Medicaid and Long-Term Care: Do Eligibility Rules Impact Asset Holdings?

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ABSTRACT

Medicaid provides a critical source of insurance against the rising costs of long-term care, and as a result, individuals may strategically offload assets (typically to children) to meet the means-tested eligibility requirement. Yet, evidence on such behaviors is limited. In this paper, we use variation in the propensity to conduct improper transfers induced by the Deficit Reduction Act of 2005 to quantify the extent of strategic transfers. The Act discouraged asset offloading by introducing significant penalties for such actions. We estimate difference-in-differences models based on the hypothesis that individuals with high levels of self-reported nursing home risk (high risk) will alter transfers based on the Act's changes, while other individuals remain unaffected. We find that over a two-year horizon, high risk individuals reduced transfers to children on the extensive margin by 10 percent and that the average total amount of transfers decreased by $1,700. We also conduct a triple-differences analysis to examine various forms of heterogeneity. We find that the reduction in transfers we document comes from high risk individuals who are less financially literate, suggesting that more financially sophisticated households either have other mechanisms to shield assets or are not sensitive to Medicaid eligibility.

Keywords: Medicaid eligibility; nursing home care; transfers; financial literacy

JEL Codes: D14; J14; I1

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INTRODUCTION

Medicaid is the largest means-tested health insurance program in the United States and provides a key source of nursing home coverage for older Americans. Current program expenditures are about $500 billion each year, of which 30% goes to nursing home and other long-term care services (CMMS 2017). As with any means-tested program, there is a concern that individuals may strategically adjust their asset holdings to meet eligibility requirements. The extent of such strategic behavior is a chief concern among government officials, especially since many types of asset transfers are not easily detectable. While there has been evidence of such behavior in other social insurance programs, the evidence on Medicaid has been "limited and often based on anecdotes" (GAO 2005).

Yet, it is difficult to ignore the prevalence of "Medicaid planning", which refers to the strategic behaviors one may undertake to meet eligibility requirements. There is an industry of elder law experts dedicated to providing such counsel, and the topic has received attention in the news (New York Times 2017) and in bookstands: e.g., Heiser (2006) writes about Medicaid "secrets" to avoid nursing home care costs. It seems clear that at least some portion of the population engages in Medicaid planning, but the extent to which such behaviors inflate Medicaid costs is unknown.

In this paper, we offer new evidence on whether individuals strategically offload assets to become Medicaid eligible. We do this by leveraging variation in penalties associated with such behaviors brought about by the Deficit Reduction Act (DRA) of 2005. Signed into law in February 2006 by President George W. Bush, the DRA attempted to reduce "improper" financial transfers with two new rules. First, the look-back period on asset transfers increased from three years to five years, meaning that transfers made over a longer period of time were counted towards one's countable holdings. Second, the DRA shifted the penalty period from the time of improper transfer to the time of Medicaid application, generating a greater disincentive to engage in such transfers. Together, these penalties made it more difficult for individuals to "spend down" for Medicaid eligibility.

The empirical challenge in assessing the DRA's impact is that since it was enacted in February 2006, at first glance the policy only enables a before-and-after analysis. Such analysis can be difficult to interpret due to the confounding effect of general time trends in asset holding behaviors. As such, we adopt a difference-in-differences technique leveraging variation from survey data: we use the respondent's self-assessed likelihood of requiring nursing home care as a proxy for treatment. Specifically, we hypothesize that individuals with high nursing home risk would alter their asset holdings in response to the DRA, while people with zero or low nursing home risk should form a useful control group by remaining unaffected. Directionally, if the DRA is effective at limiting strategic asset transfers, we expect that individuals facing high nursing home risk will reduce transfer activities.

We examine parent-to-child financial transfers as our key outcome. These transfers are easily made and difficult to detect, making them an ideal way to reduce assets if that is one's goal. Using our difference-in-differences framework, we find that the DRA caused individuals with high levels of anticipated nursing home risk to reduce parent-to-child financial transfers on both the extensive and intensive margins. These effects are statistically significant and economically meaningful: we estimate a three percent decrease in the extensive margin probability of making any transfer, and a $1,700 total decrease in the amount of transfers (though most of this is explained by the extensive margin response). These results correspond to effect sizes of 10 and 40 percent, respectively. Our findings thus show that the DRA served to reduce strategic transfers from parents to children, as intended.

