

NO. 1169 OCTOBER 2025

# Cognitive Health, Household Financial Decision-Making, and Intrahousehold Financial Spillovers

Carole Roan Gresenz | Jean M. Mitchell | R. Scott Turner | Wilbert van der Klaauw | Crystal Wang

#### Cognitive Health, Household Financial Decision-Making, and Intrahousehold Financial Spillovers

Carole Roan Gresenz, Jean M. Mitchell, R. Scott Turner, Wilbert van der Klaauw, and Crystal Wang *Federal Reserve Bank of New York Staff Reports*, no. 1169
October 2025

https://doi.org/10.59576/sr.1169

#### Abstract

We study the spillover effects of cognitive decline in one member of a coupled household on the financial outcomes of their partner and assess how "own" and spillover effects are moderated by the structure of household financial decision-making. We use a large, nationally representative longitudinal data set spanning 2000-2017 that includes credit report data merged at the individual level with Medicare claims and enrollment data. We find the own adverse financial consequences of cognitive decline depend on household financial integration and other characteristics associated with household financial management, and find significant, albeit smaller (vs own), adverse financial spillover effects on partners.

JEL classification: G51, G41, D91

Key words: debt repayment, cognitive decline, household financial management, spillover effects

Van der Klaauw: Federal Reserve Bank of New York (email: wilbert.vanderklaauw@ny.frb.org). Gresenz, Mitchell, Turner: Georgetown (emails: carole.roan.gresenz@georgetown.edu, mitchejm@georgetown.edu, raymond.turner@georgetown.edu). Wang: Standford (email: crystal.wang@stanford.edu). The authors thank Greg Lostoski at Georgetown University for programming support; Francis Mahoney and Joelle Scally at the Federal Reserve Bank of New York (FRBNY), and Belicia Rodriguez at Duke University (formerly with the FRBNY) for help with developing the merged database and data management, Jonathan Lee at the FRBNY for research assistance, and Rebecca Vanarsdall at the McCourt School of Public Policy's Massive Data Institute for project management. They thank Krista Ruffini, Carly Urban, Yunan Ji, Jeremy Burke, David Meyers, and ASHEcon conference participants for helpful comments. 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. This research was reviewed and approved by the Georgetown University Institutional Review Board (Using Digital Signals from Credit Data for Early Detection of Alzheimer's Disease and Related Dementias; STUDY00005770).

This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the author(s) and do not necessarily reflect the position of the National Institutes of Health, the Federal Reserve Bank of New York, or the Federal Reserve System. Any errors or omissions are the responsibility of the author(s).

To view the authors' disclosure statements, visit https://www.newyorkfed.org/research/staff\_reports/sr1169.html.

#### 1 Introduction

Individual characteristics such as financial literacy (Lusardi & Messy, 2023; Lusardi & Mitchell, 2008, 2014), education (Cole et al., 2014) and age (Agarwal et al., 2009) exert substantial influence on individuals' financial decision-making and financial outcomes. For individuals in coupled households, the approach used to manage household finances (Fonseca et al., 2012) may also consequentially affect their financial outcomes. Coupled households employ a variety of arrangements for managing their finances. Some pool income (Evans & Gray, 2021; Hiekel et al., 2014; Pepin, 2022) and jointly hold liabilities, such as sharing a mortgage or credit card accounts (Horymski, 2023). Other couples operate as separate economic units, with each person independently holding their income and taking responsibility for managing their own debts (Evans & Gray, 2021; Pahl, 1989). Among couples who integrate their finances, some may vest authority over financial decisions in one individual and others may make joint decisions or distribute decisions across the couple (Kim et al., 2017; Pahl, 1989).

This study examines how the approach a couple uses for household financial decision-making affects the financial outcomes of each partner when one member experiences a decline in cognitive health from the onset of Alzheimer's disease or a related dementia (ADRD). We focus on households that include an adult age 65 or over, as more than 90 percent of ADRD cases affect individuals over age 65 (National Institute on Aging (NIA), 2023). ADRD is highly prevalent, affecting more than 1 in 9 older adults and more than one in three individuals over the age of 85 (Alzheimer's Association, 2025). Our analyses focus on financial outcomes related to debt and debt management. These outcomes represent an increasingly important and sometimes under-appreciated dimension of financial well-being among the aged (Lusardi et al., 2020). We assess whether the effects of ADRD-related cognitive decline on a coupled individual's own credit outcomes are amplified or diminished depending on the approach the couple takes to financial organization. We also evaluate spillover effects on the financial outcomes of their partner, and how these effects vary with a household's financial decision-making strategy.

Our work leverages a large, nationally representative, longitudinal data set spanning 2000-2017 that includes quarterly credit report data from Equifax (Lee & van der Klaauw, 2010) merged at the individual level using Social Security number (SSN) with Medicare claims and enrollment data. We successfully merged these data with a very high quality (92 percent) match rate. Our merged data in total include 7.9 million individuals and hundreds of millions quarterly observations. Financial outcomes include credit score, which is an overall measure of an individual's credit worthiness; payment delinquency for any account and for mortgages and credit card accounts; and whether an individual is "maxed out" on their credit card accounts, which we define as using more than 90 percent of the credit available to them through their credit cards.

ADRD in its earliest stages adversely affects various domains of cognitive function, including the ability to store and process knowledge, recall specific events, plan, problem

solve, and manage emotions (Jutten et al., 2021). Additionally, ADRD is associated with neuropsychiatric symptoms such as disinhibition, irritability, apathy, and agitation, as well as personality changes that may affect conscientiousness, neuroticism, and extraversion (Eikelboom et al., 2021; Robins Wahlin & Byrne, 2011). Together, these changes can compromise individuals' financial decision-making, making them susceptible to poor financial outcomes as a result of their own actions as well as increasing their susceptibility to financial exploitation by others. Marson (2000) document reduced financial capacity (based on tests of basic monetary skills, financial conceptual knowledge, checkbook management, and bank statement management, e.g.) among individuals with early stage ADRD and Gresenz et al (2025) find early stage ADRD adversely affects credit scores, payment delinquency for both credit cards and mortgages, and credit utilization.

The financial decision-making strategy that households use before ADRD is diagnosed is likely to matter for household financial outcomes. Previous evidence shows that while couples eventually change their approach when one member faces cognitive difficulties, the change typically occurs late in the disease trajectory and often after a diagnosis (Hsu & Willis, 2013). Conceptually, household financial practices that increase opportunities for joint oversight may mitigate the financial effects of the onset of ADRD, while those that reduce opportunities for joint oversight may exacerbate them. Accordingly, there may be less protection against own adverse financial outcomes for individuals affected by ADRD in coupled households that are less integrated (i.e. they operate as separate economic units) compared to those that are more integrated (i.e., finances are jointly managed to some degree). On the other hand, the spillover effects of ADRD on the financial outcomes of a partner may be more limited in less integrated households. We measure financial integration using information on whether the couple shares any credit card, auto loan, mortgage, or other type of credit account. We examine the possible moderating effects of household financial integration on the impacts of early stage ADRD on the financial outcomes of the affected individual, and those of their partner.

Having one person in charge of financial decisions may place households at more risk compared to households in which couples share in financial decision-making, given the possibility that ADRD will affect the financial decision-maker. Changing generational norms have resulted in greater use of shared decision-making among more recent birth cohorts, with a corresponding decrease in the use of decision-making that is concentrated in one individual (Bertocchi et al., 2014; Evans & Gray, 2021; Fonseca et al., 2012; Vogler et al., 2006). Thus, more recent generations may experience reduced vulnerability to poor outcomes from early stage ADRD compared to earlier generations. At the same time, generational differences in the use of credit (expanded use in later generations) may influence the exposure of individuals to the adverse consequences of early stage ADRD; thus, the net effect of birth cohort is ambiguous. We use birth cohort to capture generational differences and compare individuals born before 1928 (often called the "Greatest Generation," born 1901-1927) to those born after 1928 (the "Silent Generation," born 1928-1945). We

examine differences in the effects of ADRD by birth cohort on financial outcomes of both couple members.

Previous research documents differences by sex among couples using a distributed approach to financial decisions, with women more likely to be responsible for paying bills and short-term spending decisions and men more likely to pay taxes and track investments (Fonseca et al., 2012; Mader & Schneebaum, 2013). Consequently, it is possible that the effect of ADRD on financial outcomes like credit score and payment delinquencies are more pronounced among coupled households when women are affected by ADRD. Additionally, women have lower average levels of financial literacy compared to men (Lusardi & Mitchell, 2008, 2014), and these differences do not decrease with age (Boyle et al., 2025). This could in principle predispose a household to more risk when women are affected by ADRD, although a recent study shows no relationship between financial literacy and debt and debt management (Angrisani et al., 2023). On the other hand, men are more likely to be identified as the more knowledgeable member of the household with respect to finances (Smith et al., 2010), which could magnify the effect of ADRD on financial outcomes when men are affected by the disease. We examine how the sex of the individual affected by ADRD moderates the disease's effect on financial outcomes in coupled households.

ADRD may not only affect the financial outcomes of the individual who is diagnosed with the disorder, but also those of their partner, especially when finances are more integrated. One mechanism through which these effects may occur is through shared credit accounts such as mortgages, which are commonly held jointly (Horymski, 2023). A delinquency on a shared account will affect the credit record of both individuals, as well as their respective credit scores. Financial effects on partners may also emanate from the availability of household resources to meet payment obligations on an individually held liability or if the person affected by ADRD holds responsibility for managing debt payments for both shared and individually held liabilities.

We find that individuals in coupled households who are less financially integrated (with no shared credit account) experience amplified effects of ADRD compared to those in coupled households with some financial integration (share at least one credit account). In less financially integrated households, effects of ADRD on financial outcomes occur earlier in the disease trajectory and are greater in magnitude. Likewise, for some financial outcomes, the effects of ADRD occur earlier in the disease lifecycle and are larger in magnitude when a female vs a male partner is affected by ADRD. This is consistent with evidence from recent studies about typical patterns of distributed financial tasks by sex in coupled households; namely, that women are more often responsible for day to day financial tasks including bill paying. Further, we find that effects of ADRD on financial outcomes also tend to begin sooner for individuals born after 1928 compared to those born before 1928, likely reflecting generational differences in credit exposure. We also find ADRD affects not only the financial outcomes of the individual who is diagnosed with the disorder, but also those of their partner. The timing of the partner effects is

similar to those of the own effects of ADRD, although the magnitudes, as expected, are weaker for partners but still notable and consequential.

Our findings contribute to the emerging literature on intrahousehold financial decision making (Gomes et al., 2021). This includes studies of within household bargaining power and its effect on participation in financial markets, equity holdings, asset diversification, and returns on investments (Guiso & Zaccaria, 2023) and gender differences in bargaining power within a household (Gu et al., 2024). Unlike previous studies, we focus on financial outcomes on the liability vs. the asset side of a household's balance sheet.

Second, we contribute to the literature exploring health-related spillover effects between members of a household. Fadlon and Nielsen (2019), for example, show that a health shock in one member of a household affects preventive health care utilization and health behaviors among other members of the household, and Fadlon et al. (2025) examine the effect of a health shock on the use of spousal care from skilled nursing facilities. Other studies also examine spillover effects of health shocks in one person on the health care use and/or health status of their partner (Arteaga et al., 2024; Hodor, 2021). Further, Arrieta and Li (2023), Frimmel et al (2025), and Fadlon and Nielson (2021) explore the effects of health shocks on family labor supply, and Garcia-Gomez et al. (2013) examine household employment and income. Maestas et al. (2024) examine the effect of family caregiving on the employment outcomes of the caregiver. Previous studies of financial spillover effects of health shocks typically focus on the post-diagnosis time period where effects largely emanate from changes in health care spending. Distinctively, we study a health shock—the onset of a memory disorder—where spillover effects result from changes in a partner's cognitive function (and consequent financial decision-making) prior to diagnosis. Moreover, to our knowledge, this is the first study to examine the spillover effects of a health shock on partners' credit outcomes.

