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Consumer Credit Events Before and After Dementia Diagnosis

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Consumer Credit Events Before and After Dementia Diagnosis

Abstract

Anecdotal evidence suggests that changes in thinking and memory due to dementia can lead to large financial losses. We test this using linked Medicare claims and FRBNY/Equifax CCP data. We find that missed payments increase up to 4 years prior to a dementia diagnosis and persist after diagnosis. Tracking financial outcomes could potentially contribute to earlier dementia diagnosis or help financial institutions identify suspicious transactions and take steps to protect consumers.

Citation

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Rapid growth in the elderly population combined with a lack of effective medical treatments to reverse or delay Alzheimer's disease and related dementias are estimated to lead to more than 12 million older adults living with dementia by 2050 (1). Nearly half of Americans 65 and older live alone or with a cognitively impaired spouse (2). Without a spouse or caregiver present to observe declines in thinking and memory that may indicate early signs of cognitive impairment, this group faces an elevated risk of delayed diagnoses and greater exposure to the health and financial consequences associated with disease progression. One of the earliest signs of cognitive decline and dementia is impaired financial capacity, which can manifest as difficulties managing money and paying bills or making erratic and uncharacteristically risky financial decisions (3-5). Cognitively impaired patients frequently overestimate their financial abilities, placing them at risk of financial fraud, inappropriate asset allocation, credit delinquency from unpaid bills, and other losses (5-10).

In many cases, cognitive impairment is not discovered until after patients have lost significant sums of money and experienced greater functional decline. While researchers have not been able to quantify the extent of dementia-related financial losses, the lay press has described numerous anecdotes of spouses and children first learning of a patient's cognitive decline through catastrophic financial events such as foreclosure and asset depletion (11).

Because the financial symptoms of dementia are poorly understood, we linked national data characterizing consumer credit events to Medicare claims to study adverse consumer credit events before and after dementia diagnosis.

Methods

Consumer credit behavior

The Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP/Equifax) is a longitudinal 5% random sample of all credit files for U.S. persons with Social Security numbers drawn quarterly starting with the first quarter of 1999 from one of the three major credit bureaus (12-14). The data also contains records for all individuals living at the same address as the sampled individual, yielding approximately 40 million credit reports quarterly. The panel is regularly updated to include new credit files and remove the files of deceased persons or those with inactive credit files, so as to maintain its representativeness of persons with credit reports and Social Security numbers. Our sample includes all CCP/Equifax primary sample members who lived in single-person households in the second quarters of 2014 to 2018 and were born in or before 1946. We define single-person households as individuals who are not living at the same address with any other adult (with a credit report and a Social Security number) within 20 years of their age.

The CCP/Equifax includes our dependent variables of interest: credit score (Equifax Risk Score), a summary measure of the person's likeliness to default on a loan in the future; an indicator for debt payment delinquency (30 or more days past due), new tax liens or judgements in the past two years, which typically indicate missed tax payments; large increases (of $500 or more) in credit card balances. We also consider two measures that are likely to reflect fraud in this population; an indicator for any new loans obtained in the last six months and any large increases in nonhousing loan debt. The CCP/Equifax is completely anonymized; the data set contains no consumer names nor actual addresses.

Dementia and comorbid health conditions

We use the Medicare beneficiary summary file chronic conditions data to identify beneficiaries who have met the Chronic Condition Warehouse algorithm identifying Alzheimer's Disease and Related Dementias (ADRD) in at least two outpatient or one inpatient healthcare encounter (15). We also control for additional health conditions that could plausibly influence financial outcomes through hospitalization, out-of-pocket spending, and associated instrumental activities of daily living limitations including diabetes, stroke, hypertension, congestive heart failure, ischemic heart disease, chronic obstructive pulmonary disease, chronic kidney disease, atrial fibrillation, and cancer.

To verify that the patterns we identify are unique to ADRD diagnosis, we identify two acute health conditions, hip fracture and heart attack, and two chronic health conditions with gradual onset, arthritis and glaucoma, as placebo tests.

Medicare demographics and enrollment Information

We use a Medicare vital status file pulled in June 2018 to identify beneficiaries who were the only person living in their exact address at the time of death for those dying between 2014 and 2017 and through June 2018 for those still alive in 2018. Since utilization, and consequently dementia status, is not observed when beneficiaries are enrolled in Medicare Advantage (MA) plans, we use the master beneficiary summary file (MSF) to restrict our sample to beneficiaries with no MA enrollment or enrollment that starts after the initial ADRD diagnosis. We also use the MSF to control for beneficiary age, sex, Black, Hispanic, or other race/ethnicity.