We then examine the extent to which these effects are heterogeneous by different variables such as financial literacy and existing long-term care insurance or Medicaid coverage through a triple-differences analysis. While we are unable to identify any statistically significant relationships for the latter two variables, we find that the DRA's impact appears to be driven by individuals with less financial literacy. We find this result particularly interesting as it reveals the predictive power of financial literacy even after controlling for other factors such as education and wealth, consistent with prior literature on the importance of this metric (Lusardi and Mitchell 2017; 2011). Our finding that individuals with financial literacy may not change behavior in response to the DRA makes sense if these individuals were using other mechanisms to shield assets, which is plausible since the direct transfer of assets to children provides little remaining control over these funds. Alternatively, financially literate individuals may shield assets through increased home equity, annuities, certain types of long-term care insurance, or other instruments.

In estimating the impact of asset transfer penalties on Medicaid eligibility, we build on existing literature addressing these concerns. For example, Bassett (2007) uses national survey data from 1993 to show that individuals with high nursing home risk engaged in greater levels of parent-to-child transfers. At least two papers argue that strategic asset transfers are not widespread, however: Norton (1995) shows that Medicaid spend-down is not prevalent, and Lee, Kim and Tanenbaum (2006) argues that parent-to-child transfers occur but are too small to require oversight. In related work, Grabowski and Gruber (2007) shows that the generosity of Medicaid's nursing home coverage is not linked with its rate of utilization, alleviating concerns that people may "become" eligible when benefits improve. There is less work on the DRA in particular, though Reif (2010) provides a legal overview of the Act's impact on senior citizens. To the best of our knowledge, our paper is the first to move beyond descriptive associations in quantifying the impact of Medicaid eligibility rules altered by the DRA on asset transfers.

This research is related to the large body of work on precautionary saving and social insurance that demonstrates the moral hazard effects of safety nets. Hubbard, Skinner and Zeldes (1995) provide seminal theoretical predictions on this topic. In terms of Medicaid and old-age care, Brown, Coe and Finkelstein (2007) demonstrate significant crowd-out effects of Medicaid on the decision to purchase long-term care insurance through the private market. There are also well-documented interactions between long-term care insurance purchase, a form of precautionary saving, and the availability of social insurance (Brown and Finkelstein 2009; 2008). In evaluating recent policies, Moffitt (2015) shows that the expansion of social insurance and unemployment benefits during the Great Recession were linked with meaningful disincentives to work.

This research is also tied to the literature on inter vivos transfers, which explores the reasons for intergenerational transfers. Why would parents give money to their children when they themselves face high health expenditure risk? Several papers have studied the reasons for such transfers, which include altruism and efforts to elicit caregiving (Mukherjee 2018; Coe, Goda and Van Houtven 2015; McGarry and Schoeni 1995). The current analysis shows that at least some transfers may be made for the purposes of meeting means-testing eligibility requirements. Transfers to children motivated for this reason are particularly appealing if children can effectively save the money for their parents, thereby allowing the parental assets to be both protected and shielded from means-testing requirements.

The aging population in the United States is growing and increasingly vulnerable with respect to health and income; recent research indicates that individuals are entering late-life with greater levels of debt while facing increased income and health inequalities (Lusardi, Mitchell and Oggero 2018; Kaestner and Lubotsky 2016). The Medicaid program is critical for even the high-income elderly (Borella, De Nardi and French 2016) and has large impacts on a range of economic behaviors as documented in recent work (Kaestner et al. 2017; Soni et al. 2017). Our paper adds to this literature by exploring the ways in which government policy impacts Medicaid eligibility for older Americans.

This paper proceeds as follows. We first provide a brief background on Medicaid eligibility and the DRA to motivate our empirical work. We then detail our data and provide summary statistics for our sample. We follow this with an outline of our empirical methods, including laying out the double- and triple-difference specifications. We follow this by presenting and discussing our results and robustness checks. The final section offers concluding remarks.

BACKGROUND

Medicaid is a dominant payer of long-term care services, which includes nursing home care and other services for the elderly. To qualify for coverage, individuals must demonstrate financial neediness as determined by the calculation of "countable" assets. Countable assets vary by state to account for differences in cost of living and to reflect differences in public program generosity, but the main excluded asset is a minimum of \$534,000 in home equity. After all exclusions, countable assets must total no more than \$2,000 for an individual to be Medicaid-eligible.[1]

The Deficit Reduction Act of 2005 was designed to reduce the levels of fraud related to the provision of long-term care services in the Medicaid program.[2] Specifically, its goal was to reduce the incidence of "Medicaid planning", in which individuals alter financial behaviors for the purposes of program eligibility. The DRA was signed into law in February 2006 and became effective immediately. While the law was comprehensive and laid out many new rules,[3] the two main provisions featured a two-year extension in the look-back period for asset transfers in determining Medicaid eligibility, and new rules by which penalties accrued for transfers deemed improper.

