a flag signifying an MA quarter to account for incomplete information on the presence or absence of other chronic conditions during these time periods.

delinquency and a measure of the dollar amount of the delinquent balance. For these analyses, we limit the sample to individuals who hold such an account. We choose these account types because they represent the two largest components of debt among individuals 70 and over (Federal Reserve Bank of New York 2022).

1.5 Empirical Strategy

We implement a difference-in-differences event study model with individual and time fixed effects following Equation 1.

$$F_{it} = \gamma X_{it} + \sum_{\tau=t_i-J}^{t_i+J} ADRD_i \cdot 1(t=\tau)\beta_\tau + \lambda_i + \theta_{st} + \epsilon_{it} \tag{1}$$

Where F_{it} represents financial outcomes for individual i in time period t. X_{it} includes time-varying demographic and health variables. These include a set of indicator variables capturing age at each observation as well as indicators for household size and probable spouse constructed from information on secondary CCP sample members. We base the presence or absence of a probable spouse on whether there is another adult in the household aged within +/- 15 years of the primary sample member for households in which there are fewer than 9 members. In addition, we include a set of indicators for each of the chronic conditions measured along with a count of total chronic conditions for each individual in each time period.

$ADRD_i$ is an indicator of whether an individual is ever diagnosed with ADRD, while t_i represents the date of this diagnosis. The specification includes a set of indicators, representing time-distance from the date of ADRD diagnosis, capturing lead and lag effects on the financial outcome. For example, β_{-1} represents the change in outcome the quarter prior to diagnosis, while β_8 captures the change in the outcome 8 quarters after diagnosis. The non-parametric event study specification allows the coefficients on each of the lag/lead indicators to vary freely, providing for flexibility in the pattern of outcomes over time relative to diagnosis (Clarke and Tapia-Schythe 2021). We set the maximum J to 28, thus allowing for estimation of the potential effects of early stage ADRD up to 7 years prior to diagnosis. We set the maximum number of lag effects similarly. The effects of early stage ADRD on financial outcomes $\beta_\tau, \tau = -1, \cdots, -J$ are identified from individual-specific changes over time among those ever diagnosed with ADRD, relative to individual-specific changes over time among those never diagnosed with ADRD. These coefficients are the key coefficients of interest. λ_i represent individual fixed effects, and θ_{st} is a vector of state-time fixed effects that account for within-state macroeconomic trends.

1.6 Estimation

We employ propensity score weighting to account for the non-random selection of individuals afflicted by ADRD. We develop a propensity score model that includes variables that in theory are likely to influence the probability of ADRD and financial outcomes (Caliendo and Kopeinig 2008). Specifically, we account for gender, race/ethnicity, time period of observation, household structure, and state of residence. We also include a lagged financial measure—credit score at age 65—in the propensity score model to control for fixed but unobserved differences in initial conditions across individuals. We ensure common support by comparing the minimum and maximum of the propensity score distribution for the two groups (those ever diagnosed with ADRD and those never diagnosed with ADRD) and setting the propensity score to missing if it is lower than the minimum or higher than the maximum of the propensity score distribution of the alternative group (2008). We trim extreme tails of the distribution of the predicted propensity scores (less than .0001 and higher than .999) and weight our analyses on the (inverse of the) propensity score to obtain a balanced sample of treated and untreated individuals (Abadie 2005; Imbens 2004; Wooldridge 2010).

We estimate fixed-effect, propensity score weighted linear regression models for continuous outcomes (credit score, delinquent balances). For dichotomous outcomes (delinquency flags), we use fixed-effect, propensity-score weighted linear probability models (Konetzka, Stuart, and Werner 2018; Marton, Yelowitz, and Talbert 2014). We choose this estimation approach over alternatives (e.g., fixed effect logit or conditional logit models) to avoid issues associated with the incidental parameter problem and facilitate estimation of marginal effects (Angrist and Pischke 2009; Greene 2004; Neyman and Scott 1948). We cluster the standard errors at the individual level in all analyses.

In additional analyses, we examine whether the effect of ADRD prior to diagnosis varies across demographic groups by estimating separate regressions stratified by race and gender. We also test the sensitivity of our results by estimating unweighted fixed-effect models and conducting analyses in which we include a control for out-of-pocket health care spending. Our main analyses omit this variable because redundant or otherwise unnecessary health care spending represents one channel through which impaired cognitive function from ADRD prior to diagnosis may affect credit outcomes. Nonetheless, we control for out-of-pocket health care spending in a supplemental analysis to account for possible additional health care costs that may be associated with obtaining an ADRD diagnosis or for unusual cases in which treatment is prescribed prior to diagnosis. Lastly, recognizing the possibility that individuals in the control group may be diagnosed with ADRD

immediately or shortly after the endpoint of the observation window (2017), we also re-estimate our models using only observations through 2013, although the control group remains identified using information on health status through 2017.

2 Results

Tables 1 and 2 provide descriptive results. Our main analytic sample includes 2,437,143 individuals, 478,098 (19.6 percent) of whom are ever diagnosed with ADRD and 1,956,045 never been diagnosed with ADRD. On average, individuals are observed for 56.3 quarters (approximately 14 years), yielding 137.3 million person-quarter observations in total. The percentage of our sample ever diagnosed with ADRD is 19.6 percent. We use annual ADRD incidence ratios to benchmark our sample. Our estimated ADRD incidence ratios among individuals ages 65-74 (0.9%), 75-84 (2.8%) and 85 and over (6.2%) align with published estimates for AD (Rajan et al. 2019) and for dementia (Olfson et al. 2021).[5]

Race and gender differences are apparent between the ADRD and the non-ADRD sample, underscoring the importance of propensity score weighting. A higher percentage of the ADRD sample is female (59.1 vs 52.9 percent) and Black (8.9 vs 8.2 percent) and a lower percentage of the ADRD sample is Asian (1.2 vs 2.1 percent). Observed race and gender differences are consistent with well-established patterns of prevalence of ADRD (Alzheimer's Association 2023). Household structure also varies across individuals in the ever ADRD and no ADRD samples. Individuals in the ever ADRD sample are observed in single person households in 21.3 percent of the quarters they are observed, compared to 17.7 percent of quarters among individuals in the non-ADRD sample. Likewise, in 50.8 percent of observed quarters individuals in the ADRD sample have a probable spouse vs 61.2 percent among the non-ADRD sample. The presence of other health conditions also varies across the ADRD and non-ADRD samples. With few exceptions, the percentage of observations in which other chronic conditions are present is higher among the ADRD sample. For example, depression is present in 15.8 percent of observations in the ADRD sample, compared to 6.8 percent in the non-ADRD sample. Our analyses control for the presence of each of these chronic conditions in each quarter.

Table 2 provides person-quarter level descriptive statistics for outcomes. The mean credit score among the full sample is 745.8.[6] A 30 day or more delinquency is recorded in 8.1 percent of

[5] Rajan et al. (2019) report standardized incidence rates for AD of 0.4%, 3.2%, and 7.5% for the age groups 65-74, 75-84, 85 or over, respectively. using 1994 to 2012 data from 2,794 individuals in the Chicago Health and Aging Population study. Olfson et al. (2021) report incidence rates of dementia for 60 year old men and women (0.8%, 0.7%), 80 year old men and women (3.4%, 3.6%) and 90 year old men and women (8.8%, 9.6%) using Medicare data from 2007-2017.

[6] The mean credit score in the entire CCP population is 715. Average credit scores increase with age: the average

Table 1: Descriptive Statistics

	Full Sample		Ever ADRD		No ADRD	
	Mean	(std dev)	Mean	(std dev)	Mean	(std dev)
DEMOGRAPHICS						
Female	0.541	0.498	0.591	0.492	0.529	0.499
White	0.861	0.346	0.874	0.332	0.858	0.349
Black	0.084	0.277	0.089	0.285	0.082	0.275
Hispanic	0.047	0.211	0.039	0.193	0.048	0.215
Asian	0.020	0.139	0.012	0.111	0.021	0.145
Other	0.020	0.139	0.009	0.096	0.022	0.147
HOUSEHOLD STRUCTURE						
Household size=1	0.184	0.387	0.213	0.409	0.177	0.382
Household size=2	0.397	0.489	0.383	0.486	0.400	0.490
Household size=3	0.205	0.404	0.192	0.393	0.208	0.406
Household size=4	0.097	0.296	0.091	0.288	0.098	0.297
Household size=5	0.043	0.203	0.042	0.200	0.043	0.203
Household size=6 or more	0.075	0.263	0.080	0.271	0.074	0.261
Probable spouse	0.593	0.491	0.508	0.500	0.612	0.487
CONDITIONS						
Acute myocardial infarction (AMI)	0.006	0.080	0.009	0.095	0.006	0.074
Anemia	0.173	0.379	0.261	0.439	0.145	0.352
Asthma	0.034	0.182	0.041	0.198	0.032	0.177
Atrial fibrillation	0.068	0.252	0.103	0.304	0.057	0.232
Breast cancer	0.027	0.162	0.031	0.173	0.026	0.158
Colorectal cancer	0.012	0.107	0.014	0.119	0.011	0.103
Endometrial cancer	0.002	0.048	0.002	0.048	0.002	0.048
Lung cancer	0.008	0.088	0.007	0.084	0.008	0.089
Prostate cancer	0.032	0.176	0.037	0.188	0.030	0.171
Cataracts	0.202	0.402	0.237	0.425	0.191	0.393
Chronic heart failure (CHF)	0.119	0.324	0.194	0.396	0.095	0.293
Chronic kidney disease	0.101	0.302	0.141	0.348	0.089	0.284
Chronic obstructive pulmonary disorder (COPD)	0.088	0.284	0.120	0.325	0.078	0.268
Depression	0.090	0.286	0.158	0.364	0.068	0.251
Diabetes	0.216	0.411	0.260	0.439	0.201	0.401
Glaucoma	0.092	0.290	0.114	0.317	0.086	0.280
Hip or pelvis fracture	0.005	0.073	0.013	0.113	0.003	0.054
Hyperlipidemia	0.384	0.486	0.420	0.494	0.372	0.483
Hyperplasia (benign prostatic)	0.054	0.226	0.067	0.249	0.050	0.218
Hypertension	0.481	0.5	0.594	0.491	0.445	0.497
Hyperthyroidism (acquired)	0.109	0.312	0.145	0.352	0.097	0.297
Ischemic heart disease	0.268	0.443	0.367	0.482	0.235	0.424
Osteoporosis	0.054	0.227	0.085	0.279	0.044	0.206
Rheumatoid/osteoarthritis	0.244	0.430	0.327	0.469	0.218	0.413
Stroke/transient ischemic attack (TIA)	0.031	0.174	0.065	0.247	0.020	0.140
Count of chronic conditions	1.992	2.584	3.707	3.023	1.615	2.313

Notes: Summary statistics are calculated using person-quarters except for demographic characteristics which are calculated for individuals. Chronic conditions indicate the presence of a condition in the quarter. Full sample includes 2,437,143 individuals (137,252,639 person-quarter observations). 478,098 individuals (24,704,856 person-quarters) are in the ever diagnosed with ADRD group. 1,956,045 individuals (112,547,783 person-quarters) are in the never diagnosed with ADRD group. Differences in means across the ever/no ADRD subgroups are all statistically significant ($p<.01$).