Study population

Our study population consists of single older adults in both data sets who share the same census block code in their most recent address, the same zip code in 2012, 2013, 2014, and 2015, and the same birth year. We start with 5,705,069 Medicare beneficiaries who were alive in 2018 and 2,642,117 who died between 2014 and 2018. In this study, we restrict our analysis to combinations of the six match variables that are unique in each of the two data sets, which yields 55,721 matched beneficiaries.

Statistical methods

We estimate linear event study regressions of consumer credit events on a vector of dummy variables measuring time from an ADRD diagnosis, the demographic and health characteristics described above, and vectors of age, state, and year fixed effects, as well as quarter fixed effects to control for seasonality in the credit events. We are particularly concerned with differentiating between credit events that characterize the aging process and those specific to dementia, so we include a control group that never develops dementia. They are normalized to $t = 0$ in all years. We adjust standard errors to account for clustering at the beneficiary level.

To verify that the patterns we observe are unique to ADRD and not simply indicative of disease or change in health status, we replicate our analysis for two gradual-onset placebo health conditions, arthritis and glaucoma, and two acute health events, heart attack and hip fracture.

Results

Table 1 describes our sample. Since our data are limited to single-person households, it is not surprising that our sample is primarily female. The average age is older than 75 and roughly 85% of the sample is white.

Figure 1 summarizes our regression results (Table 2). Difficulties paying bills manifest several years before an ADRD diagnosis. Increases in payment delinquencies are statistically significant between two to four years before the diagnostic threshold is achieved, with tax liens and increased credit card balances first occurring in the two years prior to diagnosis. These effects are also large in magnitude; the 1.1 to 2.7 percentage point increases in delinquencies represent between 8% to 21% of the sample mean rate of 13%. The delinquencies and tax liens are picked up in the credit score, but declines do not reach statistical significance until two to four years after the ADRD diagnosis.

There is growing concern that ADRD patients could be fraud victims. We do not see evidence of growing nonhousing debt or new account openings, areas where we might expect to see evidence of fraudulent activity. Indeed, both of these outcomes decline following the ADRD diagnosis.

In Table 3, we eliminate our control group and compare changes over time within the ever-ADRD sample only. We generally observe a similar pattern, although our point estimates are frequently imprecise, with the exception of credit score, which is significantly negative in all years relative to four or more years prior to diagnosis and becoming larger in magnitude as cognition declines.

It is possible that the financial patterns we observe before and after a dementia diagnosis are characteristic of new health conditions more broadly. Although we control for a number of health conditions in our main models, we next consider several placebo health conditions to provide greater confidence that the increase in adverse financial outcomes starting years prior to diagnosis is unique to ADRD. We find no increases in delinquency or tax liens with arthritis, though credit card and other loan balances increase before and after diagnosis (Table 4). We observe a steady improvement in credit scores and payment delinquencies for individuals with glaucoma (Table 5). Credit scores also begin declining starting in the four years prior to a heart attack and continue to decline post-event (Table 6). Beyond single spikes in tax liens and payment delinquencies, however, there are no consistent patterns associated with diagnosis. Finally, we see no patterns in credit events around hip fractures beyond a single-period increase in payment delinquencies in the period of hospitalization (Table 7). Overall, the placebo health conditions provide confidence that the patterns we observe with dementia are symptomatic of ADRD and not characteristic of being ill more broadly.