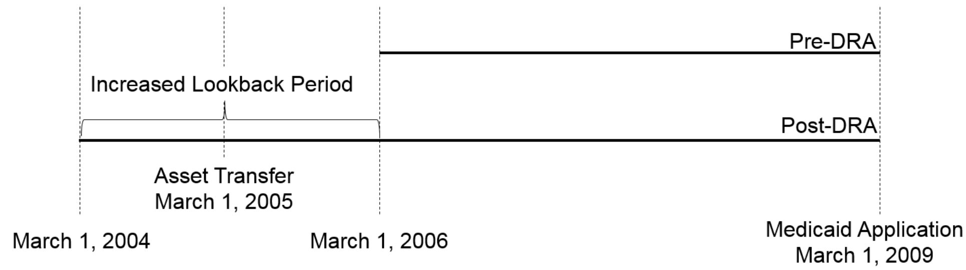
Figure 1 illustrates the change in the look-back period. For illustration, consider an individual who applies for Medicaid on March 1, 2009, and made a significant asset transfer four years prior on March 1, 2005. Prior to the DRA, this individual could qualify for Medicaid without regard to any transfers made prior to March 1, 2006, as the look-back period on asset transfers was three years. Post the enactment of the DRA, however, this individual would face penalties for any assets transferred over the past *five* years, thus including the March 1, 2005 transfer.

[1] Bitler and Zavodny (2017) and Gruber (2003) provide useful overviews of the Medicaid program.

[2] There are a number of papers examining Medicaid fraud related to other aspects of the program such as billing practices, as studied in Perez and Wing (2018).

[3] Specifically, the DRA had various provisions including changes in the treatment of annuities, life estates, large amounts of home equity, and other financial products, which we do not analyze in the present analysis.

Figure 1: Impact of the DRA on the Asset Transfer Look-back Period

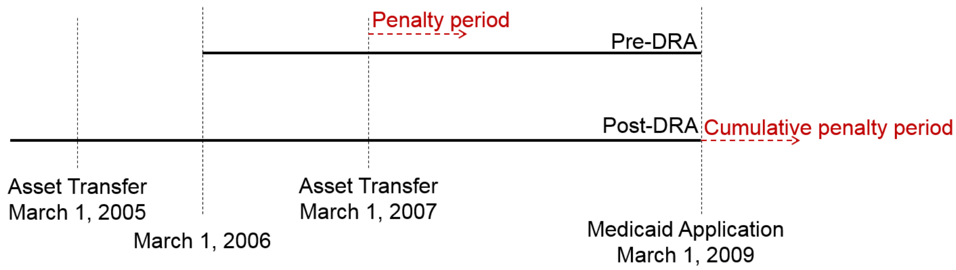


Notes: Figure depicts the two-year extension in the asset transfer look-back period stipulated by the DRA. According to the dates in the figure, an asset transfer on March 1, 2005 would not be counted against Medicaid eligibility pre-DRA, but would be counted post-DRA.

The penalty associated with these transfers is in units of time and calculated as the transfer amount divided by the monthly nursing home cost incurred by Medicaid in that state. For example, if the asset transfer was \$50,000 and the monthly nursing home cost was \$8,000, the penalty is a delay of $\frac{\$50{,}000}{\$8{,}000} = 6.25$ months in Medicaid eligibility. Prior to the DRA the Medicaid program rounded down the penalty to the nearest month—in this case, the penalty period would have been six months—but post the DRA, penalties are incurred less discretely.