Third, our findings contribute to the growing literature on the susceptibility of individuals with latent memory disorders to adverse financial outcomes. We confirm and extend earlier findings that those in coupled households experience considerable negative effects of early stage ADRD (Gresenz et al., 2025). Findings from our analyses are important for understanding which households may be at risk for greater adverse effects from latent memory disorders and may facilitate targeting of policy solutions and interventions. In addition, our examination of the effects of ADRD on partners provides a more comprehensive understanding of the full effects of ADRD.

Our findings point to the importance of steps that seniors should consider to help reduce the potential adverse consequences of early stage ADRD and other conditions that may impair cognitive function. Seniors in coupled households may want to consider opportunities to increase information sharing, shared financial decision making, and joint oversight of financial accounts and bill paying with their partner to help mitigate against the potential for poor financial outcomes in the face of an adverse cognitive health shock. Establishing trusted contacts for financial accounts, designating a financial power

of attorney, and identifying a trusted family member or friend with whom they conduct regular financial reviews are additional actions to help mitigate against potential adverse consequences in these circumstances (Consumer Financial Protection Bureau, 2025; Rosengren, 2024).

#### 2 Methods

#### 2.1 Data

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 [SSN]) 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. Details of the data sources and file construction are described elsewhere (Gresenz et al., 2025). We highlight key features of the data in what follows. Parts of the data description draw from Gresenz et al. (2025), authored by the several members of the same team.

The CCP is based on credit reporting data collected by Equifax and is 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 & van der Klaauw, 2010). 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. These are known as primary sample members. For each primary sample member in the CCP, information is then collected on other individuals living at the exact same address (secondary sample members). Primary sample members are consistently followed over time while secondary sample members are only included if they remain in the same household as the primary sample member and thus may enter and leave the sample over time. To create a longitudinal panel, the sampling scheme was repeated for every quarter from the first quarter of 1999 through the present day.

We select a CCP target sample that includes all individuals (primary or secondary sample members) who were 65 years or older during the 2000-2017 period (n=12,456,009). We merge the 2000-2017 CCP data for this sample with Medicare claims and enrollment data for the same time period. The enrollment data are from the base segment of the Master Beneficiary Summary File (MBSF) and include information on all Medicare enrollees for a given calendar year including Medicare enrollment type (traditional or Medicare Advantage), along with age, sex, and race/ethnicity (Centers for Medicare & Medicaid Services, 2023b). We successfully match the CCP and Medicare base segment MBSF data for 91.8% of individuals (n=11,436,425) in the sample using SSN.

Claims data are used as the basis for the Chronic Conditions file, which captures

 $<sup>^{1}</sup>$ The merge was implemented using a three-party data arrangement to maintain anonymity and confidentiality. For a discussion of similar credit report data merges, see Gibbs et al. (2025).

the presence or absence of various conditions based on claims-based diagnosis codes, and the Cost & Use file, which provides information on health care spending. The Chronic Conditions file identifies individuals who are diagnosed with ADRD and 25 other chronic conditions using well-established algorithms developed by CMS (Chronic Conditions Data Warehouse, 2023). For each condition, the date of first occurrence is measured, and flags earmark mid- and end-of year presence of the condition.<sup>2</sup>

Claims data are only available for individuals enrolled in traditional (fee-for-service) Medicare, as no claims are generated for individuals enrolled in Medicare Advantage (MA). Our data include health status and health care spending information for 69 percent of individuals in the matched database (n=7,912,464). Of these, 2,723,983 are primary sample members and 5,179,481 are secondary sample members (i.e., adults who were part of the same household as the primary sample for at least one quarter).

#### 2.2 Analytic Samples

Our analyses examine individuals in coupled households and we construct two samples. The first ("index" sample) includes the primary sample members in coupled households and the second includes their partners ("partner" sample). We use the index sample to analyze how characteristics associated with the organization of household financial management affect the outcomes of individuals affected by a health shock (onset of ADRD) and the partner sample to analyze the spillover effects of the health shock on their partner.

To construct the index sample, we begin with primary sample members from the merged CCP/Medicare data for whom health information is available from claims data (n=2,723,983). After imposing a set of exclusion restrictions, the primary sample includes 2,437,144.

To identify coupled households, we rely on information in the CCP, as Medicare enrollment data do not include marital status or household composition. We classify households as coupled if the primary sample member resides with another adult who is within +/- 12 years of their age (Dokko et al 2015) and if total household size is less than 9 (the latter is intended to ensure we are capturing households and not larger group home settings). Our definition of coupled households includes people who share a household together and are likely to have some degree of commingled financial interests, including both traditional (e.g. spouses, romantic partners) and non-traditional partners (e.g. siblings living together). We identify a unique partner in 89 percent of coupled households. For the

<sup>&</sup>lt;sup>2</sup>Claims-based approaches to identifying ADRD have been used in previous research (Gresenz et al., 2025; Gresenz et al., 2019). 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.

<sup>&</sup>lt;sup>3</sup>Exclusion restrictions are: no credit report data during the study time period or before death; residence in U.S. territories; likely residence in an institutional setting (always observed at an address shared by 100 or more individuals); diagnosed with ADRD prior to age 65 or 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.

<sup>&</sup>lt;sup>4</sup>Traditional coupled households are the predominant type of household among seniors living with

remaining households, multiple individuals exist who are candidate partners. We discriminate among them based on whether they share debt with the primary sample member (choosing those who share debt vs not) and then on age difference between candidate partners (choosing the person with the minimum difference).

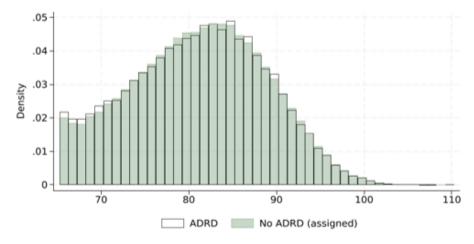
We select primary sample members who are in coupled households at the anchor point of their observation window. For those diagnosed with ADRD, the anchor point is defined as the quarter in which the primary household member was diagnosed with ADRD. For primary members never diagnosed with ADRD, the anchor point is a "shadow" quarter, where shadow quarters are chosen such that the distribution of age at the shadow quarter (for the never diagnosed) matches the empirical distribution of actual diagnosis ages (for the ever diagnosed).<sup>5</sup> We array the never ADRD group from oldest to youngest using the last age observed and array the shadow ages (from the distribution of age at diagnosis of the ever ADRD group) from oldest to youngest. We compared each last observed age from the never ADRD group to each shadow age and established a match if the shadow age was less than the last observed age. The first pass matched 87.4 percent of shadow ages to a sample member from the never ADRD group. We assigned the shadow age to the never ADRD observation. We cycled through this process four times and ultimately matched 98.8 percent of shadow ages. Our analytic sample includes 478,343 households, 228,396 of which had a primary sample member ever diagnosed with ADRD and the remainder representing matched households whose primary sample members were never diagnosed with ADRD.

The approach of matching the distribution of the age of diagnosis for the ever diagnosed with the distribution of the shadow ages for the never diagnosed is designed to ensure that we capture individuals ever or never diagnosed with ADRD at similar points in their lifecycle. Figure 1 shows the distribution of the age at diagnosis of individuals ever diagnosed with ADRD and the distribution of the shadow ages of the comparison group of individuals never diagnosed with ADRD for the index sample. The similarity of the two age distributions in the figure corroborates the success of our process for creating a comparison group.

We construct the partner sample using information from the CCP on partners of individuals in the index sample. Not all partners have enrollment and/or health information in the Medicare data because they may be younger than age 65 or enrolled in MA rather than traditional Medicare. Our main partner sample includes partners regardless of whether they are observed in the Medicare data (and thus whether their health status is observed). To test the sensitivity of our findings, we also construct auxiliary index and partner samples, where the auxiliary index sample is restricted to primary sample

other adults. Among non-institutionalized seniors 60 and over neither living alone nor living just with an adult child/children, 85 percent are in traditional coupled households (Ausubel, 2020).

<sup>&</sup>lt;sup>5</sup>We included primary sample members who were single or coupled at the time of diagnosis when we implemented the process of matching the distribution of shadow age among those never diagnosed with the distribution of age at diagnosis for those ever diagnosed to allow for additional analysis of single vs coupled individuals (Figure 2).



Source: Authors' analysis of merged CCP and Medicare data

Figure 1: Distribution of Age at Diagnosis Among Individuals Ever Diagnosed with ADRD and Shadow Age for Individuals Never Diagnosed with ADRD.

members in coupled households for whom we observe the health status of their partner, and the auxiliary partner sample is likewise restricted to those whose health status is observed.

#### 2.3 Observation Windows and Outcome Variables

We create an observation window for each sample member by looking backward from the anchor date (quarter of diagnosis for those ever diagnosed with ADRD and shadow quarter for those never diagnosed with ADRD) and only including quarters prior to the anchor date in which household composition is stable. We define this as no change in coupled status, household size remains less than 9, and no change in residential address.<sup>6</sup> A look-back change in any of these three dimensions triggers the end of the observation window.<sup>7</sup> The observation window also includes quarters after the anchor date, and these are not constrained to be stable in terms of household composition. The maximum length of each individual's observation window is 72 quarters (18 years).

We examine several financial outcomes. Credit score (Equifax Risk Score 3.0) was developed by Equifax and assesses the probability that a consumer will become seriously

<sup>&</sup>lt;sup>6</sup>The stability in household size requirement is designed to avoid capturing transition to nursing homes or other institutions. Residential address changes sometimes take effect at different time points in credit report data for different individuals in the same household, which can create the appearance of compositional changes in households. Thus, we require stability in address as well.

<sup>&</sup>lt;sup>7</sup>Our analytic sample only includes primary sample members who have at least 2 quarters in their observation window prior to the anchor date. The observation window for each individual excludes 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. 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.

delinquent (90+ days past due) over the next 12 months. It can be viewed as an indicator of an individual's overall creditworthiness. The score ranges from 280-850, with higher scores representing better credit risk. We also analyze an indicator for whether an individual is current (paid as agreed) on all accounts or has at least one account that is 30 or more days past due. In addition, we examine payment delinquency for mortgages and credit card accounts. Credit card accounts are an example of a revolving account which offers access to an ongoing line of credit and usually requires a minimum monthly payment. Mortgages are typically (but not always) installment accounts. These are accounts for which individuals borrow a lump sum and payments on the loan are made on a regularly scheduled basis. Credit card accounts and mortgages represent the two largest components of debt among people aged 70 and older (Federal Reserve Bank of New York, 2022). We also examine a variable capturing whether the individual's credit card utilization rate is over 90 percent, which we refer to as being "maxed-out." High credit utilization is considered a strong predictor of future missed payments.

#### 2.4 Empirical Strategy

Identification of early stage disease effects on financial outcomes relies on variation in the timing of diagnosis and within-individual changes over time in outcomes (among those ever diagnosed with ADRD), as well as a comparison group including individuals never diagnosed with ADRD. We implement stratified event study models with individual and time fixed effects following Equation 1.

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

where  $F_{pt}$  represents financial outcomes for individual p in time period t, and p=i for primary sample members and p=j for the partner of primary sample members.  $X_{it}$  includes time-varying demographic and health variables of the primary sample member. These include a set of indicator variables that capture age at each observation, indicators of household size because household size is permitted to vary after the anchor quarter, indicators for a set of chronic diseases, and a count of total chronic diseases in each period of time.  $ADRD_i$  is an indicator of whether a primary sample member is ever diagnosed with ADRD, and  $t_i$  represents the date of this diagnosis.

The specification includes a set of 20 leads and 20 lags that represent the number of quarters before and the number of quarters after the time of ADRD diagnosis. The 20 quarterly lead indicators represent a composite measure of cognitive, personality and neuropsychiatric changes associated with the disease. As ADRD is progressive, quarters just before diagnosis are associated with greater average symptoms and quarters further before diagnosis with more limited symptoms (Amieva et al., 2005; Jack Jr et al., 2018; Mistridis et al., 2015). Although previous research identifies an effect of early stage

ADRD on financial outcomes up to 28 quarters prior to diagnosis, we focus on the 20 quarters prior to diagnosis because our observation windows are shorter as a result of the stable household requirement and our sample size, especially in stratified analyses, is more limited than in previous research. Normalizing the effects more than 20 quarters prior to diagnosis to zero will lead to a slight underestimation of the negative impacts of ADRD on financial outcomes.  $\lambda_p$  represent individual fixed effects, and  $\theta_{st}^p$  is a vector of state-time fixed effects that account for within-state macroeconomic trends.