Table 2: Descriptive Statistics: Financial Outcomes

	Full Sample		Ever ADRD		No ADRD	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Credit score	745.8	86.29	749.4	83.98	745.0	86.77
Any delinquency	0.081	0.272	0.082	0.274	0.080	0.272
Credit card holder	0.811	0.391	0.746	0.436	0.826	0.379
Any credit card delinquency*	0.055	0.228	0.063	0.243	0.053	0.225
Delinquent balance credit card*	341.05	3,076.14	383.602	3,110.90	332.54	3,069.08
Mortgage borrower	0.305	0.46	0.177	0.382	0.333	0.471
Any mortgage delinquency**	0.023	0.149	0.028	0.165	0.022	0.147
Delinquent balance mortgage**	2,722.24	33,860.52	2,910.00	30,936.20	2,700.55	34,182.16

*Among credit card holders
**Among mortgage borrowers
Notes: Calculated using person-quarter observations. The full sample includes 137,252,639 observations. The ADRD sample includes 24,704,856 and the non ADRD sample 112,547,783 observations.

observations. Credit card delinquency (5.5 percent) is more common than mortgage delinquency (2.3 percent) among account holders of each type although the average balance in delinquency (among delinquent and non-delinquent account holders combined) is larger for mortgages ($2722) vs. credit cards ($341). Rates of mortgage and credit card delinquency are higher in the ever ADRD compared to the non-ADRD sample.

Figure 2 provides results for the analyses of credit score and any payment delinquency. Tables with coefficient estimates from these models are provided in Appendix A, along with estimates of the propensity score models. In Figure 2 and other figures, the x axis measures the number of quarters from diagnosis, where t=0 indicates quarter of diagnosis. Although our primary interest is the time period prior to ADRD diagnosis, we also provide post-diagnosis findings. We evaluate the magnitude of effect sizes using baseline averages measured 6 years prior to ADRD diagnosis.

Credit scores consistently decline leading up to ADRD diagnosis (Figure 2). We observe statistically significant effects even in the disease's early stage. In the three to five years before diagnosis (quarters -11 to -20 in Figure 2), credit scores are on average 1 to 2 points lower than baseline. The magnitude of the effect increases with proximity to diagnosis. In the second year prior to diagnosis (quarters -5 to -8 in Figure 2), credit scores are on average 2.7 to 3.7 points lower than baseline and are on average 4 to nearly 6 points lower during the year (quarters -1 to -4 in Figure 2) just preceding ADRD diagnosis. The spread between the thresholds for super-prime and sub-prime credit scores is 100 points, and between prime and sub-prime is 40 points, which point to the practical significance of the 4 point drop in credit score prior to diagnosis. A 4 point reduction in

is 766 for those 65 and older, and 773 for those 75 and older at the end of 2023.

credit score represents an 0.05 standard deviation decrease in credit score. After diagnosis, credit scores further descend and remain more than 9 points (0.1 standard deviation decrease) below baseline levels during the seven years following diagnosis.

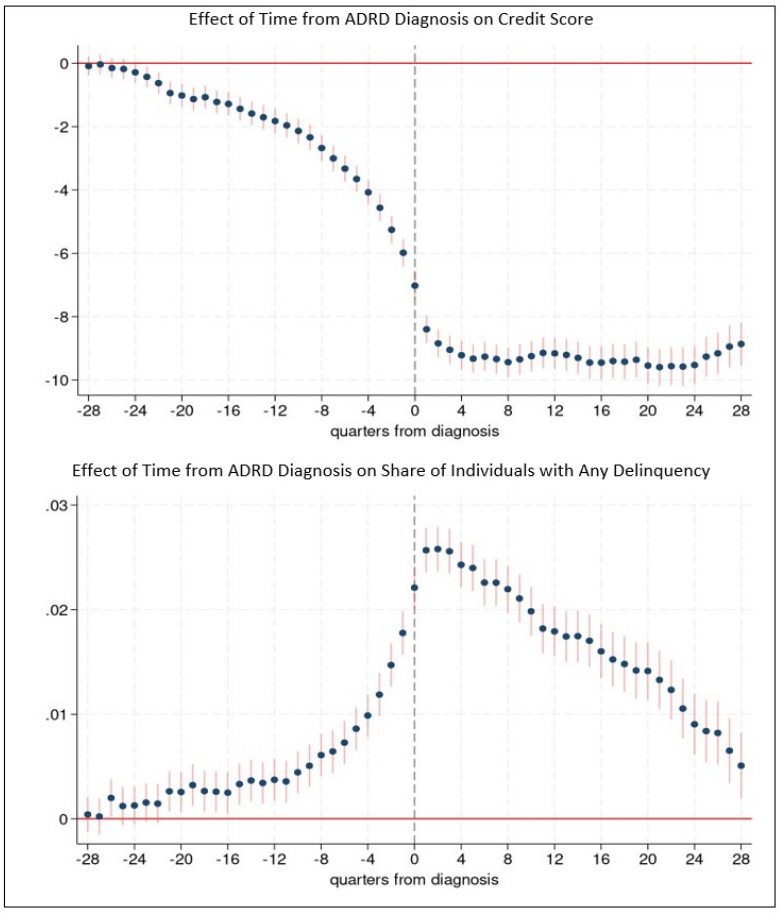

Figure 2: Effect of Time from ADRD Diagnosis on Credit Score and Share of Individuals with Any Delinquency

The probability of any payment delinquency increases leading up to ADRD diagnosis (Figure 2), and, as with credit scores, we find evidence of an effect in the disease's very early stage. The probability of delinquency is 0.25 percentage points higher five years prior to diagnosis compared to baseline, for example. The magnitude of the effect increases for time periods closer to diagnosis. The probability of delinquency is 0.37 percentage points higher three years before diagnosis, 0.61 percentage points higher two years prior to diagnosis, and is between 0.99 and 1.8 percentage points higher during the year just prior to diagnosis. A 1 percentage point change in the probability of delinquency represents a 13.2 percent increase, evaluated at the mean baseline probability of delinquency among individuals with ADRD (7.6 percent). In the six months after diagnosis, the probability of delinquency reaches its highest level, 2.58 percentage points (34 percent) higher than baseline. The probability of delinquency remains more than 2 percentage points higher than

baseline during the subsequent two years and then declines but remains elevated compared to baseline levels in the years thereafter.

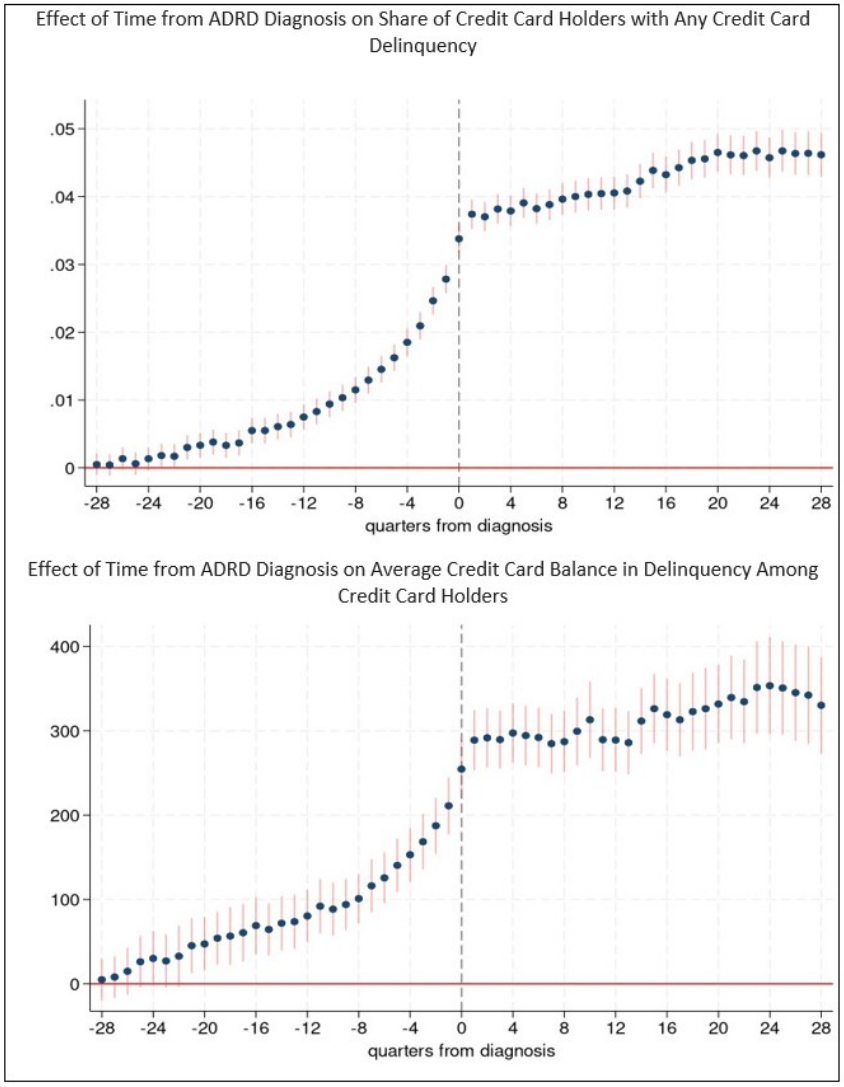

Figure 3: Effect of Time from ADRD Diagnosis on Share of Credit Card Account Holders with Any Credit Card Delinquency and Average Credit Card Balance in Delinquency Among Credit Card Account Holders

Figure 3 provides results for the probability of credit card delinquency and average credit card balance in delinquency. Among those with a credit card account we find a higher probability of credit card delinquency during the 21 quarters (5.25 years) prior to diagnosis, with larger probabilities as diagnosis nears. In terms of magnitude, the probability of credit card delinquency is approximately 0.75 percentage points higher than baseline three years prior to diagnosis. This represents a 13.9 percent increase over the mean baseline probability of credit card delinquency among those with ADRD (5.4 percent). The probability of credit card delinquency is 1.2 percentage points higher two years prior to diagnosis, and in the year prior to diagnosis is 1.9 to 2.8 percentage

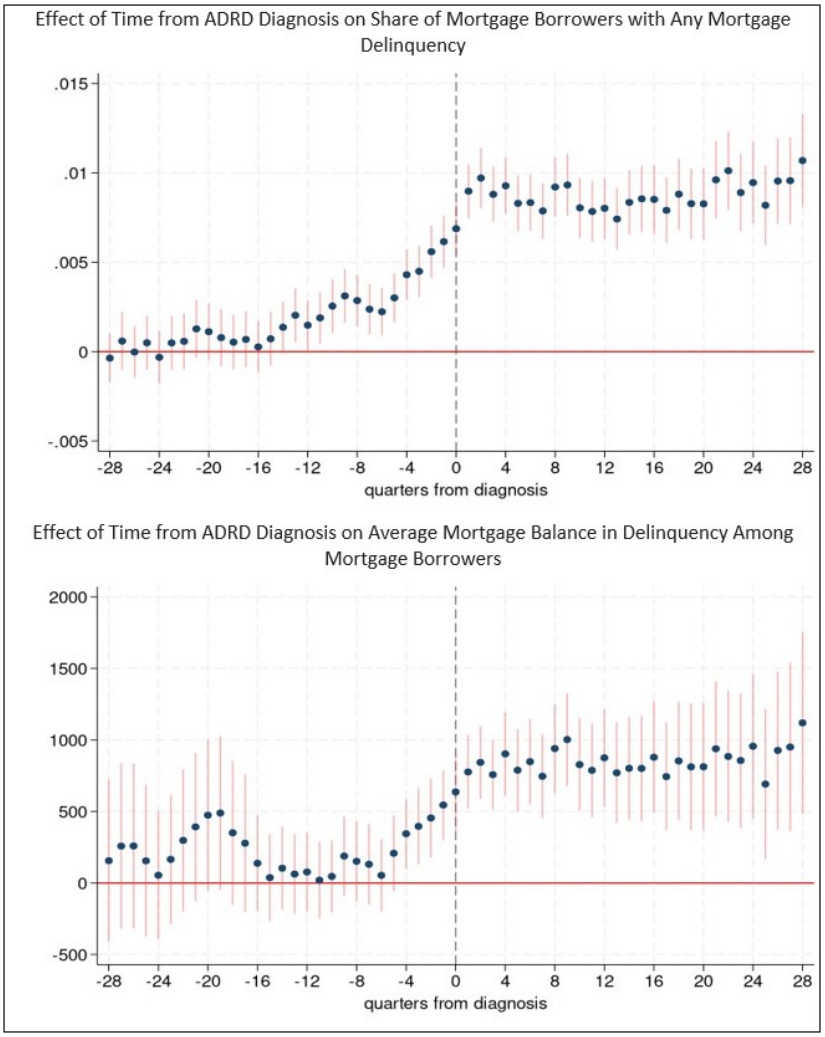

Figure 4: Effect of Time from ADRD Diagnosis on Share of Mortgage Borrowers with Any Mortgage Delinquency and Average Mortgage Balance in Delinquency Among Mortgage Borrowers

points (34 to 52 percent) higher than baseline.