Discussion

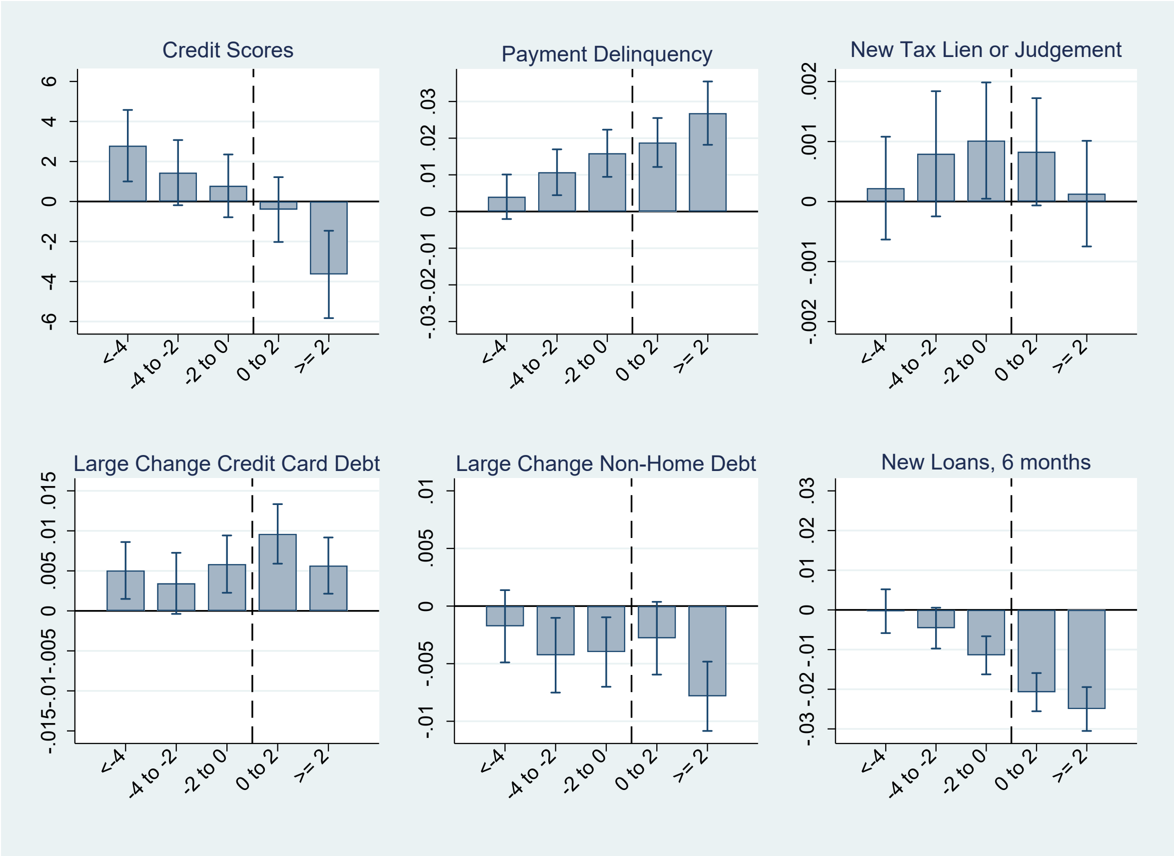
Using probabilistically matched Medicare claims and CCP/Equifax panel data, we show that single adults exhibit increased difficulty managing money in the years prior to an ADRD diagnosis, which manifests as payment delinquencies, tax liens, and growing credit card balances. Despite widespread concerns of fraud, we do not find evidence of increased loan activity or new accounts in the years surrounding a dementia diagnosis.

Our findings represent the first large-scale evidence of the financial challenges associated with ADRD, especially in the years prior to diagnosis. As additional research clarifies the financial phenotype characterizing early signs of ADRD, it may be possible to use data on payments and other financial behavior, in conjunction with other clinical symptoms, to diagnose patients earlier and engage family and other surrogates in financial decision-making.

We note the following limitations to our study. We exclude people who enter Medicare HMOs prior to developing ADRD because their use cannot be observed, thus, our study is only representative of fee-for-service Medicare beneficiaries. We only include people who are in single-person households, which likely excludes many people living in apartment buildings, assisted living, and other group quarters where other social support or assistance may be available. We are only able to identify ADRD using the chronic conditions warehouse, a measure with known limitations. Our control group likely includes people with ADRD who have not yet been diagnosed, this would bias our results toward 0. Finally, our matching strategy relies on age and geography rather than exact identifiers or any personally identifying information. This likely introduces noise and reduces our precision, but does not bias our results.

Financial data represent a potentially important tool for detecting cognitive impairment and preventing financial exploitation of patients and their families. Further research should assess ways of safely and securely integrating financial information for diagnostic purposes.

Figure 1: Consumer Credit Outcomes Relative to Time of Alzheimer's & Related Dementia Diagnosis



Notes: Bars represent coefficients from binned regressions of credit outcomes on time from ADRD diagnosis. FRBNY/Equifax CCP quarterly credit data probabilistically linked to Medicare claims by age and geography. Dependent variables are as follows: Credit score (Equifax Risk Score); any record of delinquency; new tax lien or judgment in the past 12 months; large increase in credit card debt; large increase in nonhousing debt; and any new accounts in the past 6 months. Regressions also control for demographic and health characteristics and state, quarter, and year fixed effects. Standard errors adjusted to allow for clustering at the beneficiary level.