Figure 2 illustrates the other consequential change brought about by the DRA, which is the timing of these penalties. Prior to the DRA, an individual who transferred \$50,000 during the look-back period would incur the six-month penalty starting on the date of the transfer, in this example March 1, 2007. Thus, the individual would become eligible for Medicaid reimbursements starting September 1, 2007. Post-DRA, however, this individual would incur a 6.25-month penalty starting at the date of Medicaid application, depicted as March 1, 2009, for this individual. This shift in timing of the penalty significantly impacted Medicaid eligibility if large transfers occurred during the look-back window. A related change made by the DRA regards the treatment of multiple transfers in the look-back period. Prior to the DRA, the individual incurred the associated penalties with each transfer from the

Figure 2: Impact of the DRA on the Penalty Period

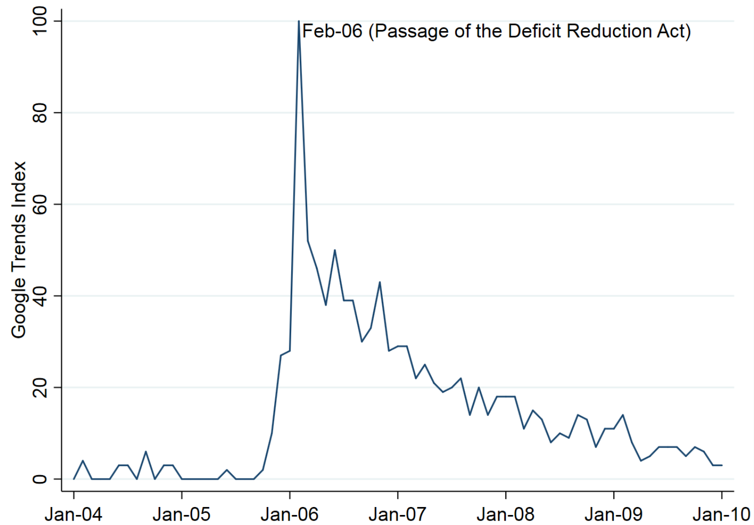


Notes: Figure depicts the change in penalty period for asset transfers stipulated by the DRA. According to the dates in the figure, an asset transfer on March 1, 2007 would be penalized beginning at that date pre-DRA. Post-DRA, both asset transfers on March 1, 2005 and March 1, 2007 would count and incur cumulative penalties starting at the date of Medicaid application.

starting date of each transfer. Post-DRA, the penalties for these transfers were cumulated and started with the date of Medicaid application.

As we are studying the extent to which individuals responded to the DRA, a primary concern is whether this Act was anticipated. If individuals responded to the DRA prior to its actual passage, our estimates will suffer from attenuation bias. We examine the salience of the DRA by analyzing an index of Google searches for the term "Deficit Reduction Act" and related terms (as defined by Google), shown in Figure 3. The index is plotted from January 2004 through January 2010. We observe a peak of web-searches for this term in the month of the Act's passage. While we have not conducted a formal analysis, this chart provides some indication that the DRA was not widely anticipated; there is almost no density in the Google searches related to the term prior to January 2006. For this reason, we consider observations occurring after the DRA's passage as "post" treatment data in our main analyses.

Figure 3: Salience of the DRA, Google Trends Data (2004-2010)



Notes: Figure shows the Google Trends index, which takes values from 0 to 100, for the term "Deficit Reduction Act" and related terms. The peak interest corresponds to the passage of the DRA in February 2006.

DATA AND DESCRIPTIVES

We use data from the Health and Retirement Study (HRS) to analyze the impact of the DRA on asset transfer behaviors. The HRS is suitable for this study because of its focus on older Americans and the extensive information available about their economic and household behaviors. The survey is conducted every two years and is longitudinal, thus capturing data on individual behaviors over time. We use data from the 1998 through 2010 surveys as this timespan includes the DRA and contains repeated measures of key information such as parent-to-child financial transfers and self-assessed probabilities of requiring nursing home care. We also use information from the special modules conducted in 2004 and 2010 to obtain data on respondent financial literacy. Since the survey collects information from individuals about their activities in the two years prior, we categorize only the 2008 and 2010 surveys as being "post" DRA. We show robustness to this choice in later analyses.

The key outcome we study regards financial transfers to the next generation, which was asked in each survey during the timespan studied. The survey question is copied below:

> Including help with education but not shared housing or shared food (or any deed to a house), [in the last two years] did you (or your (late) [husband/wife/partner]) give financial help totaling $500 or more to [your child/any children] (or grandchild(ren))?

We also examine the self-assessed probability of needing nursing home care in the next five years, which is obtained from the following question. This question was also asked in each survey between 1998 and 2010:

> (If respondent is 65 years of age and older) What is the percent chance that you will move to a nursing home in the next five years?

The HRS has a number of useful variables that serve as controls in our regression analysis. We discuss these variables later in this section.