We use the index sample to analyze own effects (p=i). We stratify these analyses by the sex and birth cohort of the primary sample member and whether or not the couple shares at least one credit account. We check whether the credit reporting data for each person in the couple shows a jointly held account for any account type (mortgage, credit card, auto loan and other). We code shared account=1 if the credit report data for the primary sample member and the partner indicate both individuals have a joint (shared) account of the same type. Stratification is designed to allow for potential heterogeneity in the effect of early stage ADRD on financial outcomes by household characteristics associated with the organization and management of household finances. We use the partner sample to analyze the spillover effects of ADRD experienced by the index member on the financial outcomes of their partner (p=j).

We estimate fixed-effect, propensity score weighted linear regression models for credit score and fixed-effect, propensity-score weighted linear probability models (Konetzka et al., 2018; Marton et al., 2014) for all other outcomes. We choose this estimation approach to avoid issues associated with the incidental parameter problem and facilitate estimation of marginal effects (Angrist & Pischke, 2009; Greene, 2004; Neyman & Scott, 1948). We cluster the standard errors at the person/household level in all analyses.

We use propensity score weighting to adjust for observed differences in covariates between individuals who are ever or never diagnosed with ADRD, reducing the potential for bias in the effects of early stage ADRD we estimate. We develop a propensity score model that includes variables that in theory are likely to influence the probability a person develops ADRD and which may be correlated with financial outcomes (Caliendo & Kopeinig, 2008). These include the presence at the anchor point of chronic conditions that are associated with ADRD (depression, hypertension, high cholesterol, and diabetes) as well as Census tract or county level measures of additional risk factors associated with dementia (smoking, excessive drinking, physical inactivity, obesity, education, air pollution) (Livingston et al., 2024). We also account for state of residence, time period of observation, household structure, birth year, sex, race/ethnicity, and credit score at age 65. The latter is intended 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

<sup>&</sup>lt;sup>8</sup>The variable is a proxy for a credit account shared between the primary sample member and the probable partner because the data in the CCP do not include account identifiers for individuals to allow for linking accounts across credit reports.

score distribution for 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 (Caliendo & Kopeinig, 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). Raw and propensity score-weighted means and the propensity score distribution before and after weighting are provided in Appendix Table A2 and Figure A1.

#### 2.5 Robustness Checks and Sensitivity Analyses

We compare our estimates of own effects among coupled households to previous estimates that use a sample which only includes primary sample members who are coupled at the time of death or last observation (Gresenz et al., 2025).

We also examine the sensitivity of our results in analyses that use the auxiliary index and partner samples. The auxiliary samples are less representative of the full distribution of coupled households over 65 (see Section 3.1). We use the auxiliary samples to compare results with and without accounting for partner health status. This comparison enables us to assess the extent to which the own and partner effects of ADRD based on the main sample may be capturing correlation in health status among partners. We account for partner health status by excluding couples in which the partner is diagnosed with a memory disorder prior to the primary sample member, controlling for whether the partner later develops ADRD (within the subsequent five years), and controlling for the presence/absence of a partner having other chronic conditions in each quarter.

We also perform analyses using the auxiliary subsample that examine how the own effects of ADRD we estimate vary across couples based on partner ADRD status. Specifically, we stratify coupled households into those in which the partner is or is not diagnosed with ADRD prior to the primary sample member and compare results across these strata.

#### 3 Results

#### 3.1 Descriptive Results

Table 1 provides descriptive results for the main sample of coupled households. Characteristics are measured at the anchor point of the observation window (quarter of diagnosis for those with ADRD and shadow quarter for those never diagnosed with ADRD). The sample includes 228,396 coupled households where the primary sample member is ever diagnosed with ADRD and 249,947 coupled households in which the primary sample

<sup>&</sup>lt;sup>9</sup>In previous work, we confirmed the robustness of our analytic approach to the inclusion vs exclusion of propensity score weights, to keeping vs. dropping the comparison group of individuals never diagnosed with ADRD, and with placebo treatment tests (Gresenz et al., 2025).

member is never diagnosed with ADRD. The median observation window is 42 quarters (10.5 years) among individuals ever diagnosed with ADRD and 53 quarters (13.25 years) among those never diagnosed with ADRD. 58.3 percent of couples in the comparison group (primary sample member never diagnosed with ADRD) have a shared credit account vs. 51.9 percent of couples in the ever ADRD group. Credit scores (measured at time of diagnosis or shadow quarter) are higher among coupled primary sample members who are never diagnosed with ADRD compared to those ever diagnosed (782.1 vs. 764.7) and delinquency rates are lower (1.8 and 2.1 for mortgage and credit card delinquency compared to 4.0 and 5.7 percent). Among partners, average credit scores are lower among those whose partner is ever diagnosed with ADRD vs never diagnosed with ADRD (767.5 vs 781.0); delinquency rates are higher (3.3 and 4.1 for mortgage and credit card delinquency vs 1.5 and 2.0); and the rate of maxing out on credit cards is higher (4.7 vs 2.9 percent).

In our causal analysis of the financial impacts of ADRD we control for differences in average characteristics between those ever diagnosed and never diagnosed through the inclusion of individual fixed effects and through (inverse) propensity score weighting.

Appendix Table A1 provides a comparison of the auxiliary and main samples. The auxiliary sample only includes couples for whom health status is observed for both the primary sample member and their partner. We use this sample for sensitivity analyses. The auxiliary sample includes 57 percent (n=275,421) of coupled households in our main sample. Couples in the auxiliary sample are more likely to have a shared credit account (70.4 vs 51.9 percent among ever ADRD and 74.8 vs 58.3 percent among never ADRD for sensitivity and main samples, respectively) Couples in the auxiliary sample also differ from the main sample in terms of age (younger) and sex (greater proportion of couples with male primary sample members). The latter may reflect differences in the conditional probabilities of a man vs. a woman choosing a Medicare plan that matches that of their partner, although few studies speak to Medicare plan choices within a family (Lei et al., 2024). With more shared credit accounts and matching health plan choices, the auxiliary sample likely represents more tightly integrated households compared to the main sample.

# 3.2 Effect of ADRD on Own Financial Outcomes Among Coupled Households

Figure 2 shows the effects of ADRD on primary sample members' own financial outcomes for all coupled households. Financial outcomes include credit score, any delinquency, any credit card delinquency, any mortgage delinquency, and whether or not the individual is maxed out on their credit card accounts. For comparison, Figure 2 also provide estimates for single primary sample members.<sup>10</sup> In Figure 2 and other figures, the x-axis measures the number of quarters from diagnosis, where t = 0 indicates quarter of diagnosis. We

<sup>&</sup>lt;sup>10</sup>Construction of the comparison sample of single individuals follows the same approach used for the index sample of individuals who are part of coupled households.

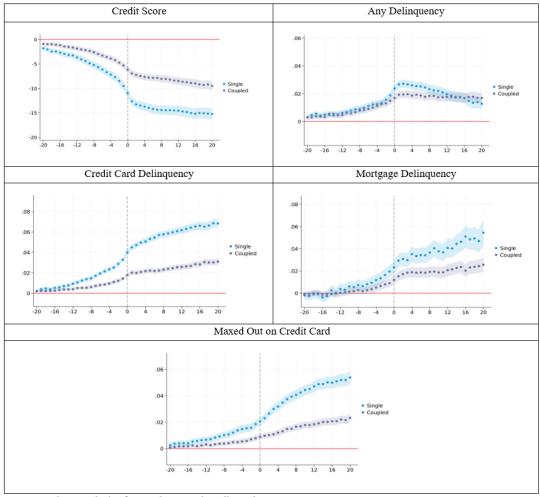
Table 1: Descriptive Statistics for Analytic Sample of Couples by Primary Sample Member Ever/Never Diagnosed with ADRD

	Eve	r ADRD	Neve	er ADRD
	(n=	228,396)	(n=	249,947)
	Mean	(Std Dev)	Mean	(Std Dev)
Age	79.6	(7.44)	79.6	(7.48)
Female	0.515	(0.500)	0.503	(0.500)
Credit score @ 65	758.5	(71.8)	769.0	(58.6)
White	0.886	(0.317)	0.904	(0.295)
Black	0.063	(0.243)	0.044	(0.205)
Hispanic	0.031	(0.173)	0.028	(0.166)
Asian	0.012	(0.107)	0.016	(0.125)
Other	0.008	(0.091)	0.008	(0.089)
Household size $= 2$	0.537	(0.499)	0.580	(0.494)
Household size $= 3$	0.248	(0.432)	0.241	(0.428)
Household size $= 4$	0.117	(0.322)	0.101	(0.302)
Household size $= 5$	0.053	(0.225)	0.043	(0.203)
Household size = 6-8	0.045	(0.206)	0.035	(0.184)
Count of conditions	6.580	(2.925)	3.127	(2.582)
Shared credit account	0.519	(0.500)	0.583	(0.493)
Financial Outcomes of Primar	ry Sampl	le Member		
Credit score	764.7	(76.6)	782.1	(57.0)
Any delinquency	0.071	(0.257)	0.031	(0.172)
Any mortgage delinquency*	0.040	(0.197)	0.018	(0.134)
Any credit card delinquency*	0.057	(0.231)	0.021	(0.143)
Credit utilization $> 90\%$ *	0.052	(0.222)	0.028	(0.165)
Financial Outcomes of Partne	r			
Credit score	767.5	(69.5)	781.0	(55.5)
Any delinquency	0.044	(0.206)	0.022	(0.147)
Any mortgage delinquency*	0.033	(0.178)	0.015	(0.121)
Any credit card delinquency*	0.041	(0.199)	0.020	(0.140)
Credit utilization $> 90\%$ *	0.047	(0.212)	0.029	(0.167)

Notes: Authors' analysis of merged CCP and Medicare data. "Ever ADRD" is primary sample member ever diagnosed with ADRD. "Never ADRD" is primary sample member never diagnosed with ADRD. \*Conditional on having a mortgage or credit card. All statistics calculated at the quarter of diagnosis (ever ADRD) or shadow quarter (never ADRD). Partner financial outcomes are measured using the partner sample (228,344 partners of ever ADRD sample members and 249,889 partners of never ADRD sample members) All other measures are from index sample.

focus our discussion on the time period prior to ADRD diagnosis. We evaluate the magnitude of effect sizes using baseline averages measured 5 years prior to ADRD diagnosis. Coefficient estimates for selected models and the associated propensity score models are in Appendix Tables A3 and A4.

We find pervasive effects of ADRD prior to diagnosis on the own financial outcomes of individuals in coupled households. The timing of effects of ADRD on credit scores, any delinquency, and credit card delinquency are the same for coupled households as they are for single individuals, with effects observed during all 20 quarters prior to diagnosis, and



Source: Authors' analysis of merged CCP and Medicare data.

Figure 2: Effects of ADRD on Own Financial Outcomes Among Individuals in Coupled Households Compared to Singles

similar for high credit utilization (starting 20 quarters prior to diagnosis for singles vs. 18 for coupled individuals). Effects of ADRD on mortgage delinquency begin somewhat later for individuals in coupled vs single households. We find statistically stronger effects among singles for credit scores, credit card delinquency, and high credit utilization (being maxed out on credit cards). One year prior to diagnosis, for example, credit scores are 7.1 points (0.96 percent) lower than baseline among singles vs. 3.9 points (0.50 percent) among individuals in coupled households. Credit card delinquency is 2.3 percentage points higher (34 percent) a year prior to diagnosis compared to baseline among singles and 0.95 percentage points higher (33 percent) among coupled individuals. One year prior to diagnosis, high credit utilization is 1.5 vs 0.5 percentage points (18.1 vs 14.0 percent) higher among singles/couples.