Average credit card balances in delinquency, which reflect both the probability of delinquency and the amount delinquent, follow a similar pattern. Balances in delinquency are higher during the 21 quarters prior to diagnosis compared to baseline, and increase with proximity to diagnosis. Three years prior to diagnosis, for example, average credit card balances in delinquency are $80 (25 percent) higher compared to baseline ($327) and are $101 (31 percent) higher two years prior to diagnosis. A year prior to diagnosis, average credit card balances in delinquency are $153 (more than 50 percent) higher.

The probability of credit card delinquency among credit card holders increases immediately after diagnosis, and remains more than 4 percentage points higher than baseline thereafter. Average credit card balances in delinquency also remain elevated post-diagnosis, at or above $300 higher

per credit card account holder in most quarters compared to baseline.

Figure 4 provides results for the probability of mortgage delinquency and the average mortgage balance in delinquency. The probability of mortgage delinquency is also heightened during early stage ADRD, with effects up to 13 quarters (3.25 years) prior to diagnosis. Effects increase with proximity to diagnosis. Roughly three years prior to diagnosis, the probability of mortgage delinquency is 0.2 percentage points higher than baseline, representing an 8.1 percent increase in the mortgage delinquency rate (evaluated at the baseline of 2.5 percent). One year prior to diagnosis, the probability of a mortgage delinquency is 0.4 percentage points (17.2 percent) higher than baseline. Average mortgage balances in delinquency (which are the product of the probability of delinquency and the amount delinquent) among individuals with a mortgage are higher than baseline during the year prior to diagnosis. They are $345 (11 percent) higher one year prior to diagnosis, for example, compared to baseline ($3,008). Both the probability of mortgage delinquency and average balance in delinquency for mortgages remain elevated in the years following diagnosis. For instance, five years following diagnosis, average mortgage balances in delinquency are on average $813 (27 percent) higher compared to baseline.

Figure 5 and 6 provides results for analyses of the effect of time to ADRD diagnosis on credit score and the probability of any delinquency stratified by race. We focus on results for White, Black, and Hispanic subgroups as limited sample sizes for other racial subgroups (e.g., Asian, other) preclude precise estimation. Because sample sizes are relatively limited in the analyses of Black and Hispanic subpopulations, we limit our focus to the effect of ADRD during the 20 quarters before and after diagnosis.

The pattern of effects are similar for White and Black subgroups, but the magnitude of the effect of ADRD prior to diagnosis is larger among Black individuals. Three years (12 quarters) prior to diagnosis, for example, the effect of early stage ADRD among Black individuals is more than double that among White individuals (3.5 vs 1.7 point reduction in credit score compared to baseline). One year prior to diagnosis, credit scores are 7.8 points and 3.8 points lower among Black and White individuals, respectively, compared to baseline. Following diagnosis, credit scores drop to more than 16 points lower than baseline among Blacks individuals compared to a maximum drop of just under 10 points from baseline among White individuals.

Similarly, the effects on the probability of any delinquency are on average larger among Black compared to White individuals in quarters prior to diagnosis. Three years prior to diagnosis, early stage ADRD increases the probability of any delinquency 1.4 and 0.3 percentage points among Black and White individuals, respectively. The probability of delinquency is highest for both groups in the few quarters just following diagnosis, but the maximum increase in the probability of

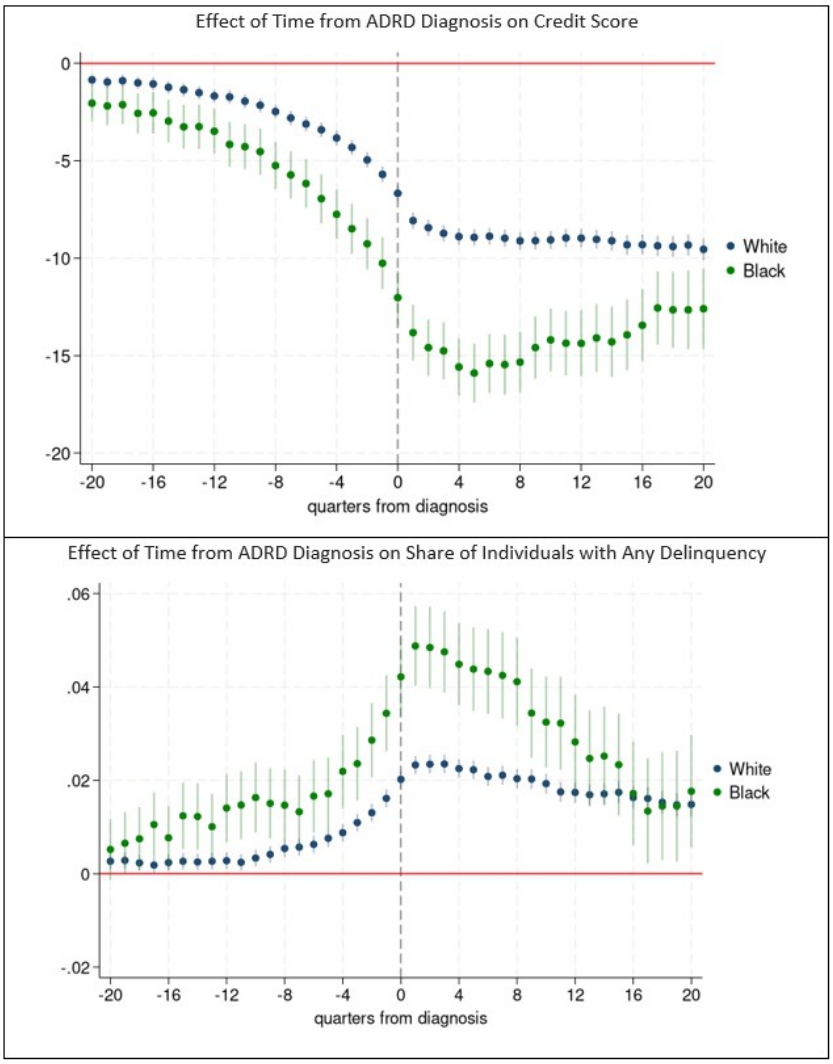

Figure 5: Effect of Time from ADRD Diagnosis on Credit Score and Share of Individuals with Any Delinquency by Race: Non-Hispanic Black vs. Non-Hispanic White

delinquency is 4.9 percentage points among Black individuals whereas it is 2.4 percentage points among White individuals.

By contrast, the pattern of effects of ADRD prior to diagnosis on credit scores among Hispanic and non-Hispanic White individuals are similar. Effects in most years after diagnosis are also indistinguishable among these subgroups, as shown by the overlapping confidence intervals in most years. Results are also similar with respect to the probability of delinquency. The effect of ADRD is somewhat greater among Hispanics in a few quarters before and after diagnosis, but not consistently so.

Figure 7 provides results for analyses stratified by gender. The patterns of effects on credit scores are essentially identical for men and women prior to diagnosis. Notably, however, credit scores recover more quickly among men compared to women post-diagnosis. Two years after

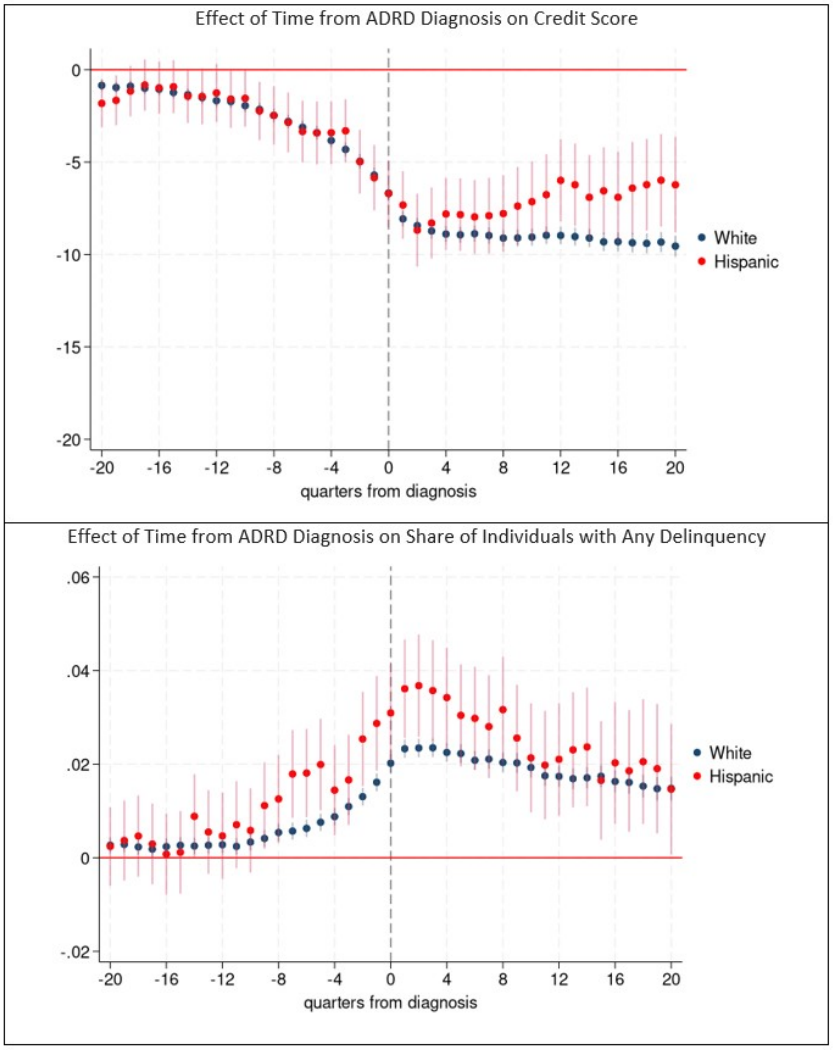

Figure 6: Effect of Time from ADRD Diagnosis on Credit Score and Share of Individuals with Any Delinquency by Race: Hispanic vs. Non-Hispanic White

ADRD diagnosis, credit scores are 8.5 points lower than baseline among men and 10.1 points lower than baseline among women, for example. We also find no gender differences in the effects of ADRD prior to diagnosis on the probability of any delinquency. In the years just after diagnosis, the point estimates of the effects of ADRD appear greater among women compared to men but the confidence intervals overlap.