Table 1: Sample Characteristics by Time Relative to Dementia Diagnosis

Years to Dementia	Never	>4 Pre	2-4 Pre	0-2 Pre	0-2 Post	2+ Post
Demographic/Health Characteristics						
Age	75.6	74.6	76.3	77.7	78.6	80.8
Male	0.31	0.29	0.28	0.28	0.27	0.24
Black	0.10	0.10	0.11	0.11	0.12	0.13
Hispanic	0.010	0.025	0.030	0.033	0.037	0.042
Other race	0.03	0.05	0.05	0.05	0.05	0.05
Diabetes	0.24	0.28	0.33	0.37	0.43	0.47
Stroke	0.08	0.10	0.14	0.18	0.27	0.34
Heart Failure	0.14	0.16	0.21	0.26	0.33	0.39
Heart disease	0.33	0.41	0.47	0.53	0.61	0.67
COPD	0.15	0.17	0.21	0.24	0.29	0.33
Cancer	0.11	0.11	0.13	0.14	0.16	0.16
N	1,507,256	122,482	76,625	83,731	78,609	103,741

Table 2: Consumer Credit Outcomes Relative to Time of Alzheimer's & Related Dementia Diagnosis

	Credit Score	**Any Delinquency**	**Tax Lien or Judge**	**Card Balances**	**Nonhome Debt**	**New Accounts**
Variable mean	753.9	0.13	0.004	0.13	0.091	0.21
> -4 years	2.789**	0.004	0	0.005**	-0.002	0
	(0.9119)	(0.0031)	(0.0004)	(0.0018)	(0.0016)	(0.0028)
-4 to -2 years	1.442	0.011***	0.001	0.003	-0.004**	-0.005
	(0.8312)	(0.0032)	(0.0005)	(0.0019)	(0.0017)	(0.0026)
-2 to 0 years	0.781	0.016***	0.001*	0.006**	-0.004**	-0.011***
	(0.8004)	(0.0033)	(0.0005)	(0.0018)	(0.0015)	(0.0024)
0 to 2 years	-0.402	0.019***	0.001	0.010***	-0.003	-0.021***
	(0.8268)	(0.0034)	(0.0005)	(0.0019)	(0.0016)	(0.0025)
2 to 4 years	-3.646**	0.027***	0	0.006**	-0.008***	-0.025***
	(1.1140)	(0.0044)	(0.0004)	(0.0018)	(0.0015)	(0.0028)
N	55,418	55,721	55,721	55,721	55,721	55,721
N * t	1,972,443	2,089,965	2,089,965	2,089,965	2,089,965	2,089,965

Notes: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Binned regressions of credit outcomes on time from ADRD diagnosis. FRBNY/Equifax CCP quarterly credit data probabilistically linked to Medicare claims by age and geography. Dependent variables are as follows: Credit score (Equifax Risk Score); any record of delinquency; new tax lien or judgment in the past 12 months; large increase in credit card debt; large increase in nonhousing debt; and any new accounts in the past 6 months. Regressions also control for demographic and health characteristics and state, quarter, and year fixed effects. Standard errors adjusted to allow for clustering at the beneficiary level.

Table 3: Consumer Credit Outcomes Relative Alzheimer's & Related Dementias Diagnosis, Ever-ADRD Only

	Credit Score	Any Delinquency	Tax Lien or Judge	Card Balances	Nonhome Debt	New Accounts
Variable mean	752.7	0.15	0.005	0.13	0.085	0.19
-4 to -2 years	-1.522*	0.003	0.001	-0.002	-0.001	0
	(0.7723)	(0.0030)	(0.0006)	(0.0026)	(0.0022)	(0.0032)
-2 to 0 years	-2.751*	0.005	0.001	0.003	0.001	-0.001
	(1.1086)	(0.0042)	(0.0007)	(0.0029)	(0.0024)	(0.0038)
0 to 2 years	-4.253**	0.007	0.001	0.007*	0.002	-0.009*
	(1.4082)	(0.0052)	(0.0008)	(0.0030)	(0.0026)	(0.0043)
2 to 4 years	-7.586***	0.013	0	0.003	-0.002	-0.011*
	(1.9748)	(0.0070)	(0.0008)	(0.0033)	(0.0029)	(0.0053)
N	12,967	13,048	13,048	13,048	13,048	13,048
N * t	465,187	500,160	500,160	500,160	500,160	500,160