### 3.3 Effect of ADRD on Own Financial Outcomes Among Coupled Households Stratified by Birth Cohort, Sex, and Shared Credit Account

Figure 3 shows the effects of ADRD on coupled individuals by birth cohort. Effects tend to begin sooner for individuals born after 1928. For any delinquency and credit card delinquency, for example, effects start 20 vs 8 quarters prior to diagnosis among those born after/before 1928. For credit scores, we observe statistically significant effects 20 quarters prior to diagnosis among those born after 1928 vs 15 quarters among those born before 1928. For most outcomes, effect sizes are statistically indistinguishable across birth cohorts. For any delinquency, magnitudes are greater for those born after 1928. One year prior to diagnosis, delinquency rates are 1.3 percentage points higher (25.6 percent higher) among those born after 1928 vs 0.6 points higher (23.6 percent) among those born before 1928.

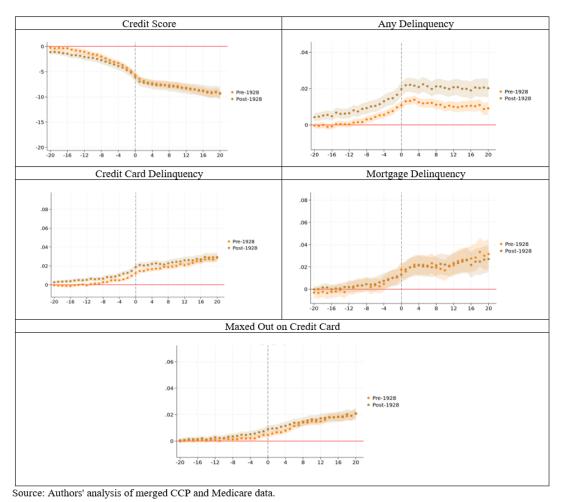


Figure 3: Own Effects of ADRD by Birth Cohort Among Coupled Households

Figure 4 shows the effects of ADRD on coupled individuals by sex of the individual diagnosed with ADRD. For high credit utilization (maxing out credit cards) and mortgage delinquency, effects begin sooner when women are affected by ADRD. For high credit utilization, for example, effects start 20 quarters prior to diagnosis when women are affected by ADRD vs 6 quarters when men are affected by ADRD. Moreover, we find no statistically significant effects on mortgage delinquency when men in coupled household are affected by ADRD whereas we find effects 11 quarters prior to diagnosis when women are affected. By contrast, for credit score, any delinquency, and credit card delinquency,

the timing of effect of ADRD is the same whether a man or a woman in the coupled is affected by ADRD. For credit scores, the magnitude of effect sizes are larger in quarters proximate to diagnosis when women vs men are affected. We conducted additional analyses that examine the effect of ADRD on financial outcomes of single individuals by sex and find the same differential patterns in the timing and magnitude of effects of ADRD by sex (Appendix Figure A2).

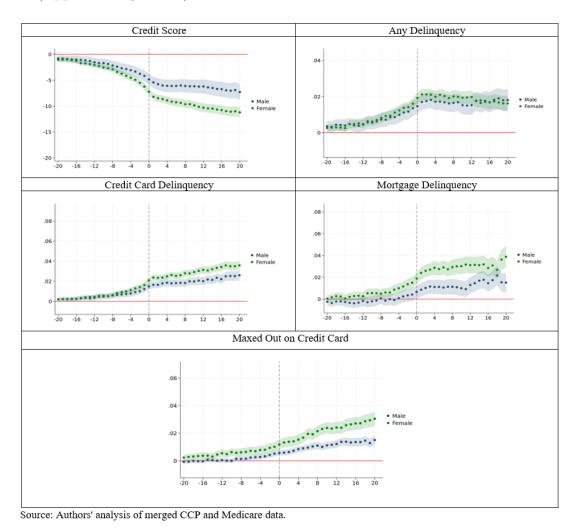
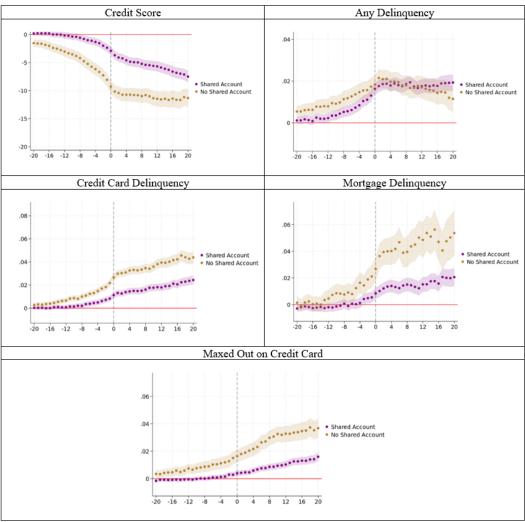


Figure 4: Own Effects of ADRD by Sex Among Coupled Households

Figure 5 shows the effects of ADRD on individuals in coupled households by whether the couple shares at least one credit account. We find meaningful differences in the timing and magnitude of effects across couples contingent on whether the couple shares a credit account. Effects occur sooner in the disease trajectory and are larger in magnitude for individuals in couples where no credit accounts are shared compared to individuals in couples that share a credit account. Among couples who have no shared credit accounts, the effects of ADRD on credit scores, any delinquency, credit card delinquency and high credit utilization appear 5 years (20 quarters) prior to diagnosis. For individuals in coupled households that share a credit account, effects of ADRD on credit scores consistently appear only in the 7 quarters prior to diagnosis; on any delinquency in the 12 quarters prior to diagnosis; on credit card delinquency in the 7 quarters prior to diagnosis; and on

high credit utilization in the 2 quarters prior to diagnosis. For mortgage delinquency, the timing of the effect of early-stage ADRD differs as well, starting 11 vs 3 quarters prior to diagnosis for individuals in couples that do not share vs share a credit account.



Source: Authors' analysis of merged CCP and Medicare data.

\*Note: Shared credit account status is determined by debt in the quarter of diagnosis or shadow quarter.

Figure 5: Own Effects of ADRD by Shared Credit Account Among Coupled Households

We also find that effects are considerably bigger in magnitude among couples without shared credit accounts for credit scores, any credit card delinquency and high credit utilization. One year prior to diagnosis, for example, credit scores are 6.15 points (or 0.8 percent) lower than baseline for individuals in couples who do not share a credit account vs 1.31 points (0.17 percent) among individuals in coupled households with a shared credit account. Six months prior to diagnosis, the probability of being maxed out on credit card accounts is 1.3 percentage points (24 percent) higher than baseline among individuals with no shared credit account vs 0.3 percentage points (11 percent) higher among individuals with a shared credit account. The probability of credit card delinquency is 1.5 vs 0.5 percentage points (34 vs 29 percent) higher a year prior to diagnosis for individuals with no vs. any shared credit account.

#### 3.4 Spillover Effects of ADRD on Partner Financial Outcomes

Figure 6 compares estimated effects of ADRD on the financial outcomes of individuals who are themselves affected by ADRD (in blue) with those of their partners (in purple). For each outcome (credit score, any delinquency), we show results among all couples and among couples stratified by sex of the person affected by ADRD and whether the couple shares a credit account. These analyses use our main sample which does not include measures of partner health status. However, we test the sensitivity of our results to the inclusion of controls for partner health status with additional analyses on an auxiliary sample that includes health information for both members of the couple (see Section 3.5).

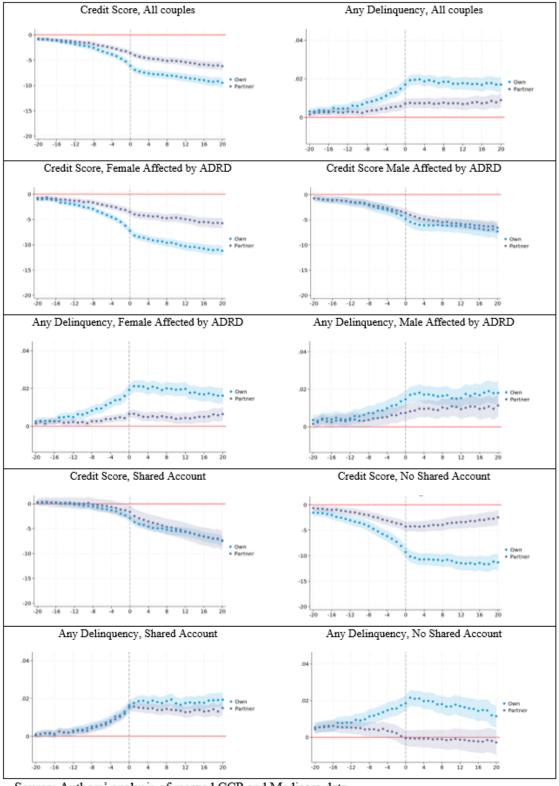
We find that ADRD in one member of a couple affects both the credit score and the probability of delinquency of their partner. Among all couples, the timing of the partner effects are similar to those of the own effects of ADRD although the magnitudes are weaker. Both own and partner effects begin 20 quarters prior to diagnosis for credit scores and any delinquency. One year prior prior to diagnosis, credit scores are 3.9 points lower (0.5 percent) for the individual affected by ADRD vs. 2.6 points (0.3 percent) for their partner. Similarly, the probability of delinquency is 1.1 percentage points higher (24.3 percent) one year prior to diagnosis among individuals affected by ADRD vs 0.5 percentage points higher (14.7 percent) among their partners.

Similar patterns are observed for both outcomes when we limit our focus to households in which a female is affected by ADRD. In coupled households in which the male is affected by ARDD, we see no statistically significant differences in own vs. partner effects on credit scores and delinquency. The same is true for couples that share a credit account; that is, we see no statistically significant differences in own and partner effects. For couples with no shared credit accounts, the timing of partner effects on credit score are similar to own effects, but the effect sizes are weaker (than for own effects). Similarly, the spillover effects of ADRD on a partner's probability of any delinquency are more limited among couples who are less financially integrated. Patterns of own/partner effects for couples born before/after 1928 are similar to those for all couples (Appendix Figure A3).

#### 3.5 Results from Robustness Checks and Sensitivity Analyses

Figure A4 compares our estimates of own effects using the index sample (which includes individuals who are coupled at the anchor date of either quarter of diagnosis or shadow quarter) to estimates from previous research that use a sample of primary sample members who are coupled at the time of death or last observation (Gresenz et al., 2025). For completeness, we also compare estimates of own effects among individuals who are single at the anchor date (Figure 2) to previous estimates using individuals who are single at the time of death or last observation (Gresenz et al., 2025). Results are similar across the two samples for couples and singles.

Results using the auxiliary sample that includes only couples for which we have health

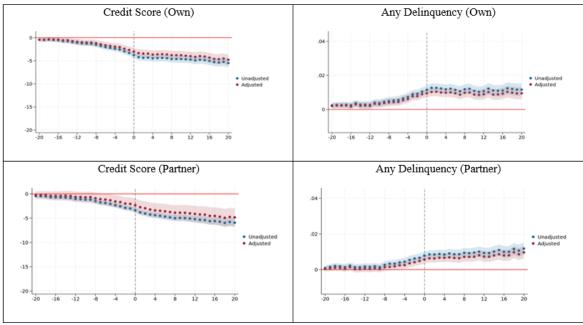


Source: Authors' analysis of merged CCP and Medicare data.

Figure 6: Own and Partner Effects of ADRD Among Coupled Households

information on both members are shown in Figure 7. Red indicates analyses that exclude households in which the partner is diagnosed with ADRD before the primary sample member and that also control for partner health status. Blue indicates analyses that include all coupled households regardless of partner health status and do not otherwise

control for partner health status. Point estimates for own and partner effects of ADRD are generally slightly larger in analyses that exclude health controls compared to those that include health controls, but these differences are not statistically significant.



Source: Authors' analysis of merged CCP and Medicare data.

Figure 7: Own and Partner Effects of ADRD on Financial Outcomes Using Auxiliary Sample: Unadjusted/Adjusted for Partner Health Status

We also perform analyses using the auxiliary sample that examine the effects of ADRD on an individual's own financial outcomes stratified by whether the partner has already been diagnosed with ADRD. These results are shown in Figure A5. As expected, the effects of ADRD in one member are much stronger when their partner has already been affected by ADRD.