2.1 Sensitivity analyses

The results are robust in specifications that are unweighted, include out-of-pocket costs, and limit the endpoint of the data to 2013. The magnitude of the effects are slightly attenuated, as expected, in analyses that control for out of pocket costs and are slightly larger in analyses that limit the time frame of the data. Appendix A provides results.

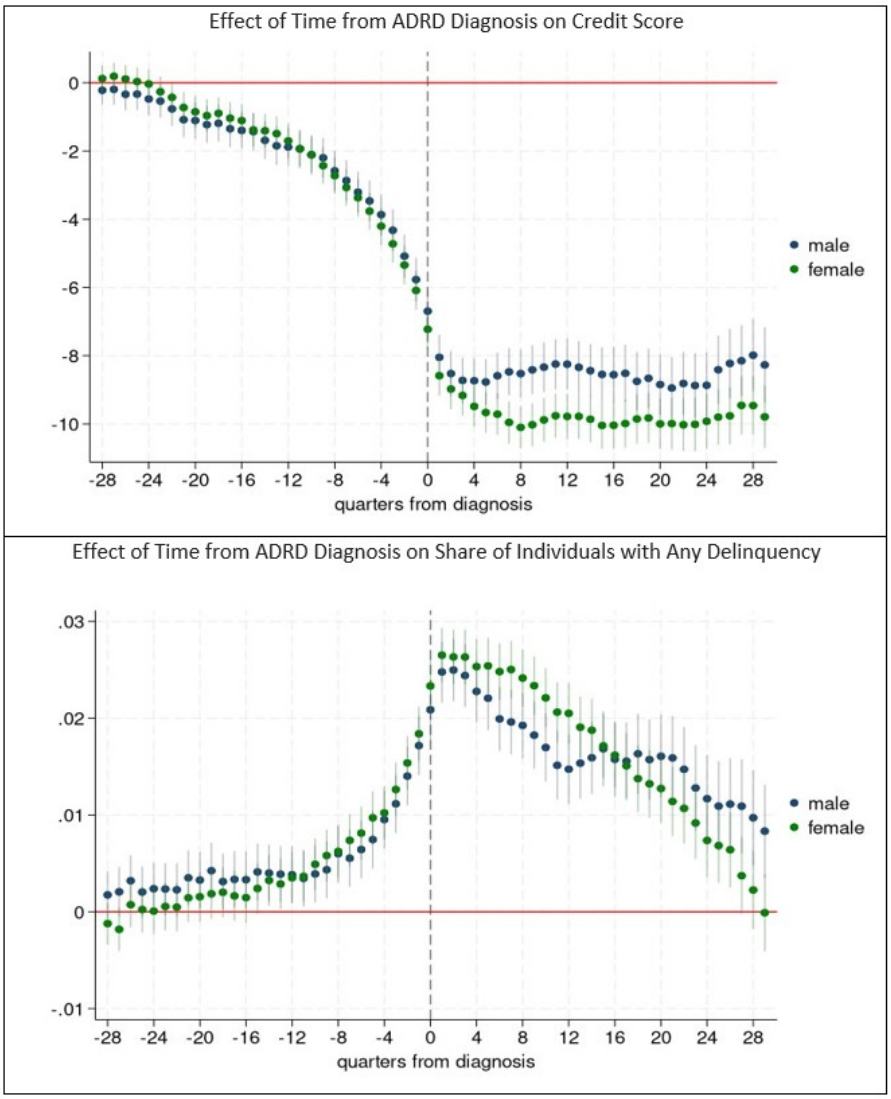

Figure 7: Effect of Time from ADRD Diagnosis on Credit Score and Share of Individuals with Any Delinquency by Gender

3 Discussion

Our results can be viewed as an extension of the literature examining the effect of health shocks (such as cancer) on financial well-being (Pak, Kim, and Kim 2020; Richard et al. 2021). Distinctively, however, we study the effect of an undiagnosed condition (memory disorder) for which the primary mechanism of effect is through impaired cognitive function. By contrast, the financial effects of other health shocks often occur after diagnosis from changes in health care spending for treatment.

Our findings improve upon and extend the incipient research on the influence of ADRD on household financial behavior. We capitalize on the power offered by the large, nationally representative, longitudinal dataset with individually-matched health and financial debt and debt

repayment information. These unique data permit identification of the effect of early stage ADRD from individual-specific changes over time in financial outcomes. Additionally, our analyses include individuals in both single- and multi-person households, which is important in light of the variety of arrangements that characterize senior living and the potential for early stage ADRD to affect financial outcomes among those who are married, partnered or live with others (Gresenz et al. 2019). We also examine potential heterogeneity in treatment effects by gender and race.

Average credit scores begin to deteriorate during early stage ADRD, five years prior to diagnosis, and steadily weaken leading up to diagnosis. A decline in credit scores can follow from the inception of a delinquency, an increase in the number of accounts delinquent, growth in the amount of delinquency, the origination of one or more new credit accounts, an increase in credit utilization rates and/or disproportionate growth in a particular type of credit account (e.g. a surge in credit card accounts as a share of all accounts). The predisposition of individuals with undiagnosed ADRD to these and related behaviors represent a serious potential threat to their financial well-being. This is especially concerning given the substantial financial demands imposed by the disease in its later stages (Hurd et al. 2013). Notably, however, credit scores among those with ADRD do not recover even years after diagnosis, suggesting an element of permanency in the impacts of pre-diagnosis financial behavior. The continued suppression of credit scores post-diagnosis may also reflect the negative impact of new resource demands associated with the disease, such as costs of caregiving or supportive living arrangements, on financial solvency.

We also find effects of ADRD prior to diagnosis on payment delinquency, overall and for mortgages and credit accounts, which are the largest components of debt for older adults. The propensity towards delinquency rises the nearer an individual is to diagnosis. These increases in delinquency are large, varying between 8 and 21 percent across total, mortgage, and credit card debt two years prior to diagnosis, for example, and between 13 and 35 percent one year prior to diagnosis. Our estimates imply that roughly 600,000 delinquencies on some debt will occur over the next 10 years as a consequence of yet-to-be diagnosed ADRD.

Delinquency may be the product of cognitive inattention associated with the disease–i.e., forgetting to pay bills–and may also or alternatively reflect the disease's effect on decisions related to debt initiation and structure, including from financial exploitation, that negatively affect financial solvency. The overall magnitude of the increase in delinquencies as well as the long pre-diagnosis period over which we observe effects is remarkable in light of the relatively frequent use of automatic bill payment. Although not everyone in early stage ADRD will experience a payment delinquency, for those who do, the scale of the change in delinquency is substantial. One year prior to diagnosis, average credit card balances in delinquency increase by more than 50 percent and

average mortgage balances in delinquency are 11 percent higher.

The probability of any delinquency falls after diagnosis, which is consistent with the signaling power that diagnosis may offer. Namely, a diagnosis alerts family members and loved ones that the affected individual is cognitively vulnerable and may require support with financial decision-making. Family members may not only provide oversight and ensure payment for existing debt, but also reduce credit account holding for affected family members. The latter may be particularly important as we observe no decline in credit card or mortgage delinquency after ADRD diagnosis among those who continue to hold such accounts.

We find substantially larger effects of early stage ADRD on credit score and the probability of delinquency for Black compared to White individuals, with effects generally estimated to be at least twice as large for Black individuals. Lin et al. (2021) and Tsoy et al. (2021) find Black individuals are on average diagnosed at a later stage of the disease than Whites. This lag in diagnosis likely contributes to some of the observed differences. But more work is needed to understand factors underlying the much larger effects of the disease on financial outcomes among Black adults.

There are several possible explanations for the slower recovery among women vs. men of at least some financial outcomes following ADRD diagnosis. First, this pattern could reflect lower out-of-pocket costs associated with formal caregiving for men who are affected by ADRD because wives more commonly provide informal care for a husband than vice versa (Alzheimer's Association 2023). Second, this finding could also reflect differences in the type and level of financial oversight offered by friends and family depending on whether the financial head of household is the person diagnosed with ADRD. If the oversight response is more muted when the person who is not the financial head of household is affected, this could contribute to the observed gender differences in financial outcomes after diagnosis since men are more likely than women to serve as the financial head of multi-person households among older adults in the generation we study (Smith, McArdle, and Willis 2010). Third, this finding could reflect differences in the effect of household structure (e.g. living alone vs with others) by gender on financial outcomes. Additional research is needed to better understand the interplay between ADRD, household dynamics, and financial outcomes.

3.1 Limitations

There are several limitations to our proposed research. First, Medicare claims data identify individuals who are diagnosed with ADRD, and not all individuals affected by ADRD receive a diagnosis. One factor in underdiagnosis (false negatives) may be physicians' willingness to document the disease (Koller and Bynum 2015). Amjad et al. (2018) find that individuals who are Hispanic, have less than high school education, attend medical visits alone, or have fewer functional impairments

are more likely to be undiagnosed. While the estimated sensitivity and specificity for Medicare claims data-based diagnoses of dementia are reassuring (Taylor et al. 2009), our estimates of the effect of ADRD can be thought of as lower bounds given underdiagnosis.

Additionally, some individuals in our control group may be diagnosed with ADRD after the endpoint of our observation window. The extent to which this occurs represents contamination in the control group and leads to a downward bias on our estimates. Consistent with this, sensitivity analyses in which we identify the control and treatment groups using information on conditions through 2017 and drop observations after 2013 show effect sizes that are somewhat stronger in magnitude.

Our data exclude individuals in Medicare Advantage plans, whose health care service utilization is tracked in encounter data vs. claims records. During the time frame of our data, fee-for-service accounted for the majority of Medicare enrollment and claims data have been the basis of research for decades. The Center for Medicaid and Medicare Services (CMS) recently began releasing encounter data for Medicare Advantage enrollees; however, the completeness of these data has been identified as an issue and more generally the strengths and limitations of these data are only beginning to be understood (Jung, Carlin, and Feldman 2022). Additionally, some individuals have no credit history and thus will not be represented in credit data. These may include, for example, individuals who are undocumented (who also will lack Medicare enrollment/claims data). However, credit data is available for the vast majority—an estimated 89 percent—of U.S. adults (Brevoort, Grimm, and Kambara 2015). Moreover, the exclusion of individuals without credit accounts from our analysis does not represent a potential source of bias in our estimates of the effect of ADRD on credit outcomes (since the universe of people with credit scores and credit accounts are included in analysis). Finally, credit history and credit scores can vary across credit bureaus and our data rely on only one source (Equifax). But, differences across the bureaus in their data are largely idiosyncratic, individual level differences, such as those related to disputes over particular items that may be removed from one but not another credit report, as opposed to systematic differences related to method or scope of data collection (Avery et al. 2003).

3.2 Conclusions

Our findings are important for several reasons. First, the adverse effects of undiagnosed ADRD on credit scores and payment delinquency carry consequent financial costs in both the short- and long-term. Immediate pecuniary costs include late fees and interest charges associated with payment delinquency, while future costs may include reduced access to the credit market and less advantageous terms of available credit such as restricted credit limits and—because credit scores

are used by lenders in pricing credit—higher interest rates on credit cards and personal loans (Brevoort, Grodzicki, and Hackmann 2020). Additionally, delinquency on mortgage payments can be a precursor to eventual foreclosure, a costly event for both households and communities (Gallagher, Gopalan, and Grinstein-Weiss 2019; Campbell, Giglio, and Pathak 2011).