Notes: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Binned regressions of credit outcomes on time from ADRD diagnosis, restricting the sample to patients who ever develop ADRD. FRBNY/Equifax CCP quarterly credit data probabilistically linked to Medicare claims by age and geography. Dependent variables are as follows: Credit score (Equifax Risk Score); any record of delinquency; new tax lien or judgment in the past 12 months; large increase in credit card debt; large increase in nonhousing debt; and any new accounts in the past 6 months. Regressions also control for demographic and health characteristics and state, quarter, and year fixed effects. Standard errors adjusted for clustering at the beneficiary level.

Table 4: Consumer Credit Outcomes Relative to Time of Arthritis Diagnosis

	Credit Score	**Any Delinquency**	**Tax Lien or Judge**	**Card Balances**	**Nonhome Debt**	**New Accounts**
Variable mean	753.8	0.13	0.004	0.13	0.091	0.21
> -4 years	1.209	-0.005	0	0.006**	0.004*	0.005
	(1.1491)	(0.0036)	(0.0006)	(0.0022)	(0.0020)	(0.0034)
-4 to -2 years	0.203	0.001	0.001	0.005*	0.003	0.011***
	(0.9085)	(0.0032)	(0.0005)	(0.0020)	(0.0019)	(0.0029)
-2 to 0 years	0.15	-0.004	0.001*	0.005**	0.002	0.014***
	(0.7761)	(0.0028)	(0.0005)	(0.0017)	(0.0015)	(0.0024)
0 to 2 years	-0.139	-0.003	0	0.005***	0.006***	0.020***
	(0.6600)	(0.0023)	(0.0003)	(0.0014)	(0.0012)	(0.0021)
2 to 4 years	-0.195	-0.004	0	0.006***	0.005***	0.023***
	(0.6795)	(0.0025)	(0.0003)	(0.0011)	(0.0010)	(0.0018)
N	55,634	55,938	55,938	55,938	55,938	55,938
N * t	1,980,511	2,098,588	2,098,588	2,098,588	2,098,588	2,098,588

Notes: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Binned regressions of credit outcomes on time from diagnosis. FRBNY/Equifax CCP quarterly credit data probabilistically linked to Medicare claims by age and geography. Dependent variables are as follows: Credit score (Equifax Risk Score); any record of delinquency; new tax lien or judgment in the past 12 months; large increase in credit card debt; large increase in nonhousing debt; and any new accounts in the past 6 months. Regressions also control for demographic and health characteristics and state, quarter, and year fixed effects. Standard errors adjusted to allow for clustering at the beneficiary level.

Table 5: Consumer Credit Outcomes Relative to Time of Glaucoma Diagnosis

	Credit Score	Any Delinquency	Tax Lien or Judge	Card Balances	Nonhome Debt	New Accounts
Variable mean	753.9	0.13	0.004	0.13	0.091	0.21
> -4 years	3.426*	-0.010*	0	0.009**	0.001	0.015**
	(1.4813)	(0.0049)	(0.0008)	(0.0032)	(0.0028)	(0.0048)
-4 to -2 years	4.974***	-0.010*	0	0.002	-0.001	0.003
	(1.1533)	(0.0042)	(0.0007)	(0.0029)	(0.0026)	(0.0039)
-2 to 0 years	5.052***	-0.013***	-0.001*	0	0.003	0.002
	(0.9539)	(0.0036)	(0.0005)	(0.0024)	(0.0022)	(0.0032)
0 to 2 years	5.931***	-0.014***	-0.001***	0.002	0.002	0.002
	(0.6972)	(0.0026)	(0.0003)	(0.0017)	(0.0016)	(0.0024)
2 to 4 years	5.722***	-0.007**	-0.001**	0.003*	0	0.003
	(0.7094)	(0.0028)	(0.0003)	(0.0012)	(0.0010)	(0.0019)
N	55,507	55,813	55,813	55,813	55,813	55,813
N * t	1,975,689	2,093,622	2,093,622	2,093,622	2,093,622	2,093,622

Notes: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Binned regressions of credit outcomes on time from diagnosis. FRBNY/Equifax CCP quarterly credit data probabilistically linked to Medicare claims by age and geography. Dependent variables are as follows: Credit score (Equifax Risk Score); any record of delinquency; new tax lien or judgment in the past 12 months; large increase in credit card debt; large increase in nonhousing debt; and any new accounts in the past 6 months. Regressions also control for demographic and health characteristics and state, quarter, and year fixed effects. Standard errors adjusted to allow for clustering at the beneficiary level.