#### 4 Discussion

We show that the risk of adverse financial outcomes for individuals affected by ADRD varies with characteristics associated with the organization and management of household finances and that the financial effects of ADRD in one member of a coupled household also extend to their partner.

In particular, we find that the effects occur earlier in the disease trajectory and are greater in magnitude among couples without shared credit accounts compared to those who share at least one credit account. This likely reflects the increased opportunities for joint oversight when couples integrate their finances by jointly holding liabilities (Horymski, 2023), which we measure, and/or by pooling income (Evans & Gray, 2021; Hiekel et al., 2014; Pepin, 2022), which we do not observe but may be more likely among households

<sup>\*</sup>Notes: Blue (unadjusted) indicates analyses with no controls for spouse health status; red (adjusted) indicates analyses that exclude households in which the partner is diagnosed with ADRD before the primary sample member and that control for partner health status.

that share liabilities. Among individuals in coupled households with less integrated finances, we find the magnitude of the own health shock effect is similar to that experienced by individuals who are single.

We also find some differences in the effect of ADRD prior to diagnosis by generation. Effects of ADRD on financial outcomes tend to begin sooner for individuals born after 1928 (Silent Generation) compared to those born before 1928 (Greatest Generation). Otherwise, the magnitude of the effect of ADRD on financial outcomes is similar across birth cohorts. The timing differences may reflect generational differences in the use of credit, with less credit used in the earlier generation and thus more limited opportunities for ADRD to affect credit outcomes. Although the use of shared financial decision-making among couples was more limited in earlier generations (Bertocchi et al., 2014; Evans & Gray, 2021; Fonseca et al., 2012; Vogler et al., 2006), the protection offered by more limited use of credit appears to outweigh any adverse effects of household financial decision-making that is not shared.

Women and men often play different roles in financial management and organization within the household, and we find differences in the financial consequences of early stage ADRD depending on the sex of the person affected. Increases in the probability of high credit utilization from ADRD occurs much earlier in the disease lifecycle when women vs men are affected by ADRD. We find no effect of ADRD on mortgage delinquency when men in coupled households are affected by ADRD whereas we find effects on mortgage delinquency 11 quarters prior to diagnosis when ADRD occurs in women. Notably, however, single women appear no more susceptible to adverse financial consequences from ADRD compared to single men. Thus, greater financial effects when female vs male members of coupled households are affected by ADRD likely reflect differences in the role each plays in household financial management. Previous research finds women are more likely to be responsible for paying bills and short-term spending decisions (Fonseca et al., 2012; Mader & Schneebaum, 2013), roles that are particularly likely to affect credit use and bill non-payment.

ADRD affects not only the financial outcomes of the individual who is diagnosed with the disorder, but also those of their partner. For coupled households, the cumulative toll of ADRD on both members of the couple must be considered. With just over half of those ever diagnosed with ADRD coupled at diagnosis, the implication is that for every two individuals diagnosed with ADRD, three experience the effects of the disease on their financial outcomes. To our knowledge these are the first analyses of financial spillover effects from a partner's cognitive health shock. The timing of the partner effects is similar to those of the own effects of ADRD, although the magnitudes, as expected, are somewhat weaker for partners. These effects may emanate from shared credit accounts which affect the credit record of both individuals and/or from the availability of household resources to meet payment obligations on an individually held liability. We see no statistically significant differences in own and partner effects for couples who share a credit account,

while we see smaller partner effects (than own effects) for couples with no shared credit account. We hypothesized that some of the effects we observe on partners may reflect correlation in health status across members of the couple. However, we found no statistically significant differences in partner effects in analyses that controlled or did not control for partner health status using a sample of couples for which we have health information for both members.

#### 4.1 Limitations

Neither the CCP nor CMS data include a direct measure of marital status. However, we use shared exact address and age gaps to impute single/partner status. We also lack direct information regarding how coupled households organize and manage their finances. We approach this limitation by examining how financial outcomes differ according to characteristics associated with household financial management, such as having a shared credit account, birth cohort, and sex of the person affected by ADRD. Our main data set does not include measures of partner health status among all coupled households. However, we conduct additional analyses on a subsample of our data that includes health information for both members of the couple. Additionally, we do not observe whether an adult child in or outside of the household may be monitoring their parents' finances, although our analyses include a control for the number of other adults in the household.

Our data include individuals in traditional (fee-for-service) Medicare but not individuals in Medicare Advantage plans, whose health care service utilization is tracked in encounter data vs. claims records. However, between 65 and 83 percent of Medicare beneficiaries each year were enrolled in traditional Medicare during the 2000-2017 time span of our data (Freed et al., 2021). During the time period of our study, Medicare Advantage plans were not required to submit encounter data to CMS, although CMS has recently begun releasing such data. Our data also exclude individuals who have no credit history, such as those who are undocumented (who also will lack Medicare enrollment/claims data). However, credit report data are available for an estimated 97.3 percent of U.S. adults (Consumer Financial Protection Bureau, 2025).

Our analyses use samples that are conditioned on household structure at the time of diagnosis. Symptoms associated with ADRD could affect marital status. Some studies find no relationship between chronic health and dissolution of marriage after age 50 (Lin et al., 2018); however, Monin et al. (2023) find that severe neuropsychiatric symptoms such as agitation, aggression and disinhibition are associated with a higher likelihood of divorce or separation. To the extent this occurs, the sample of individuals who are single at diagnosis may include individuals who experienced more severe such symptoms prior to diagnosis. As a consequence, some of the differences we observe in financial outcomes among single individuals vs. coupled households could be attributable to differences in these symptoms, in addition to differences in opportunities for financial oversight.

#### 4.2 Conclusion

This study shows the household financial risk associated with the onset of a cognitive impairment. We find that the financial consequences of a cognitive health shock in older households extend beyond individuals who themselves experience cognitive decline and carry significant consequences for the credit-related outcomes of their partners. Our findings highlight the importance of household financial management to curbing the potential consequences of cognitive health shocks on financial outcomes of older adults in coupled households. There are a number of measures that seniors can consider to help reduce the potential adverse consequences of the onset of ADRD and other conditions that may affect cognition. Individuals can establish trusted contacts for their financial accounts, designate a financial power of attorney, and identify a trusted family member or friend with whom they conduct regular financial reviews (Consumer Financial Protection Bureau, 2025; Rosengren, 2024). While shared credit accounts can offer some protection against adverse own financial outcomes for individuals affected by ADRD, they can also increase potential spillover financial effects on their partner. What is more clear is that seniors in coupled households may want to consider opportunities to increase information sharing, shared financial decision making, and joint oversight of financial accounts and bill paying with their partner to help mitigate against poor financial outcomes for either partner.

#### References

- Abadie, A. (2005). Semiparametric difference-in-differences estimators. The Review of Economic Studies, 72, 1–19. https://www.jstor.org/stable/3700681
- Agarwal, S., Driscoll, J. C., Gabaix, X., & Laibson, D. (2009). The age of reason: Financial decisions over the life cycle and implications for regulation. *Brookings Papers on Economic Activity*, 2009, 51–101. Retrieved July 31, 2025, from http://www.jstor.org/stable/25652729
- Alzheimer's Association. (2025). Alzheimer's disease facts and figures. https://www.alz.org/alzheimers-dementia/facts-figures
- Amieva, H., Jacqmin-Gadda, H., Orgogozo, J.-M., Le Carret, N., Helmer, C., Letenneur, L., Barberger-Gateau, P., Fabrigoule, C., & Dartigues, J.-F. (2005). The 9 year cognitive decline before dementia of the alzheimer type: A prospective population-based study. Brain, 128(5), 1093–1101.
- Angrisani, M., Burke, J., Lusardi, A., & Mottola, G. (2023). The evolution of financial literacy over time and its predictive power for financial outcomes: Evidence from longitudinal data. *Journal of Pension Economics and Finance*, 22(4), 640–657. https://doi.org/10.1017/S1474747222000154
- Angrist, J. D., & Pischke, J.-S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

- Arrieta, G. R., & Li, G. (2023). Caring to work or working to care: The intra-family dynamics of health shocks. *American Journal of Health Economics*, 9(2), 175–204.
- Arteaga, C., Vigezzi, N., & Garcia-Gomez, P. (2024). In sickness and in health: The broad impact of spousal health shocks. *Working Paper*.
- Ausubel, J. (2020). Older people are more likely to live alone in the US than elsewhere in the world. *Pew Research Center*.
- Bertocchi, G., Brunetti, M., & Torricelli, C. (2014). Who holds the purse strings within the household? the determinants of intra-family decision making. *Journal of Economic Behavior & Organization*, 101, 65–86.
- Boyle, P., Mitchell, O. S., Mottola, G. R., & Yu, L. (2025). Declining financial and health literacy among older men and women. *The Journal of the Economics of Ageing*, 30, 100547. https://doi.org/https://doi.org/10.1016/j.jeoa.2025.100547
- Caliendo, M., & Kopeinig, S. (2008). Some practical guidance or the implementation of propensity score matching. *Journal of Economic Surveys*, 22, 31–72.
- Centers for Medicare & Medicaid Services. (2023a, September). Chronic conditions.
- Centers for Medicare & Medicaid Services. (2023b, September). Master beneficiary summary file (mbsf) lds.
- Chronic Conditions Data Warehouse. (2023). Condition categories. https://www2.ccwdata.org/web/guest/condition-categories
- Cole, S., Paulson, A., & Shastry, G. K. (2014). Smart money? the effect of education on financial outcomes. *The Review of Financial Studies*, 27(7), 2022–2051.
- Consumer Financial Protection Bureau. (2025). Recommendations and report for financial institutions on preventing and responding to elder financial exploitation. Washington, DC. https://www.consumerfinance.gov/consumer-tools/educator-tools/resources-for-older-adults/protecting-against-fraud/
- Eikelboom, W. S., van den Berg, E., Singleton, E. H., Baart, S. J., Coesmans, M., Leeuwis, A. E., Teunissen, C. E., van Berckel, B. N., Pijnenburg, Y. A., Scheltens, P., et al. (2021). Neuropsychiatric and cognitive symptoms across the alzheimer disease clinical spectrum: Cross-sectional and longitudinal associations. *Neurology*, 97(13), e1276–e1287.
- Evans, A., & Gray, E. (2021). Cross-national differences in income pooling among married and cohabiting couples. *Journal of Marriage and Family*, 83(2), 534–550.
- Fadlon, I., Gross, T., Hoagland, A., & Layton, T. (2025). The protective effects of a healthy spouse: Medicare as the family member of last resort (tech. rep.). Working Paper.
- Fadlon, I., & Nielsen, T. H. (2019). Family health behaviors. *American Economic Review*, 109(9), 3162–3191.
- Fadlon, I., & Nielsen, T. H. (2021). Family labor supply responses to severe health shocks: Evidence from danish administrative records. *American Economic Journal: Applied Economics*, 13(3), 1–30.