For individuals and households facing a memory disorder diagnosis, simultaneously confronting diminished access to credit, poorer credit terms, and/or a heightened potential of foreclosure is likely to substantially exacerbate an already destabilizing circumstance. Once diagnosed, average dementia-related caregiving and health care costs run in the tens of thousands of dollars annually (Hurd et al. 2013). As such, demand for credit among individuals and households afflicted by memory disorders may increase just as its supply is restricted.

Our findings lend urgency to the need for further consideration of the roles federal agencies and financial institutions can play in reducing financial risk among older households with undiagnosed memory disorders (Chandra, Coile, and Mommaerts 2023; DeLiema et al. 2020; Wood and Lichtenberg 2017; Consumer Financial Protection Bureau 2016). Moulton et al. (2014) point to the potential importance of low-cost interventions in credit markets such as external monitoring while Agarwal et al. (2009) describe options that include financial "driver's licenses," advance directives, and expanded fiduciary requirements.

Further, our findings point to the potential of using information on credit outcomes to develop machine learning algorithms for identifying individuals at risk for ADRD who should receive additional clinical evaluation to facilitate earlier diagnosis. Recent advances in treatment for ADRD, including a new FDA-approved (and Medicare-covered) treatment for Alzheimer's (lecanemab) that effectively slows cognitive decline and is indicated for use in the early stage of disease, add urgency to the need for earlier diagnosis (Food and Drug Administration 2023). Moreover, earlier diagnosis provides value to afflicted individuals by helping explain early signs and symptoms an individual may be experiencing such as mood changes; supporting informed choices that maximize quality of life for as long as an individual is able; facilitating planning regarding preferences for support and care; helping avoid or ameliorate negative financial outcomes associated with early-stage disease (as our findings highlight); accelerating entrée into support systems; addressing potential health and safety concerns including driving and taking daily medications; and providing an opportunity to address modifiable risk factors such as lifestyle habits and management of comorbidities which may contribute to AD etiology and pathological consequences (Rasmussen and Langerman 2019; Gresenz et al. 2019; Edwards III et al. 2019).

Available diagnostic tools rely primarily on the manifestation of cognitive symptoms that interfere with everyday activities, while current biomarkers used in ADRD research are either expensive

or invasive (Atri 2019) and thus not good candidates for use as wide-scale screening tools (Chandra, Coile, and Mommaerts 2023). The cost, availability, and accessibility of brain imaging limit the scalability of machine learning approaches that rely on such data (Qiu et al. 2020; Antor et al. 2021). By contrast, credit data are already collected by credit bureaus for the vast majority of the roughly 250 million adults in the U.S. Furthermore, financial data are highly granular, updated continuously, and over the time span, for most adults, from early adulthood forward. Our findings substantiate the strength of the information signal from credit data for the possible early identification of those at risk for ADRD. Additional work is required to explore the application of machine learning to credit data in support of algorithm development.

At the same time, more needs to be understood about the mechanisms that underlie the deterioration in credit scores observed among individuals in the earliest stages of a memory disorder. Beyond susceptibility to payment delinquency, early stage ADRD may affect new account openings and debt accumulation, credit utilization, and/or credit mix. These are important questions that warrant additional investigation.

Bibliography

Abadie, Alberto. 2005. "Semiparametric Difference-in-Differences Estimators." *The Review of Economic Studies* 72 (1): 1–19. https://www.jstor.org/stable/3700681.

Agarwal, Sumit, John C. Driscoll, Xavier Gabaix, and David Laibson. 2009. "The Age of Reason: Financial Decisions Over the Lifecycle and Implications for Regulation." *Brookings Papers on Economic Activity*, 2009.

Agarwal, Sumit, and Bhashkar Mazumder. 2013. "Cognitive Abilities and Household Financial Decision Making." *American Economic Journal: Applied Economics* 5 (1): 193–207.

Alzheimer's Association. 2023. *2023 Alzheimer's Disease Facts and Figures: Special Report - The Patient Journey In An Era Of New Treatments*. https://www.alz.org/media/documents/alzheimers-facts-and-figures.pdf.

Amjad, Halima, David L. Roth, Orla C. Sheehan, Constantine G. Lyketsos, Jennifer L. Wolff, and Quincy M. Samus. 2018. "Underdiagnosis of Dementia: An Observational Study of Patterns in Diagnosis and Awareness in US Older Adults." *Journal of General Internal Medicine* 33 (July): 1131–1138.

Angrisani, Marco, and Jinkook Lee. 2019. "Cognitive Decline and Household Financial Decisions at Older Ages." *The Journal of the Economics of Ageing* 13:86–101.

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Antor, Morshedul Bari, A.H.M. Shafayet Jamil, Maliha Mamtaz, Mohammad Monirujjaman Khan, Sultan Aljahdali, Manjit Kaur, Parminder Singh, and Mehedi Masud. 2021. "A Comparative Analysis of Machine Learning Algorithms to Predict Alzheimer's Disease." *Journal of Healthcare Engineering* 2021.

Atri, Alireza. 2019. "The Alzheimer's Disease Clinical Spectrum: Diagnosis and Management." *Medical Clinics of North America* 103 (March): 263–293.

Ausubel, Jacob. 2020. "Older People are More Likely to Live Alone In the US than Elsewhere in the World." *Pew Research Center*, 2020.

Avery, Robert B., Paul S. Calem, Glenn B. Canner, and Raphael W. Bostic. 2003. "An Overview of Consumer Data and Credit Reporting." *Federal Reserve Bulletin* 89:47.

Brevoort, Kenneth, Daniel Grodzicki, and Martin B. Hackmann. 2020. "The Credit Consequences of Unpaid Medical Bills." *Journal of Public Economics* 187 (July).

Brevoort, Kenneth P., Philipp Grimm, and Michelle Kambara. 2015. "Credit Invisibles." *Consumer Financial Protection Bureau Office of Research Reports Series*, nos. 15-1.

———. 2016. "Credit Invisibles and the Unscored." *Cityscape* 18 (2): 9–34.

Brown, Meta, John Grigsby, Wilbert van der Klaauw, Jaya Wen, and Basit Zafar. 2016. "Financial Education and the Debt Behavior of the Young." *The Review of Financial Studies* 29, no. 9 (September): 2490–2522. Accessed March 23, 2023. https://doi.org/10.1093/rfs/hhw006.

Caliendo, Marco, and Sabine Kopeinig. 2008. "Some Practical Guidance or the Implementation of Propensity Score Matching." *Journal of Economic Surveys* 22 (February): 31–72.

Campbell, John Y., Stefano Giglio, and Parag Pathak. 2011. "Forced Sales and House Prices." *American Economic Review* 101 (5): 2108–2131.

Centers for Medicare & Medicaid Services. 2023a. Chronic Conditions. Https://www.cms.gov/data-research/statistics-trends-and-reports/chronic-conditions/chronic-conditions.

———. 2023b. Master Beneficiary Summary File (MBSF) LDS. Https://www.cms.gov/data-research/statistics-trends-and-reports/chronic-conditions/chronic-conditions.

Chandra, Amitabh, Courtney Coile, and Corina Mommaerts. 2023. "What Can Economics Say about Alzheimer's Disease?" *Journal of Economic Literature* 61 (2): 428–470.

Chen, Cynthia, and Julie M. Zissimopoulos. 2018. "Racial and Ethnic Differences in Trends in Dementia Prevalence and Risk Factors in the United States." *Alzheimer's & Dementia: Translational Research & Clinical Interventions* 4:510–520.

Chêne, Geneviève, Alexa Beiser, Rhoda Au, Sarah R. Preis, Philip A. Wolf, Carole Dufouil, and Sudha Seshadri. 2015. "Gender and Incidence of Dementia in the Framingham Heart Study from Mid-adult Life." *Alzheimer's & Dementia* 11 (3): 310–320.

Christelis, Dimitris, Tullio Jappelli, and Mario Padula. 2010. "Cognitive Abilities and Portfolio Choice." *European Economic Review* 54 (1): 18–38.

Chronic Conditions Data Warehouse. 2023. Condition Categories. https://www2.ccwdata.org/web/guest/condition-categories.

Clarke, Damian, and Kathya Tapia-Schythe. 2021. "Implementing the Panel Event Study." *The Stata Journal* 21 (4): 853–884.

Consumer Financial Protection Bureau. 2016. "Recommendations and Report for Financial Institutions on Preventing and Responding to Elder Financial Exploitation." *Washington, DC*, 2016.

DeLiema, Marguerite, Martha Deevy, Annamaria Lusardi, and Olivia S. Mitchell. 2020. "Financial Fraud among Older Americans: Evidence and Implications." *The Journals of Gerontology: Series B* 75 (4): 861–868.

Edwards III, George A., Nazaret Gamez, Gabriel Escobedo Jr, Olivia Calderon, and Ines Moreno-Gonzalez. 2019. "Modifiable Risk Factors for Alzheimer's Disease." *Frontiers in Aging Neuroscience* 11:146.

Federal Reserve Bank of New York. 2022. *Quarterly Report on Household Credit and Debt, 2022.*

Food and Drug Administration. 2023. FDA Converts Novel Alzheimer's Disease Treatment to Traditional Approval. https://www.fda.gov/news-events/press-announcements/fda-converts-novel-alzheimers-disease-treatment-traditional-approval.

Freed, Meredith, Jeannie Fuglesten Biniek, Anthony Damico, and Tricia Neuman. 2021. "Medicare Advantage in 2021: Enrollment update and key trends." *Kaiser Family Foundation*, 2021.

Gallagher, Emily A., Radhakrishnan Gopalan, and Michal Grinstein-Weiss. 2019. "The Effect of Health Insurance on Home Payment Delinquency: Evidence from ACA Marketplace Subsidies." *Journal of Public Economics* 172 (April): 67–83.

Gerardi, Kristopher, Lorenz Goette, and Stephan Meier. 2013. "Numerical Ability Predicts Mortgage Default." *Proceedings of the National Academy of Sciences* 110 (28): 11267–11271.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai. 2021. "Household Finance." *Journal of Economic Literature* 59, no. 3 (September): 919–1000. https://www.aeaweb.org/articles?id=10.1257/jel.20201461.

Greene, William. 2004. "The Behaviour of the Maximum Likelihood Estimator of Limited Dependent Variable Models in the Presence of Fixed Effects." *The Econometrics Journal* 7 (1): 98–119.

Gresenz, Carole Roan, Jean M. Mitchell, James Marrone, and Howard J. Federoff. 2019. "Effect of Early-stage Alzheimer's Disease on Household Financial Outcomes." *Health Economics (United Kingdom)* 29 (January): 18–29.

Grinblatt, Mark, Matti Keloharju, and Juhani T. Linnainmaa. 2012. "IQ, Trading Behavior, and Performance." *Journal of Financial Economics* 104 (2): 339–362.

Grodstein, Francine, Chiang-Hua Chang, Ana W. Capuano, Melinda C Power, David X. Marquez, Lisa L. Barnes, David A. Bennett, Bryan D. James, and Julie P.W. Bynum. 2022. "Identification of Dementia in Recent Medicare Claims Data, Compared with Rigorous Clinical Assessments." *The Journals of Gerontology: Series A* 77 (6): 1272–1278.