Table 6: Consumer Credit Outcomes Relative to Time of Heart Attack

	Credit Score	**Any Delinquency**	**Tax Lien or Judge**	**Card Balances**	**Nonhome Debt**	**New Accounts**
Variable mean	753.9	0.13	0.004	0.13	0.091	0.21
> -4 years	-3.406	0.012	0.001	-0.005	-0.003	-0.005
	(2.3801)	(0.0084)	(0.0012)	(0.0048)	(0.0042)	(0.0072)
-4 to -2 years	-4.398*	0.015	0.004*	0.004	0.003	0.001
	(2.0030)	(0.0077)	(0.0018)	(0.0052)	(0.0044)	(0.0066)
-2 to 0 years	-4.439*	0.017*	0.001	-0.006	-0.003	-0.001
	(1.8169)	(0.0074)	(0.0012)	(0.0044)	(0.0039)	(0.0061)
0 to 2 years	-2.41	0.012	0	-0.001	-0.001	-0.010*
	(1.6365)	(0.0065)	(0.0010)	(0.0039)	(0.0034)	(0.0053)
2 to 4 years	-4.241*	0.007	-0.001	-0.004	0	-0.007
	(1.8125)	(0.0069)	(0.0006)	(0.0028)	(0.0025)	(0.0046)
N	55,410	55,713	55,713	55,713	55,713	55,713
N * t	1,972,156	2,089,665	2,089,665	2,089,665	2,089,665	2,089,665

Notes: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Binned regressions of credit outcomes on time from heart attack. FRBNY/Equifax CCP quarterly credit data probabilistically linked to Medicare claims by age and geography. Dependent variables are as follows: Credit score (Equifax Risk Score); any record of delinquency; new tax lien or judgment in the past 12 months; large increase in credit card debt; large increase in nonhousing debt; and any new accounts in the past 6 months. Regressions also control for demographic and health characteristics and state, quarter, and year fixed effects. Standard errors adjusted to allow for clustering at the beneficiary level.

Table 7: Consumer Credit Outcomes Relative to Time of Hip Fracture

	Credit Score	Any Delinquency	Tax Lien or Judge	Card Balances	Nonhome Debt	New Accounts
Variable mean	753.9	0.13	0.004	0.13	0.091	0.21
> -4 years	-1.026	0.007	0	0.005	0.001	-0.003
	(1.8508)	(0.0065)	(0.0008)	(0.0040)	(0.0035)	(0.0057)
-4 to -2 years	-1.574	0.013	0.002	-0.002	-0.001	-0.002
	(1.6548)	(0.0068)	(0.0013)	(0.0043)	(0.0036)	(0.0055)
-2 to 0 years	-2.172	0.017*	0.001	-0.004	-0.003	-0.007
	(1.5277)	(0.0068)	(0.0011)	(0.0038)	(0.0031)	(0.0048)
0 to 2 years	-1.102	0.003	0.001	0.003	-0.001	-0.012*
	(1.4878)	(0.0064)	(0.0009)	(0.0040)	(0.0032)	(0.0049)
2 to 4 years	1.652	0	0	-0.002	-0.007**	-0.013**
	(1.7477)	(0.0078)	(0.0006)	(0.0031)	(0.0025)	(0.0047)
N	55,403	55,706	55,706	55,706	55,706	55,706
N * t	1,971,926	2,089,385	2,089,385	2,089,385	2,089,385	2,089,385

Notes: Standard errors in parentheses. *** p < 0.001, ** p < 0.01, * p < 0.05. Binned regressions of credit outcomes on time from hip fracture. FRBNY/Equifax CCP quarterly credit data probabilistically linked to Medicare claims by age and geography. Dependent variables are as follows: Credit score (Equifax Risk Score); any record of delinquency; new tax lien or judgment in the past 12 months; large increase in credit card debt; large increase in nonhousing debt; and any new accounts in the past 6 months. Regressions also control for demographic and health characteristics and state, quarter, and year fixed effects. Standard errors adjusted to allow for clustering at the beneficiary level.

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