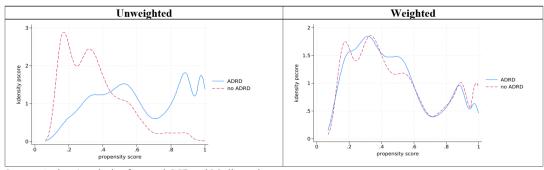
- Federal Reserve Bank of New York. (2022). Quarterly report on household credit and debt, 2022 (tech. rep.). Center for Microeconomic Data, Federal Reserve Bank of New York.
- Fonseca, R., Mullen, K. J., Zamarro, G., & Zissimopoulos, J. (2012). What explains the gender gap in financial literacy? the role of household decision making. *Journal of Consumer Affairs*, 46(1), 90–106.
- Freed, M., Biniek, J. F., Damico, A., & Neuman, T. (2021). Medicare advantage in 2021: Enrollment update and key trends. *Kaiser Family Foundation*.
- Frimmel, W., Halla, M., Paetzold, J., & Schmieder, J. (2025). Health of parents, their children's labor supply, and the role of migrant care workers. *Journal of Labor Economics*, 43(3).
- García-Gómez, P., Van Kippersluis, H., O'Donnell, O., & Van Doorslaer, E. (2013). Longterm and spillover effects of health shocks on employment and income. *Journal of Human Resources*, 48(4), 873–909.
- Gibbs, C., Guttman-Kenney, B., Lee, D., Nelson, S., van der Klaauw, W., & Wang, J. (2025). Consumer credit reporting data. *Journal of Economic Literature*, 63, 598–636.
- Gomes, F., Haliassos, M., & Ramadorai, T. (2021). Household finance. *Journal of Economic Literature*, 59(3), 919–1000. https://doi.org/10.1257/jel.20201461
- Greene, W. (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, C. R., Mitchell, J. M., Rodriguez, B., Wang, C., Turner, R. S., & van der Klaauw, W. (2025). The financial consequences of undiagnosed memory disorders. *Journal of Financial Economics*, 172, 104149.
- Gresenz, C. R., Mitchell, J. M., Marrone, J., & Federoff, H. J. (2019). Effect of early-stage Alzheimer's disease on household financial outcomes. *Health Economics (United Kingdom)*, 29, 18–29.
- Grodstein, F., Chang, C.-H., Capuano, A. W., Power, M. C., Marquez, D. X., Barnes, L. L., Bennett, D. A., James, B. D., & Bynum, J. P. (2022). Identification of dementia in recent medicare claims data, compared with rigorous clinical assessments. The Journals of Gerontology: Series A, 77(6), 1272–1278.
- Gu, R., Peng, C., & Zhang, W. (2024). The gender gap in household bargaining power: A revealed-preference approach. *The Review of Financial Studies*, hhae039.
- Guiso, L., & Zaccaria, L. (2023). From patriarchy to partnership: Gender equality and household finance. *Journal of Financial Economics*, 147(3), 573–595.
- Hiekel, N., Liefbroer, A. C., & Poortman, A.-R. (2014). Income pooling strategies among cohabiting and married couples: A comparative perspective. *Demographic Re*search, 30, 1527–1560.

- Hodor, M. (2021). Family health spillovers: Evidence from the rand health insurance experiment. *Journal of Health Economics*, 79, 102505.
- Horymski, C. (2023). Joint accounts are on the decline for couples. *Experian*. https://www.experian.com/blogs/ask-experian/research/joint-accounts-are-on-the-decline-for-couples/
- Hsu, J. W., & Willis, R. (2013). Dementia risk and financial decision making by older households: The impact of information. *Journal of Human Capital*, 7(4), 340–377.
- Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics*, 86, 4–29.
- Jack Jr, C. R., Bennett, D. A., Blennow, K., Carrillo, M. C., Dunn, B., Haeberlein, S. B., Holtzman, D. M., Jagust, W., Jessen, F., Karlawish, J., et al. (2018). Nia-aa research framework: Toward a biological definition of alzheimer's disease. *Alzheimer's Dementia*, 14(4), 535–562.
- Jutten, R. J., Sikkes, S. A., Amariglio, R. E., Buckley, R. F., Properzi, M. J., Marshall, G. A., Rentz, D. M., Johnson, K. A., Teunissen, C. E., Van Berckel, B. N., et al. (2021). Identifying sensitive measures of cognitive decline at different clinical stages of alzheimer's disease. *Journal of the International Neuropsychological Society*, 27(5), 426–438.
- Kim, J., Gutter, M. S., & Spangler, T. (2017). Review of family financial decision making: Suggestions for future research and implications for financial education. *Journal of Financial Counseling and Planning*, 28(2), 253–267.
- Konetzka, R. T., Stuart, E. A., & Werner, R. M. (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.
- Lee, D., & van der Klaauw, W. (2010). An introduction to the FRBNY Consumer Credit Panel. Federal Reserve Bank of New York Staff Report 479.
- Lei, L., Levy, H., Ankuda, C., Hoffman, G. J., Kim, H. M., Strominger, J., & Maust, D. T. (2024). Partner plan choices and medicare advantage enrollment decisions among older adults. *JAMA*, 331(15), 1322–1325. https://doi.org/10.1001/jama.2024.1773
- Lin, I.-F., Brown, S. L., Wright, M. R., & Hammersmith, A. M. (2018). Antecedents of gray divorce: A life course perspective. *The Journals of Gerontology: Series B*, 73(6), 1022–1031.
- Livingston, G., Huntley, J., Liu, K. Y., Costafreda, S. G., Selbæk, G., Alladi, S., Ames, D., Banerjee, S., Burns, A., Brayne, C., et al. (2024). Dementia prevention, intervention, and care: 2024 report of the lancet standing commission. *The Lancet*, 404(10452), 572–628.
- Lusardi, A., & Messy, F.-A. (2023). The importance of financial literacy and its impact on financial wellbeing. *Journal of Financial Literacy and Wellbeing*, 1(1), 1–11.
- Lusardi, A., & Mitchell, O. S. (2008). Planning and financial literacy: How do women fare?(no. w13750). *National Bureau of Economic Research*, 10, w13750.

- Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *American Economic Journal: Journal of Economic Literature*, 52(1), 5–44.
- Lusardi, A., Mitchell, O. S., & Oggero, N. (2020). Debt and financial vulnerability on the verge of retirement. *Journal of Money, Credit and Banking*, 52(5), 1005–1034.
- Mader, K., & Schneebaum, A. (2013). The gendered nature of intra-household decision making in and across europe. Vienna University of Business and Economics Department of Economics Working Paper, 157.
- Maestas, N., Messel, M., & Truskinovsky, Y. (2024). Caregiving and labor supply: New evidence from administrative data. *Journal of Labor Economics*, 42(S1), S183–S218.
- Marson, D. C., Sawrie, S. M., Snyder, S., McInturff, B., Stalvey, T., Boothe, A., Aldridge, T., Chatterjee, A., & Harrell, L. E. (2000). Assessing financial capacity in patients with Alzheimer's disease: A conceptual model and prototype instrument. *Archives of Neurology*, 57(6), 877–884.
- Marton, J., Yelowitz, A., & Talbert, J. C. (2014). A tale of two cities? The heterogeneous impact of Medicaid managed care. *Journal of Health Economics*, 36, 47–68.
- Mistridis, P., Krumm, S., Monsch, A. U., Berres, M., & Taylor, K. I. (2015). The 12 years preceding mild cognitive impairment due to alzheimer's disease: The temporal emergence of cognitive decline. *Journal of Alzheimer's Disease*, 48(4), 1095–1107.
- Monin, J. K., McAvay, G., Zang, E., Vander Wyk, B., Carrión, C. I., & Allore, H. (2023). Associations between dementia staging, neuropsychiatric behavioral symptoms, and divorce or separation in late life: A case control study. *PLoS one*, 18(8), e0289311.
- National Institute on Aging (NIA). (2023, March). Alzheimer's disease genetics fact sheet. Retrieved February 17, 2023, from https://www.nia.nih.gov/health/alzheimers-disease-genetics-fact-sheet
- Neyman, J., & Scott, E. L. (1948). Consistent estimates based on partially consistent observations. *Econometrica: Journal of the Econometric Society*, 1–32.
- Pahl, J. (1989). Money and marriage. Macmillan.
- Pepin, J. R. (2022). A visualization of us couples' money arrangements. Socius, 8, 23780231221138719.
- Robins Wahlin, T.-B., & Byrne, G. J. (2011). Personality changes in alzheimer's disease: A systematic review. *International Journal of Geriatric Psychiatry*, 26(10), 1019–1029.
- Rosengren, J. (2024). 5 ways to prevent elder financial exploitation. AARP Bulletin. https://www.aarp.org/money/scams-fraud/prevent-financial-elder-abuse/#:~: text=A%20trusted%20contact%20is%20someone, not%20able%20to%20make%20transactions
- Smith, J. P., McArdle, J. J., & Willis, R. (2010). Financial decision making and cognition in a family context. *The Economic Journal*, 120(548), F363–F380.

- Taylor, D. H., Ostbye, T., Langa, K. M., Weir, D., & Plassman, B. L. (2009). The accuracy of medicare claims as an epidemiological tool: The case of dementia revisited. *Journal of Alzheimer's Disease*, 17, 807–815.
- Vogler, C., Brockmann, M., & Wiggins, R. D. (2006). Intimate relationships and changing patterns of money management at the beginning of the twenty-first century 1. *The British Journal of Sociology*, 57(3), 455–482.
- Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT Press.

## Appendix A Appendix



Source: Authors' analysis of merged CCP and Medicare data. Note: Shown only for coupled households in the age-matched sample.

Figure A1: Propensity Score Distribution for Treatment and Comparison Groups: Weighted and Unweighted

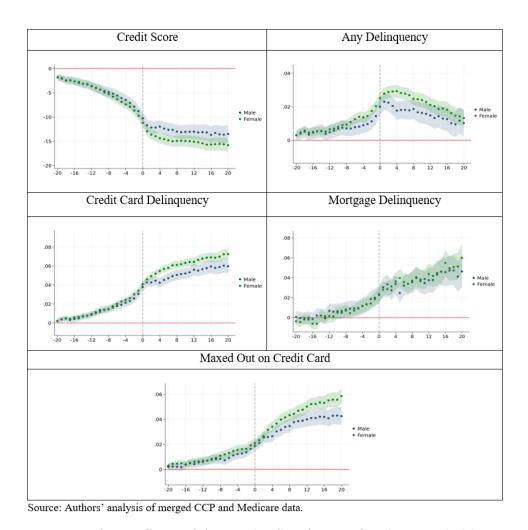
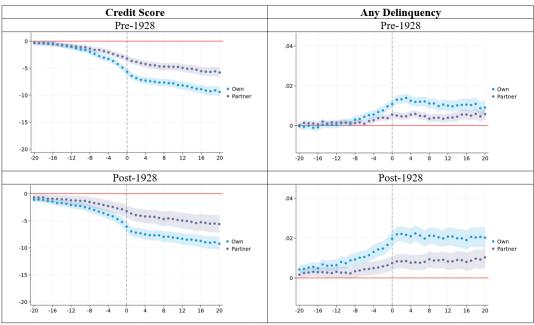
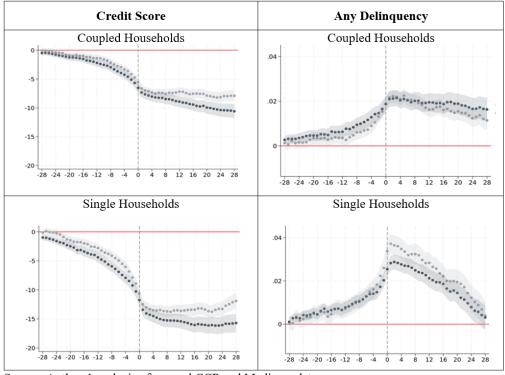


Figure A2: Effects of ADRD by Sex Among Single Households



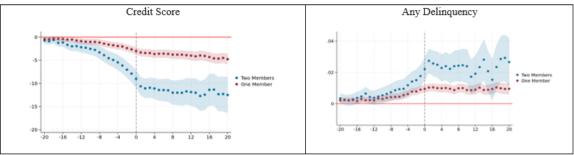
Source: Authors' analysis of merged CCP and Medicare data.

Figure A3: Own and Partner Effects of ADRD Among Coupled Households: By Birth Cohort



Source: Authors' analysis of merged CCP and Medicare data.

Figure A4: Comparison with Previous Estimates



Source: Authors' analysis of merged CCP and Medicare data.

Figure A5: Own Effect of ADRD on Financial Outcomes Using Auxiliary Sample: Couples with One vs Two Members Affected by ADRD

<sup>\*</sup>Notes: Main results in dark gray compared to previous estimates in light gray. Previous estimates use an unconditioned sample with coupled status defined at time of last observation and controls for household composition in each quarter.

<sup>\*</sup>Notes: Red indicates couples in which the partner did not have ADRD before the primary sample member; blue indicates couples in which the partner had an ADRD diagnosis before the primary sample member's diagnosis. Analyses control for spouse later diagnosed with ADRD and other spouse health conditions.