Han, S. Duke, Patricia A. Boyle, Bryan D. James, Lei Yu, and David A. Bennett. 2015a. "Mild Cognitive Impairmen is Associated with Poorer Decision-Making in Community-Based Older Persons." *Journal of the American Geriatrics Society* 63 (4): 676–683.

———. 2015b. "Mild Cognitive Impairment and Susceptibility to Scams in Old Age." *Journal of Alzheimer's Disease* 49 (3): 845–851.

Hirano, Keisuke, Guido W. Imbens, and Geert Ridder. 2003. "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score." *Econometrica* 71 (4): 1161–1189.

Hurd, Michael D., Paco Martorell, Adeline Delavande, Kathleen J. Mullen, and Kenneth M. Langa. 2013. "Monetary Costs of Dementia in the United States." *New England Journal of Medicine* 368 (14): 1326–1334.

Imbens, Guido W. 2004. "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review." *The Review of Economics and Statistics* 86 (1): 4–29.

Jacobson, Gretchen, Aimee Cicchiello, A. Shah, Michelle M. Doty, and Reginald D. Williams. 2021. "When Costs are a Barrier to Getting Health Care: Reports from Older Adults in the United States and Other High-income Countries." *Commonwealth Fund*, 2021.

Joyce, Amie T., Yang Zhao, Lee Bowman, Jennifer A. Flynn, Chureen T. Carter, and Daniel A. Ollendorf. 2007. "Burden of Illness Among Commercially Insured Patients with Alzheimer's Disease." *Alzheimer's & Dementia* 3 (3): 204–210.

Jung, Jeah, Caroline Carlin, and Roger Feldman. 2022. "Measuring Resource Use in Medicare Advantage Using Encounter Data." *Health Services Research* 57 (1): 172–181.

Koller, Daniela, and Julie P.W. Bynum. 2015. "Dementia in the USA: State Variation in Prevalence." *Journal of Public Health* 37 (4): 597–604.

Konetzka, R. Tamara, Elizabeth A. Stuart, and Rachel M. Werner. 2018. "The Effect of Integration of Hospitals and Post-Acute Care Providers on Medicare Payment and Patient Outcomes." *Journal of Health Economics* 61:244–258.

Kuo, Wei-Yu, Tse-Chun Lin, and Jing Zhao. 2014. "Cognitive Limitation and Investment Performance: Evidence from Limit Order Clustering." *The Review of Financial Studies* 28 (3): 838–875.

Lee, Donghoon, and Wilbert van der Klaauw. 2010. *An Introduction to the FRBNY Consumer Credit Panel.*

Lin, Pei-Jung, Allan T. Daly, Natalia Olchanski, Joshua T. Cohen, Peter J. Neumann, Jessica D. Faul, Howard M. Fillit, and Karen M. Freund. 2021. "Dementia Diagnosis Disparities by Race and Ethnicity." *Medical Care* 59 (8): 679.

Lines, Lisa M., Noha A. Sherif, and Joshua M. Wiener. 2014. "Racial and Ethnic Disparities among Individuals with Alzheimer's Disease in the United States: A Literature Review." *RTI Press*, 2014.

Machlin, Steven R., and Kelly Carper. 2018. "Out-of-Pocket Health Care Expenses by Age and Insurance Coverage, 2011." *Statistical Brief (Medical Expenditure Panel Survey (US))*, 2018.

Marson, Daniel C., Stephen M. Sawrie, Scott Snyder, Bronwyn McInturff, Tracy Stalvey, Amy Boothe, Traci Aldridge, Anjan Chatterjee, and Lindy E. Harrell. 2000. "Assessing Financial Capacity in Patients with Alzheimer's Disease: A Conceptual Model and Prototype Instrument." *Archives of Neurology* 57 (6): 877–884.

Martin, Roy, H. Randall Griffith, Katherine Belue, Lindy Harrell, Edward Zamrini, Britt Anderson, Alfred Bartolucci, and Daniel Marson. 2008. "Declining Financial Capacity in Patients with Mild Alzheimer Disease: A One-year Longitudinal Study." *The American Journal of Geriatric Psychiatry* 16 (3): 209–219.

Marton, James, Aaron Yelowitz, and Jeffery C. Talbert. 2014. "A Tale of Two Cities? The Heterogeneous Impact of Medicaid Managed Care." *Journal of Health Economics* 36:47–68.

Mayeda, Elizabeth R., M. Maria Glymour, Charles P. Quesenberry Jr, and Rachel A. Whitmer. 2017. "Heterogeneity in 14-year Dementia Incidence between Asian American Subgroups." *Alzheimer Disease & Associated Disorders* 31 (3): 181–186.

McArdle, John J., James P. Smith, and Robert Willis. 2011. "Cognition and Economic Outcomes in the Health and Retirement Survey." Edited by David A.Editor Wise. In *Explorations in the Economics of Aging*, 209–233. University of Chicago Press.

Moulton, Stephanie, J. Michael Collins, Cazilia Loibl, and Anya Samek. 2014. "Effects of Monitoring on Mortgage Delinquency Evidence From a Randomized Field Study." *Journal of Policy Analysis and Management* 34 (1): 184–207.

Mucha, Lisa, Sara Shaohung Wang, Brian Cuffel, Thomas McRae, Tami L. Mark, and Megan del Valle. 2008. "Comparison of Cholinesterase Inhibitor Utilization Patterns and Associated Health Care Costs in Alzheimer's Disease." *Journal of Managed Care Pharmacy* 14 (5): 451–461.

National Center for Health Statistics. 2015. Health Policy Data Requests - Percent of U.S. Adults 55 and Over with Chronic Conditions. Accessed February 17, 2023. https://www.cdc.gov/nchs/health_policy/adult_chronic_conditions.htm.

National Institute on Aging (NIA). 2019. Alzheimer's Disease Genetics Fact Sheet. Accessed February 17, 2023. https://www.nia.nih.gov/health/alzheimers-disease-genetics-fact-sheet.

Neyman, Jerzy, and Elizabeth L. Scott. 1948. "Consistent Estimates Based on Partially Consistent Observations." *Econometrica: Journal of the Econometric Society*, 1948:1–32.

Nicholas, Lauren Hersch, Kenneth M. Langa, Julie P.W. Bynum, and Joanne W. Hsu. 2021. "Financial Presentation of Alzheimer Disease and Related Dementias." *JAMA Internal Medicine* 181 (February): 220–227.

Olfson, Mark, Thomas Scott Stroup, Cecilia Huang, Melanie M. Wall, and Tobias Gerhard. 2021. "Age and Incidence of Dementia Diagnosis." *Journal of General Internal Medicine* 36:2167–2169.

Pak, Tae Young, Hyungsoo Kim, and Kyoung Tae Kim. 2020. "The Long-Term Effects of Cancer Survivorship on Household Assets." *Health Economics Review* 10 (January).

Parise, Gianpaolo, and Kim Peijnenburg. 2019. "Noncognitive Abilities and Financial Distress: Evidence from a Representative Household Panel." *The Review of Financial Studies* 32 (10): 3884–3919.

Qiu, Shangran, Prajakta S. Joshi, Matthew I Miller, Chonghua Xue, Xiao Zhou, Cody Karjadi, Gary H Chang, Anant S Joshi, Brigid Dwyer, Shuhan Zhu, et al. 2020. "Development and Validation of an Interpretable Deep Learning Framework for Alzheimer's Disease Classification." *Brain* 143 (6): 1920–1933.

Rajan, Kumar B., Jennifer Weuve, Lisa L. Barnes, Robert S. Wilson, and Denis A. Evans. 2019. "Prevalence and Incidence of Clinically Diagnosed Alzheimer's Disease Dementia from 1994 to 2012 in a Population Study." *Alzheimer's & Dementia* 15 (1): 1–7.

Rasmussen, Jill, and Haya Langerman. 2019. "Alzheimer's Disease – Why We Need Early Diagnosis." *Degenerative Neurological and Neuromuscular Disease* Volume 9 (December): 123–130.

Richard, Patrick, Nilam Patel, Yuan-Chiao Lu, Regine Walker, and Mustafa Younis. 2021. "The Financial Burden of Cancer on Families in the United States." *International Journal of Environmental Research and Public Health* 18, no. 7 (April): 3790.

Robins Wahlin, Tarja-Brita, and Gerard J Byrne. 2011. "Personality Changes in Alzheimer's Disease: a Systematic Review." *International Journal of Geriatric Psychiatry* 26 (10): 1019–1029.

Sabbagh, Marwan N., M. Boada, S. Borson, M. Chilukuri, B. Dubois, J. Ingram, Atsushi Iwata, et al. 2020. "Early Detection of Mild Cognitive Impairment (MCI) in Primary Care." *The Journal of Prevention of Alzheimer's Disease* 7:165–170.

Smith, James P., John J. McArdle, and Robert Willis. 2010. "Financial Decision Making and Cognition in a Family Context." *The Economic Journal* 120 (548): F363–F380.

Taylor, Donald H., Truls Østbye, Kenneth M. Langa, David Weir, and Brenda L. Plassman. 2009. "The Accuracy of Medicare Claims as an Epidemiological Tool: The Case of Dementia Revisited." *Journal of Alzheimer's Disease* 17 (4): 807–815.

Triebel, K.L., Roy Martin, H.R. Griffith, J. Marceaux, O.C. Okonkwo, L. Harrell, David Clark, J. Brockington, A. Bartolucci, and Daniel C. Marson. 2009. "Declining Financial Capacity in Mild Cognitive Impairment: A 1-year Longitudinal Study." *Neurology* 73 (12): 928–934.

Tsoy, Elena, Rachel E. Kiekhofer, Elan L. Guterman, Boon Lead Tee, Charles C. Windon, Karen A. Dorsman, Serggio C. Lanata, et al. 2021. "Assessment of Racial/Ethnic Disparities in Timeliness and Comprehensiveness of Dementia Diagnosis in California." *JAMA Neurology* 78, no. 6 (June): 657–665.

Vermunt, isa, Sietske A.M. Sikkes, Ardo van den Hout, Ron Handels, Isabelle Bos, Wiesje M. van der Flier, Silke Kern, et al. 2019. "Duration of Preclinical, Prodromal, and Dementia Stages of Alzheimer's Disease in Relation to Age, Sex, and APOE Genotype." *Alzheimer's & Dementia* 15 (7): 888–898.

Virnig, Beth. 2023. Sources and Use of Medicare Enrollment Information: The Master Beneficiary Summary File. Https://resdac.org/videos/sources-and-use-medicare-enrollment-information-0.

Wood, Stacey, and Peter A. Lichtenberg. 2017. "Financial Capacity and Financial Exploitation Of Older Adults: Research Findings, Policy Recommendations and Clinical Implications." *Clinical Gerontologist* 40 (1): 3–13.

Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*. MIT press.