Table A1: Comparison of Main and Auxiliary Samples

	Ever ADRD				Never ADRD					
	Ma	ain	Auxi	liary	Std	Ma	ain	Auxi	liary	Std
	Mean	SD	Mean	SD	Diff	Mean	SD	Mean	SD	Diff
Age	79.62	7.444	77.98	6.824	0.230	79.58	7.48	77.97	7.025	0.222
Female	0.515	0.500	0.420	0.493	0.192	0.503	0.500	0.424	0.494	0.158
Credit score @ 65	758.5	71.78	762.8	67.65	-0.061	769.1	58.56	771.1	55.91	-0.037
White	0.886	0.317	0.899	0.302	-0.039	0.904	0.295	0.912	0.283	-0.029
Black	0.063	0.243	0.053	0.223	0.044	0.044	0.205	0.038	0.190	0.032
Hispanic	0.031	0.173	0.028	0.166	0.015	0.028	0.166	0.025	0.158	0.018
Asian	0.012	0.107	0.012	0.110	-0.005	0.016	0.125	0.016	0.126	-0.004
Other	0.008	0.091	0.008	0.092	-0.001	0.008	0.089	0.008	0.090	-0.003
HH size=2	0.537	0.499	0.593	0.491	-0.113	0.58	0.494	0.623	0.485	-0.089
HH size=3	0.248	0.432	0.237	0.425	0.026	0.241	0.428	0.228	0.420	0.029
HH size=4	0.117	0.322	0.097	0.296	0.065	0.101	0.302	0.087	0.281	0.050
HH size=5	0.053	0.225	0.041	0.197	0.060	0.043	0.203	0.035	0.184	0.041
HH size=6-8	0.045	0.206	0.032	0.177	0.063	0.035	0.184	0.027	0.162	0.049
# of conditions	6.58	2.925	6.385	2.911	0.067	3.127	2.582	3.137	2.502	-0.004
Shared credit account	0.519	0.500	0.704	0.456	-0.387	0.583	0.493	0.748	0.434	-0.355
Financial Outcomes of	Primary	Sample	Membe	r						
Credit Score	764.7	76.56	772.9	69.14	-0.112	782.2	56.98	784.9	53.14	-0.050
Any dq	0.071	0.257	0.053	0.223	0.078	0.031	0.172	0.025	0.155	0.036
Any mort. dq*	0.040	0.197	0.027	0.161	0.077	0.018	0.134	0.014	0.115	0.038
Any CC dq*	0.057	0.231	0.040	0.195	0.079	0.021	0.143	0.016	0.126	0.033
CC util. $> 90\%$ *	0.052	0.222	0.042	0.202	0.044	0.028	0.165	0.025	0.155	0.021
Financial Outcomes of	Partner									
Credit Score	767.5	69.52	772.8	67.68	-0.077	781.0	55.51	784.5	54.16	-0.064
Any dq	0.044	0.206	0.047	0.212	-0.013	0.022	0.147	0.024	0.154	-0.014
Any mort. dq*	0.033	0.178	0.027	0.161	0.037	0.015	0.121	0.013	0.114	0.014
Any CC dq*	0.041	0.199	0.033	0.178	0.047	0.020	0.14	0.017	0.129	0.024
CC util. > 90%*	0.047	0.212	0.041	0.198	0.03	0.029	0.167	0.026	0.159	0.018

Notes: Authors' analysis of merged CCP and Medicare data. HH=Household, dq=delinquency. Std diff refers to the standardized differences. Main index sample includes 228,396 ever ADRD and 249,947 never ADRD households. Auxiliary index sample includes 119,864 ever ADRD and 155,557 never ADRD households. Partner financial outcomes are from partner samples; all other measures are from index samples.

Table A2: Raw and Propensity Score Weighted Means

		Ra	aw		Weighted			
	Ever	(Std	Never	(Std	Ever	(Std	Never	(Std
	ADRD	dev)	ADRD	dev)	ADRD	dev)	ADRD	dev)
Female	0.515	0.500	0.503	0.500	0.512	0.500	0.517	0.500
White	0.886	0.317	0.904	0.295	0.904	0.295	0.901	0.298
Black	0.063	0.243	0.044	0.205	0.051	0.220	0.052	0.221
Hispanic	0.031	0.173	0.028	0.166	0.028	0.164	0.029	0.168
Asian	0.012	0.107	0.016	0.125	0.011	0.104	0.011	0.105
Other	0.008	0.091	0.008	0.089	0.007	0.083	0.007	0.083
Household size=2	0.537	0.499	0.580	0.494	0.564	0.496	0.563	0.496
Household size=3	0.248	0.432	0.241	0.428	0.244	0.430	0.241	0.428
Household size=4	0.117	0.322	0.101	0.302	0.107	0.309	0.109	0.311
Household size=5	0.053	0.225	0.043	0.203	0.047	0.211	0.049	0.215
Household size=6-8	0.045	0.206	0.035	0.184	0.038	0.191	0.038	0.191
Count of chronic conditions	6.580	2.925	3.127	2.582	5.882	2.911	3.870	2.758
Shared credit account	0.519	0.500	0.583	0.493	0.538	0.499	0.561	0.496
Financial Outcomes of Prime	ary Samp	le Memb	per					
Credit score	764.7	76.6	782.1	57	772.5	69.5	779.7	60.1
Any delinquency (dq)	0.071	0.257	0.031	0.172	0.058	0.233	0.034	0.182
Any mortgage dq*	0.040	0.197	0.018	0.134	0.036	0.185	0.018	0.133
Any credit card dq*	0.057	0.231	0.021	0.143	0.046	0.209	0.023	0.151
CC utilization > 90%*	0.052	0.222	0.028	0.165	0.041	0.199	0.031	0.174
Financial Outcomes of Partner								
Credit score	767.5	69.5	781	55.5	773.8	63.5	779.4	57.8
Any delinquency (dq)	0.044	0.206	0.022	0.147	0.036	0.186	0.024	0.154
Any mortgage dq*	0.033	0.178	0.015	0.121	0.029	0.169	0.015	0.121
Any credit card dq*	0.041	0.199	0.020	0.140	0.034	0.181	0.022	0.148
CC utilization> 90%*	0.047	0.212	0.029	0.167	0.037	0.189	0.031	0.174

Notes: Authors' analysis of merged CCP and Medicare data. Results shown for coupled households in the age-matched sample. \*Conditional on having a mortgage or credit card. All statistics calculated at the quarter of diagnosis or shadow quarter of the primary member. Weighted sample is smaller than the raw sample because not all households received PSM weights. Ever ADRD (raw), N=228,396; Never ADRD (raw), N=249,947; Ever ADRD (weighted), N= 206,390; Never ADRD (weighted), N= 239,338.

Table A3: Full Regression Results for Coupled Households, Stratified by Shared Credit Account / No Shared Credit Account

	Shared cred			credit account
	(1) Risk (2			` '
1	Score De -2.348***	elinquency 0.0131***		Delinquency
1 quarter prior to diagnosis				
2	, ,	(-9.23)	, ,	, ,
2 quarters prior to diagnosis		0.0111***		
9		(-7.96)		
3 quarters prior to diagnosis		0.0104***		
4		(-7.6)		
4 quarters prior to diagnosis	-1.318***			
F		(-6.25)		
5 quarters prior to diagnosis	-1.112**		-5.737***	
		(-5.49)		
6 quarters prior to diagnosis	-0.997**		-5.220***	
		(-4.74)		
7 quarters prior to diagnosis	-0.781*		-4.726***	
	, ,	(-4.37)	, ,	, ,
8 quarters prior to diagnosis	-0.568			
	(-1.79)		(-8.52)	
9 quarters prior to diagnosis	-0.406			
	(-1.30)		(-7.96)	
10 quarters prior to diagnosis		0.00354**		
	(-1.20)		(-7.55)	
11 quarters prior to diagnosis	-0.24	0.00342**	-3.328***	0.00944***
	(-0.81)	(-2.94)	(-7.35)	, ,
12 quarters prior to diagnosis	-0.164	0.00225*	-3.037***	0.00791***
	(-0.57)	(-2)	(-6.88)	(-4.31)
13 quarters prior to diagnosis	-0.0227	0.00193	-2.775***	0.00795***
	(-0.08)	(-1.78)	(-6.47)	'
14 quarters prior to diagnosis	0.0217	0.00198	-2.522***	0.00774***
	(-0.08)	(-1.85)	(-6.09)	(-4.43)
15 quarters prior to diagnosis	0.0304	0.00249*	-2.369***	0.00778***
	(-0.12)	(-2.38)	(-5.90)	(-4.55)
16 quarters prior to diagnosis	0.213	0.000859	-2.013***	0.00623***
	(-0.85)	(-0.86)	(-5.20)	(-3.74)
17 quarters prior to diagnosis	0.235	0.00131	-1.834***	0.00624***
	(-0.97)	(-1.34)	(-4.91)	(-3.85)
18 quarters prior to diagnosis	0.231	0.00169	-1.640***	0.00609***
	(-0.99)	(-1.8)	(-4.61)	(-3.9)
19 quarters prior to diagnosis	0.234	0.00114	-1.581***	0.00545***
	(-1.04)	(-1.26)	(-4.65)	(-3.65)
20 quarters prior to diagnosis	0.196	, ,	, ,	, ,
-		(-1.27)	(-4.75)	(-3.79)
0 quarters after diagnosis		0.0163***		
~	(-7.73)	(-11.35)	(-16.02)	(-8.68)
	*			•

Table A3: Full Regression Results for Coupled Households, Stratified by Shared Credit Account / No Shared Credit Account

Table A3: Full Regression Results for Coupled Households, Stratified by Shared Credit Account / No Shared Credit Account

S	Shared credit account		No shared credit account		
(1	) Risk (2	) Any	(1) Risk	(2) Any	
Se	core De	elinquency	Score	Delinquency	
Number of chronic conditions	-0.107	0.000185	-0.00918	0.000101	
	(-1.06)	(-0.7)	(-0.10)	(-0.25)	
MA Quarter	0.395	0.00253	0.0813	0.00101	
	(-1.18)	(-1.49)	(-0.15)	(-0.46)	
Probable partner (@ age 65)		-0.0118***			
	(-22.92)	(-7.81)	(-11.51)	(-8.50)	
Household size= $2$ (@ age $65$ )	-2.262***	0.00454**	-1.792***	0.00842***	
	(-6.91)	(-2.66)	(-3.81)	(-4.67)	
Household size= $3$ (@ age $65$ )	-4.028***	0.00630***	-3.273***	0.0108***	
	(-10.01)	(-3.75)	(-6.51)	(-5.89)	
Household size= $4$ (@ age $65$ )	-5.522***	0.00973***	-4.653***	0.0137***	
	(-13.86)	(-4.88)	(-9.73)	(-5.88)	
Household size= $5$ (@ age $65$ )	-6.807***	0.0123***	-6.659***	0.0161***	
	(-14.19)	(-6.18)	(-12.44)	(-7.06)	
Household size= $6+$ (@ age $65$ )	-9.231***	0.0160***	-7.641***	0.0220***	
	(-12.36)	(-5.57)	(-9.24)	(-5.84)	
AMI	-0.226	0.00372**	-0.167	0.00113	
	(-0.78)	(-2.62)	(-0.39)	(-0.69)	
Anemia	0.166	0.000166	0.176	0.000387	
	(-0.84)	(-0.33)	(-0.76)	(-0.49)	
Asthma	0.125	0.0012	-0.157	0.00176	
	(-0.46)	(-1.29)	(-0.47)	(-0.96)	
Atrial fibrillation	0.498*	0.000041	0.118	0.00144	
	(-2.1)	(-0.06)	(-0.4)	(-1.3)	
Breast cancer	0.31	0.00108	1.010*	-0.000954	
	(-0.63)	(-0.96)	(-2.4)	(-0.51)	
Colorectal cancer	0.313	0.000752	0.651	0.00148	
	(-0.96)	(-0.64)	(-1.6)	(-0.87)	
Endometrial cancer	1.151	0.00131	1.139	0.000719	
	(-1.74)	(-0.55)	(-1.25)	(-0.22)	
Lung cancer	0.312	0.00143	-0.289	0.00630*	
	(-0.49)	(-0.86)	(-0.44)	(-2.51)	
Prostate cancer	0.0467	-0.000884	0.302	-0.00128	
	(-0.17)	(-1.14)	(-0.37)	(-0.40)	
Cataract	0.334*	-0.00130**	0.450*	-0.00193*	
	(-2.44)	(-2.70)	(-2.57)	(-2.27)	
CHF	-0.397*	0.00232***	0.159	0.00216*	
	(-2.05)	(-3.89)	(-0.47)	(-2.19)	
Chronic kidney disease	-0.123	0.00139*	-0.643	-0.000243	
	(-0.59)	(-2.12)	(-1.58)	(-0.22)	
COPD	-0.183	0.000857	-0.478	0.00183	
	(-1.00)	(-1.22)	(-0.74)	(-1.58)	

Table A3: Full Regression Results for Coupled Households, Stratified by Shared Credit Account / No Shared Credit Account

	Shared cred	it account	No shared credit account		
	(1) Risk (2	) Any	(1) Risk	(2) Any	
	Score D	elinquency	Score	Delinquency	
Glaucoma	0.273	-0.00281***	1.451**	-0.00282	
	(-0.61)	(-3.85)	(-3.18)	(-1.88)	
Hip or pelvis fracture	-1.153***	0.00668***	-0.845*	0.00402**	
	(-3.86)	(-5.35)	(-2.45)	(-3.04)	
Hyperplasia	-0.122	-0.000211	0.177	-0.00141	
	(-0.33)	(-0.23)	(-0.74)	(-1.64)	
Hypothyroidism	-0.0986	0.000525	0.44	-0.000546	
	(-0.46)	(-0.79)	(-1.03)	(-0.35)	
Ischemic heart disease	0.247	0.000311	-0.594	0.000821	
	(-1)	(-0.4)	(-1.65)	(-0.65)	
Osteoporosis	0.233	-0.000784	-0.293	0.00102	
	(-0.91)	(-1.44)	(-0.64)	(-0.91)	
Rheumatoid/osteoarthritis	0.00888	-0.000555	0.0505	0.0000371	
	(-0.06)	(-0.79)	(-0.21)	(-0.04)	
Stroke/TIA	0.195	0.00195*	-0.0138	0.00332*	
	(-0.86)	(-2.39)	(-0.05)	(-2.41)	
Constant	743.8***	0.0329*	728.6***	0.0955**	
	-122.95	(-2.17)	-90.3	(-2.84)	
N	11,923,549	11,923,549	9,037,448	9,037,754	

**Notes:** t statistics in parentheses, \* p<0.05, \*\* p<0.01, \*\*\* p<0.001. Coefficient estimates for state-time and age dummies not shown.

Table A4: Propensity Score Model Regression Results for Coupled Households, Stratified by Shared Credit Account/No Shared Credit Account

	(1) Ever ADRD,		(2) Ever ADRD,
	Shared Credit Ac		No Shared Credit Account
Female		812***	-0.0776***
	,	00952)	· · · · · · · · · · · · · · · · · · ·
Credit score at age 65		0128***	-0.00153***
	`	0000882)	(-0.0000813)
Household size=2		20***	-0.163***
	,	0278)	(-0.0242)
Household size=3	-0.0	979***	-0.107***
	,	0286)	(-0.0251)
Household size=4	-0.0	432	-0.0338
	(-0.0	0307)	(-0.0271)
Household size=5	0.01	.09	0.00303
	(-0.0	0356)	(-0.0311)
Black	0.13	32***	0.0691**
	(-0.0	0242)	(-0.0216)
Asian	-0.0	897**	-0.0749*
	(-0.	0308)	(-0.0298)
Hispanic	-0.2	85***	-0.245***
	(-0.0	0459)	(-0.0471)
Other race	-0.1	75**	-0.106
	(-0.	0596)	(-0.0611)
Below median percentage	`	151***	0.0229*
with HS or more (census	tract) (-0.0	0105)	(-0.0114)
Below median adult smol	,	,	-0.0287*
(county)	_	0126)	(-0.0142)
Below median adult obes	`		0.00315
(county)		0143)	(-0.016)
Below median excessive d	`	272*	-0.0159
(county)	O	0133)	(-0.0149)
Below median air pollution	`	259*	-0.0417**
(county)		0115)	(-0.0127)
Below median physical in	*	395**	0.00113
(county)	•	0153)	(-0.0165)
Depression	,	31***	1.806***
2 oprossion		0161)	(-0.0158)
Diabetes	,	8***	0.302***
Diasocos		0112)	(-0.0123)
Hyperlipidemia	,	27***	0.105***
пурстиріасния		0106)	(-0.0117)
Hypertension	,	28***	0.994***
Try per tension		011)	(-0.0126)
Birthyear 1900-1904	-0.2	,	-1.920***
Diffuyear 1900-1904			
Dinthroom 1005 1000	,	643) 53***	(-0.35)
Birthyear 1905-1909			-1.918***
	(-0.	109)	(-0.1)

Table A4: Propensity Score Model Regression Results for Coupled Households, Stratified by Shared Credit Account/No Shared Credit Account

	(1) Ever ADRD,	(2) Ever ADRD,
	Shared Credit Account	No Shared Credit Account
Birthyear 1910-1914	-1.373***	-1.737***
	(-0.047)	(-0.0539)
Birthyear 1915-1919	-1.494***	-1.871***
	(-0.0339)	(-0.0443)
Birthyear 1920-1924	-1.581***	-2.036***
	(-0.0306)	(-0.0418)
Birthyear 1925-1929	-1.747***	-2.220***
	(-0.0292)	(-0.041)
Birthyear 1930-1934	-2.347***	-2.651***
	(-0.029)	(-0.0413)
Birthyear 1935-1939	-2.415***	-2.265***
	(-0.0302)	(-0.0425)
3.states	-0.302***	-0.285***
	(-0.0512)	(-0.0571)
4.states	0.159**	0.228***
	(-0.0585)	(-0.0616)
5.states	-0.300***	-0.198***
	(-0.0434)	(-0.0457)
6.states	-0.242***	-0.166*
	(-0.0572)	(-0.0652)
7.states	-0.209***	-0.215***
	(-0.0557)	(-0.059)
8.states	-0.161*	-0.00259
	(-0.0781)	(-0.0875)
9.states	0.171	-0.107
	(-0.131)	(-0.122)
10.states	-0.168***	-0.0892*
	(-0.0432)	(-0.0452)
11.states	0.00915	0.0317
	(-0.0494)	(-0.0506)
13.states	-0.326***	-0.357***
	(-0.0731)	(-0.0899)
14.states	-0.248***	-0.115*
	(-0.0454)	(-0.0474)
15.states	-0.219***	-0.171***
	(-0.0474)	(-0.0516)
16.states	-0.346***	-0.247***
	(-0.0561)	(-0.0611)
17.states	-0.210***	-0.146*
	(-0.0567)	(-0.0633)
18.states	-0.163**	-0.00786
	(-0.0554)	(-0.0589)
19.states	-0.217***	-0.083

Table A4: Propensity Score Model Regression Results for Coupled Households, Stratified by Shared Credit Account/No Shared Credit Account

	(1) Ever ADRD,	(2) Ever ADRD,
	Shared Credit Account	No Shared Credit Account
	(-0.056)	(-0.0555)
20.states	-0.313***	-0.200*
	(-0.0753)	(-0.0835)
21.states	-0.231***	-0.088
	(-0.0493)	(-0.0524)
22.states	-0.305***	-0.193***
	(-0.0505)	(-0.0524)
23.states	-0.0864	-0.0275
	(-0.0459)	(-0.0481)
24.states	-0.564***	-0.407***
24.500005	(-0.0555)	(-0.0611)
25.states	-0.0538	0.117
20.States	(-0.063)	(-0.0625)
06 -+-+	(-0.003) -0.155**	,
26.states		-0.0918
07	(-0.0495)	(-0.0535)
27.states	-0.332***	-0.105
	(-0.0819)	(-0.0986)
28.states	-0.289***	-0.242**
	(-0.0653)	(-0.0757)
29.states	-0.180**	-0.0862
	(-0.0695)	(-0.0768)
30.states	-0.223**	-0.0493
	(-0.0765)	(-0.0846)
31.states	-0.134**	-0.0881
	(-0.0458)	(-0.0481)
32.states	-0.164*	-0.186*
	(-0.0714)	(-0.0803)
33.states	-0.318***	-0.296***
	(-0.0442)	(-0.0457)
34.states	-0.203***	-0.0243
	(-0.0456)	(-0.0493)
35.states	-0.380***	-0.0732
	(-0.101)	(-0.113)
36.states	-0.298***	-0.203***
	(-0.0445)	(-0.0469)
37.states	-0.0616	-0.0515
	(-0.0553)	(-0.0583)
38.states	-0.410***	-0.360***
5 5 13 13 10 00	(-0.0583)	(-0.0656)
39.states	-0.368***	-0.342***
30.50000b	(-0.0443)	(-0.046)
40.states	-0.385***	-0.363***
40.States		
	(-0.0904)	(-0.0956)

Table A4: Propensity Score Model Regression Results for Coupled Households, Stratified by Shared Credit Account/No Shared Credit Account

	(1) Ever ADRD,	(2) Ever ADRD,
	Shared Credit Account	No Shared Credit Account
41.states	-0.138**	0.0363
	(-0.0519)	(-0.0558)
42.states	-0.528***	-0.395***
	(-0.0922)	(-0.112)
43.states	-0.202***	0.00121
	(-0.05)	(-0.0512)
44.states	-0.00205	0.100*
	(-0.0439)	(-0.0454)
45.states	-0.318***	-0.245**
	(-0.0673)	(-0.0801)
46.states	-0.230*	-0.311*
	(-0.104)	(-0.122)
47.states	-0.0986*	-0.0399
	(-0.0482)	(-0.0512)
48.states	-0.197***	-0.103
	(-0.0496)	(-0.0566)
49.states	-0.177**	-0.216**
	(-0.0686)	(-0.0735)
50.states	-0.417***	-0.386***
	(-0.0521)	(-0.0562)
51.states	-0.115	-0.0274
	(-0.105)	(-0.131)
2001.year	0.131***	0.118*
	(-0.0384)	(-0.0545)
2002.year	0.0357	0.0731
	(-0.0358)	(-0.0506)
2003.year	0.160***	0.247***
	(-0.0355)	(-0.0501)
2004.year	0.241***	0.329***
	(-0.0356)	(-0.0498)
2005.year	0.232***	0.248***
	(-0.0352)	(-0.0492)
2006.year	0.185***	0.257***
	(-0.0352)	(-0.0489)
2007.year	0.158***	0.199***
	(-0.0354)	(-0.0488)
2008.year	0.0729*	0.176***
	(-0.0355)	(-0.0486)
2009.year	-0.02	0.141**
	(-0.0354)	(-0.0478)
2010.year	-0.0684	0.0525
	(-0.0359)	(-0.0477)
2011.year	-0.191***	0.00838

Table A4: Propensity Score Model Regression Results for Coupled Households, Stratified by Shared Credit Account/No Shared Credit Account

	(1) Ever ADRD, Shared Credit Account	(2) Ever ADRD, No Shared Credit Account
	(-0.036)	(-0.0473)
2012.year	-0.155***	-0.0564
	(-0.036)	(-0.047)
2013.year	-0.225***	-0.209***
	(-0.0362)	(-0.0469)
2014.year	-0.408***	-0.441***
	(-0.0365)	(-0.0467)
2015.year	-0.420***	-0.590***
	(-0.0372)	(-0.0467)
2016.year	0.832***	0.0129
	(-0.0412)	(-0.047)
2017.year	3.452***	3.608***
	(-0.0771)	(-0.0831)
Constant	2.024***	2.519***
	(-0.0904)	(-0.0934)
N	245,880	200,107

Notes: Authors' analysis of merged CCP and Medicare data. Variables measured as anchor point. County level data from County Health Rankings (as derived from BRFSS, CDC WONDER, and the CDC Diabetes Interactive Atlas). Census tract level information on education from the American Community Survey. Variables are dichotomous indicators for whether the area has a rate lower than the median. Standard errors in parentheses. \*p<0.05, \*\*p<0.01, \*\*\*p<0.001.