A Appendix

Table A.1: Full Results (Models in Figure 2)

	(1) **Credit Score**	**(2)** **Any Delinquency**
1 quarter prior to diagnosis	-5.984*** (0.221)	0.0178*** (0.001)
2 quarters prior to diagnosis	-5.259*** (0.218)	0.0147*** (0.001)
3 quarters prior to diagnosis	-4.563*** (0.214)	0.0119*** (0.001)
4 quarters prior to diagnosis	-4.076*** (0.211)	0.00987*** (0.001)
5 quarters prior to diagnosis	-3.656*** (0.209)	0.00861*** (0.001)
6 quarters prior to diagnosis	-3.329*** (0.209)	0.00728*** (0.001)
7 quarters prior to diagnosis	-3.004*** (0.208)	0.00644*** (0.001)
8 quarters prior to diagnosis	-2.678*** (0.205)	0.00609*** (0.001)
9 quarters prior to diagnosis	-2.341*** (0.203)	0.00507*** (0.001)
10 quarters prior to diagnosis	-2.139*** (0.201)	0.00444*** (0.001)
11 quarters prior to diagnosis	-1.962*** (0.198)	0.00357*** (0.001)
12 quarters prior to diagnosis	-1.826*** (0.196)	0.00373*** (0.001)
13 quarters prior to diagnosis	-1.707*** (0.195)	0.00342*** (0.001)
14 quarters prior to diagnosis	-1.590*** (0.193)	0.00366*** (0.001)
15 quarters prior to diagnosis	-1.440*** (0.191)	0.00332** (0.001)
16 quarters prior to diagnosis	-1.286*** (0.189)	0.00249* (0.001)
17 quarters prior to diagnosis	-1.225*** (0.186)	0.00259** (0.001)
18 quarters prior to diagnosis	-1.072*** (0.185)	0.00265** (0.001)
19 quarters prior to diagnosis	-1.132*** (0.186)	0.00322** (0.001)
20 quarters prior to diagnosis	-1.018*** (0.184)	0.00256* (0.001)
21 quarters prior to diagnosis	-0.943*** (0.180)	0.00263** (0.001)
22 quarters prior to diagnosis	-0.628*** (0.174)	0.00145 (0.001)
23 quarters prior to diagnosis	-0.431* (0.169)	0.00155 (0.001)
24 quarters prior to diagnosis	-0.288 (0.165)	0.00127 (0.001)

Table A.1: Full Results (Models in Figure 2)

	(1) **Credit Score**	**(2)** **Any Delinquency**
25 quarters prior to diagnosis	-0.180	0.00122
	(0.163)	(0.001)
26 quarters prior to diagnosis	-0.151	0.00200*
	(0.161)	(0.001)
27 quarters prior to diagnosis	-0.0381	0.000217
	(0.155)	(0.001)
28 quarters prior to diagnosis	-0.0891	0.000408
	(0.150)	(0.001)
0 quarters after diagnosis	-7.022***	0.0221***
	(0.225)	(0.001)
1 quarter after diagnosis	-8.399***	0.0257***
	(0.227)	(0.001)
2 quarters after diagnosis	-8.844***	0.0258***
	(0.227)	(0.001)
3 quarters after diagnosis	-9.047***	0.0256***
	(0.228)	(0.001)
4 quarters after diagnosis	-9.219***	0.0243***
	(0.229)	(0.001)
5 quarters after diagnosis	-9.329***	0.0240***
	(0.230)	(0.001)
6 quarters after diagnosis	-9.263***	0.0226***
	(0.232)	(0.001)
7 quarters after diagnosis	-9.340***	0.0226***
	(0.237)	(0.001)
8 quarters after diagnosis	-9.438***	0.0220***
	(0.240)	(0.001)
9 quarters after diagnosis	-9.348***	0.0211***
	(0.244)	(0.001)
10 quarters after diagnosis	-9.248***	0.0198***
	(0.247)	(0.001)
11 quarters after diagnosis	-9.146***	0.0182***
	(0.250)	(0.001)
12 quarters after diagnosis	-9.161***	0.0179***
	(0.254)	(0.001)
13 quarters after diagnosis	-9.209***	0.0174***
	(0.258)	(0.001)
14 quarters after diagnosis	-9.303***	0.0175***
	(0.263)	(0.001)
15 quarters after diagnosis	-9.450***	0.0170***
	(0.268)	(0.001)
16 quarters after diagnosis	-9.452***	0.0160***
	(0.274)	(0.001)
17 quarters after diagnosis	-9.402***	0.0152***
	(0.278)	(0.001)
18 quarters after diagnosis	-9.423***	0.0148***
	(0.284)	(0.001)
19 quarters after diagnosis	-9.364***	0.0142***
	(0.288)	(0.001)
20 quarters after diagnosis	-9.546***	0.0141***
	(0.293)	(0.001)

Table A.1: Full Results (Models in Figure 2)

	(1) **Credit Score**	**(2)** **Any Delinquency**
21 quarters after diagnosis	-9.595*** (0.299)	0.0133*** (0.001)
22 quarters after diagnosis	-9.564*** (0.304)	0.0123*** (0.001)
23 quarters after diagnosis	-9.578*** (0.310)	0.0105*** (0.001)
24 quarters after diagnosis	-9.529*** (0.316)	0.00904*** (0.001)
25 quarters after diagnosis	-9.262*** (0.324)	0.00839*** (0.002)
26 quarters after diagnosis	-9.159*** (0.331)	0.00821*** (0.002)
27 quarters after diagnosis	-8.946*** (0.339)	0.00651*** (0.002)
28 quarters after diagnosis	-8.865*** (0.345)	0.00508** (0.002)
29+ quarters after diagnosis	-9.162*** (0.361)	0.00302 (0.002)
Spouse	2.081*** (0.100)	-0.00418*** (0.001)
Household size=2	-0.927*** (0.103)	0.00384*** (0.001)
Household size=3	-2.095*** (0.121)	0.00607*** (0.001)
Household size=4	-3.316*** (0.143)	0.00868*** (0.001)
Household size=5	-4.548*** (0.168)	0.0123*** (0.001)
Household size=6 or more	-4.252*** (0.166)	0.0119*** (0.001)
Number of chronic conditions	-0.718*** (0.131)	0.00383*** (0.001)
MA quarter	0.239 (0.135)	0.00432*** (0.001)
AMI	0.218 (0.246)	-0.000909 (0.001)
Anemia	0.658*** (0.147)	-0.00405*** (0.001)
Asthma	1.216*** (0.207)	-0.00462*** (0.001)
Atrial fib	0.868*** (0.181)	-0.00323*** (0.001)
Breast cancer	0.519* (0.224)	-0.00253* (0.001)
Colorectal cancer	0.964*** (0.278)	-0.00344* (0.001)
Endometrial cancer	1.594 (0.820)	-0.00683 (0.004)
Lung cancer	0.102 (0.369)	0.00369* (0.002)

Table A.1: Full Results (Models in Figure 2)

	(1) **Credit Score**	**(2)** **Any Delinquency**
Prostate cancer	0.866***	-0.00540***
	(0.223)	(0.001)
Cataracts	1.040***	-0.00566***
	(0.138)	(0.001)
CHF	0.0420	-0.00320***
	(0.164)	(0.001)
Chronic kidney disease	0.576***	-0.00508***
	(0.169)	(0.001)
COPD	1.092***	-0.00652***
	(0.176)	(0.001)
Depression	-2.158***	0.00402***
	(0.169)	(0.001)
Diabetes	1.172***	-0.00667***
	(0.174)	(0.001)
Glaucoma	2.140***	-0.00688***
	(0.163)	(0.001)
Hip or pelvis fracture	-1.088***	0.00411***
	(0.234)	(0.001)
Hyperlipidemia	1.335***	-0.00568***
	(0.142)	(0.001)
Hyperplasia	0.720***	-0.00320***
	(0.171)	(0.001)
Hypertension	0.936***	-0.00459***
	(0.145)	(0.001)
Hyperthyroidism	0.128	-0.00138
	(0.169)	(0.001)
Ischemic heart disease	0.634***	-0.00437***
	(0.153)	(0.001)
Osteoporosis	0.893***	-0.00375***
	(0.159)	(0.001)
Rheumatoid/osteoarthritis	0.798***	-0.00357***
	(0.149)	(0.001)
Constant	716.0***	0.0710***
	(1.998)	(0.011)
N	137003469	137003469
Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001 Coefficient estimates for state-time and age dummies not shown.		

Table A.2: Propensity Score Model

	(1) **Ever ADRD**
Female	0.244*** (0.00354)
Spouse	-0.158*** (0.00450)
Credit score @ 65	-0.000843*** (0.0000237)
Household size=2	0.00734 (0.00531)
Household size=3	-0.0252*** (0.00628)
Household size=4	-0.0134 (0.00800)
Household size=5	0.00836 (0.0108)
Household size=6 or more	0.0399*** (0.00671)
Black	0.0523*** (0.00680)
Asian	-0.173*** (0.0183)
Hispanic	0.161*** (0.0159)
Other race	-0.220*** (0.0145)
1.states	0 (.)
2.states	-0.231*** (0.0471)
3.states	-0.296*** (0.0185)
4.states	0.155*** (0.0208)
5.states	-0.180*** (0.0145)
6.states	-0.273*** (0.0210)
7.states	-0.0769*** (0.0195)
8.states	0.0529 (0.0302)
9.states	0.161*** (0.0391)
10.states	-0.0116 (0.0143)
11.states	-0.0642*** (0.0168)
12.states	-0.312*** (0.0338)
13.states	-0.372*** (0.0296)

Table A.2: Propensity Score Model

	(1) **Ever ADRD**
14.states	-0.0714*** (0.0153)
15.states	-0.151*** (0.0172)
16.states	-0.245*** (0.0207)
17.states	-0.0251 (0.0214)
18.states	-0.0692*** (0.0194)
19.states	-0.0499** (0.0193)
20.states	-0.195*** (0.0267)
21.states	0.00990 (0.0176)
22.states	-0.0494** (0.0173)
23.states	-0.0490** (0.0157)
24.states	-0.670*** (0.0204)
25.states	0.0813*** (0.0209)
26.states	-0.0933*** (0.0177)
27.states	-0.286*** (0.0315)
28.states	-0.203*** (0.0253)
29.states	-0.238*** (0.0254)
30.states	-0.0408 (0.0273)
31.states	0.0326* (0.0160)
32.states	-0.253*** (0.0262)
33.states	-0.201*** (0.0149)
34.states	-0.117*** (0.0163)
35.states	-0.223*** (0.0373)
36.states	-0.244*** (0.0155)
37.states	0.0128 (0.0197)
38.states	-0.457*** (0.0221)

Table A.2: Propensity Score Model

	(1) **Ever ADRD**
39.states	-0.243*** (0.0154)
40.states	-0.216*** (0.0339)
41.states	-0.0334 (0.0185)
42.states	-0.343*** (0.0356)
43.states	-0.1000*** (0.0177)
44.states	0.0465** (0.0146)
45.states	-0.340*** (0.0264)
46.states	-0.242*** (0.0376)
47.states	-0.0285 (0.0166)
48.states	-0.208*** (0.0180)
49.states	-0.177*** (0.0235)
50.states	-0.402*** (0.0187)
51.states	-0.230*** (0.0419)
2000.year	0 (.)
2001.year	-0.821*** (0.00907)
2002.year	-0.980*** (0.00951)
2003.year	-1.101*** (0.00970)
2004.year	-1.261*** (0.0103)
2005.year	-1.398*** (0.0108)
2006.year	-1.501*** (0.0112)
2007.year	-1.647*** (0.0114)
2008.year	-1.787*** (0.0122)
2009.year	-1.883*** (0.0128)
2010.year	-2.087*** (0.0144)
2011.year	-2.318*** (0.0149)

Table A.2: Propensity Score Model

	(1) **Ever ADRD**
2012.year	-2.490*** (0.0155)
2013.year	-2.564*** (0.0166)
2014.year	-2.820*** (0.0193)
2015.year	-3.037*** (0.0222)
2016.year	-3.380*** (0.0274)
2017.year	-4.182*** (0.0498)
Constant	0.0960*** (0.0223)
N	2427882
Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001	

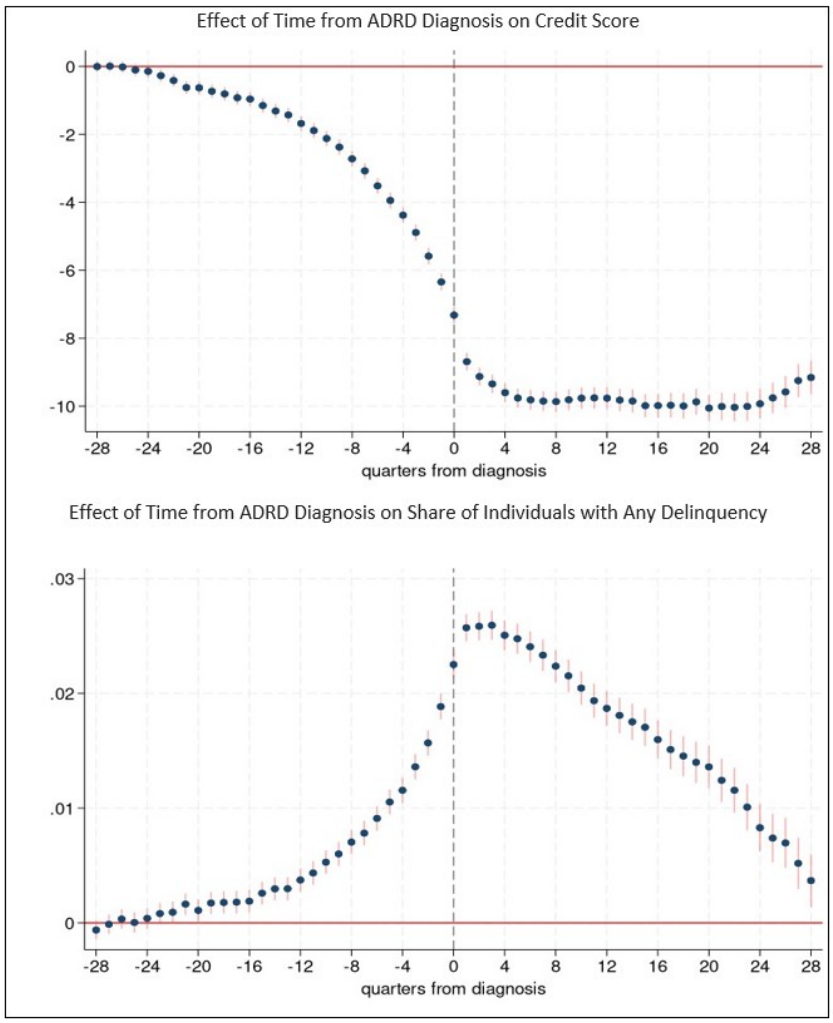

Figure A.1: Effect of Time from ADRD Diagnosis on Credit Score and Share of Individuals with Any Delinquency: Unweighted

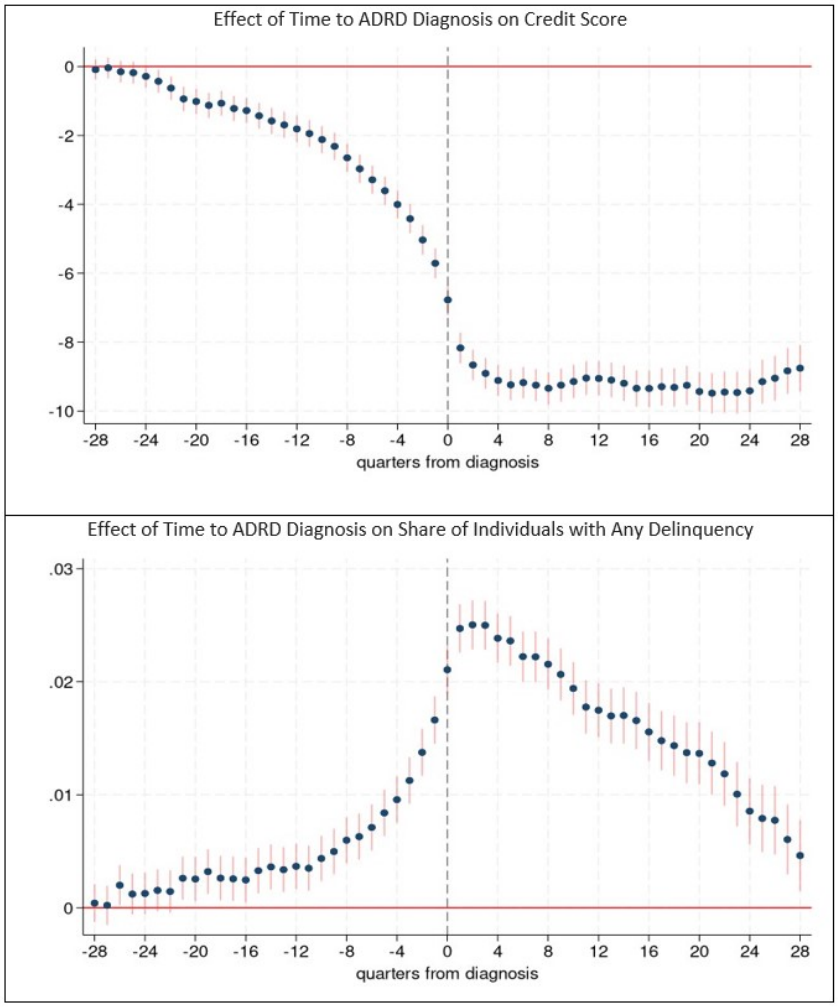

Figure A.2: Effect of Time to ADRD Diagnosis on Credit Score and Share of Individuals with Any Delinquency: Including Out of Pocket Costs

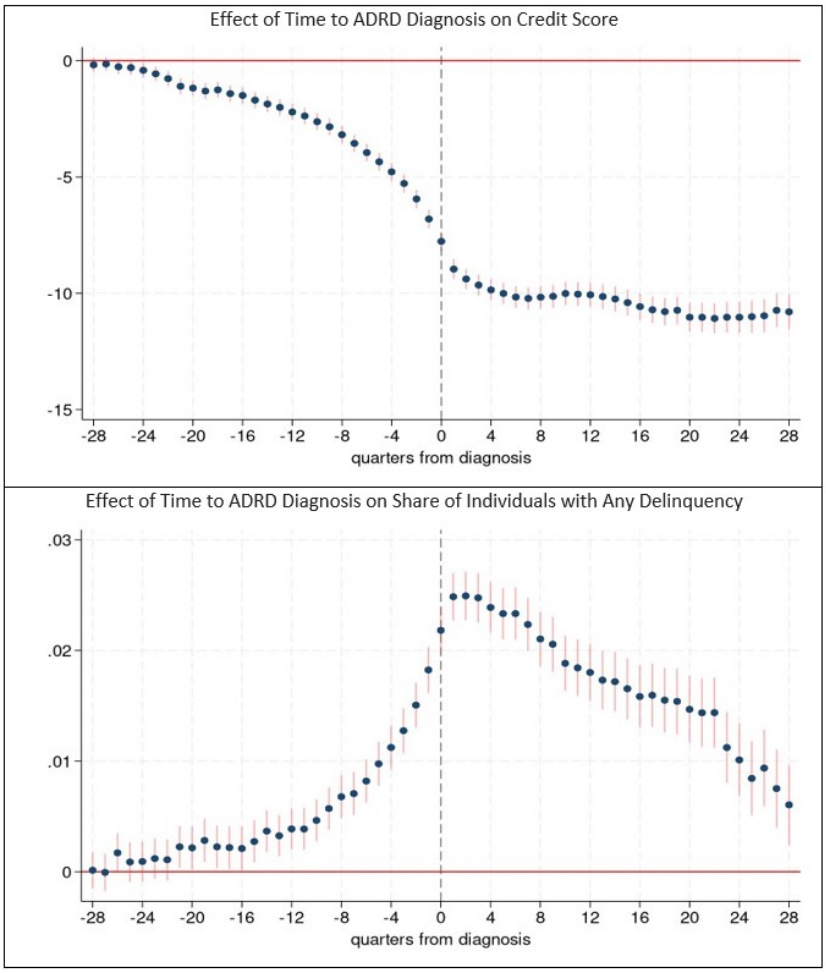

Figure A.3: Effect of Time to ADRD Diagnosis on Credit Score and Share of Individuals with Any Delinquency: Endpoint of Timeframe Limited to 2013

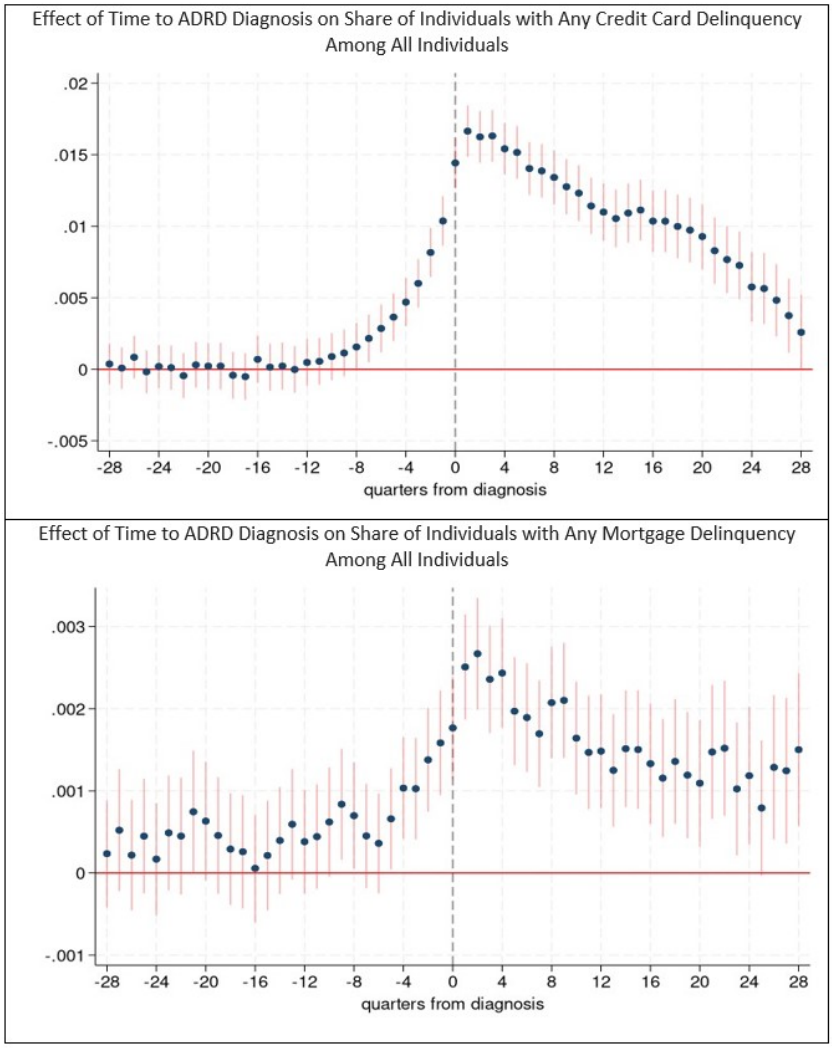

Figure A.4: Effect of Time to ADRD Diagnosis on Share of Individuals with Any Credit Card Delinquency and Any Mortgage Delinquency Among All Individuals (Not Limited to Account Holders)