Measurement of Financial Literacy

The financial literacy questions were asked in special modules of the 2004 and 2010 HRS surveys. To obtain a measure of financial literacy for our respondents, we first use data from the 2004 survey when it is available. If the respondent was not part of the special module in 2004 but was included in 2010, we obtain the financial literacy data from 2010. Each module asked the same three financial literacy questions:

> 1. Do you think that the following statement is true or false?: Buying a single company stock usually provides a safer return than a stock mutual fund. (Choices: True, False, Don't Know, Refuse to answer.)
>
> 2. Suppose you had $100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account

if you left the money to grow: more than \$102, exactly \$102, less than \$102? (Choices: More than \$102, Exactly \$102, Less than \$102, Don't Know, Refuse to answer.)

3. Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy more than, exactly the same as, or less than today with the money in this account? (Choices: More than today, Exactly the same as today, Less than today, Don't Know, Refuse to answer.)

Of these three financial literacy questions, approximately 10 percent answer all corrections incorrectly, 20 percent provide one correct answer, 38 percent provide two correct answers, and 32 percent provide three correct answers. We define a respondent to have financial literacy (i.e., the binary variable $FinLit = 1$) if the respondent correctly answered all three questions.

Sample Definition and Summary Statistics

Our sampling frame includes the 1998 through 2010 surveys, as these years included information on our key outcome, financial transfers to children, and on the key covariate, nursing home risk. The main sampling restriction was to include people with information on the probability of nursing home risk, which kept those aged 65+ and brought our sample to 61,569 observations.[4] An advantage of focusing on those aged 65+ is that they are all Medicare-eligible, allowing us to focus on incentives for dual eligibility. We then required each respondent to have at least one living child such that intergenerational transfers were feasible; this reduced our sample to 56,564 observations. Further requiring non-missing data on parent-to-child transfers reduced our sample by another 1,439 observations. Finally, the requirement of non-missing covariates reduced our sample to 52,524 respondent-year observations representing 10,617 households.

[4]From our analysis, it appears that the nursing home risk question is not answered by proxy respondents.

Table 1 shows summary statistics for the key outcomes and explanatory variables studied in this analysis. Columns (1) and (2) describe data for the full sample across all years, while columns (3) to (6) show data from only the 2006 survey to illustrate the baseline summary information. Column (1) shows that about one-third of these respondents transferred financial assets to their children over the past two years, and the average amount transferred (including zeros) was \$4,000.[5] This average implies a transfer of about $\frac{\$4{,}000}{0.33} \approx \$12,100$ conditional on giving any amount. We also observe that about 14 percent of respondents had long-term care insurance (LTCI) at any given point during the survey.

Column (1) also shows other variables of interest for the sample; these are ultimately the covariates in the regression analysis. We observe that the average respondent is aged 75 and has 3.55 children. About 58 percent of respondents are female, 87 percent are white, and 6 percent are Hispanic. In terms of education, the average years of education is just over 12 years and about one-third demonstrate financial literacy (as measured by correct responses to all three questions). About 62 percent of the respondents are married or coupled, meaning that they have a living partner; the vast majority of remaining respondents are widowed, and few are divorced or separated.

We also extracted information on health status and other economic controls from the HRS. The average number of diseases was 2.17, and respondents rated themselves as having an average score of 2.86 out of 5 (with 5 being worst) on a self-assessed measure of bad health. The average respondent had 0.27 activities that require assistance with daily living, or ADLs, measured out of six activities. We observe that average pre-2006 medical expenditures over the past two years was approximately \$2,600. We do not include post-2006 medical expenditures in the calculation of this variable as it may be endogenous, and we treat the calculation of wealth in the same manner. In terms of wealth, we observe that the average respondent has total pre-2006 wealth of about \$510,000; these individuals are likely to be

[5] The distribution of these transfers is shown in Figure A.2. We winsorized this variable at the 99.5^{th} percentile to avoid the impact of outliers. We applied this same treatment to wealth and child-to-parent transfer amounts.

marginally eligible for Medicaid if housing forms a large component of this wealth. Despite the older ages observed in our sample, we observe that about 19 percent of them are currently working.[6]

Columns (3) to (6) restrict the sample to 2006 to provide a sense of baseline information. We observe 5,305 respondents with nursing home risk (NHR) below 0.20, and 1,975 respondents with nursing home risk at or above 0.20. We choose the cutoff of 0.20 to be the median level of reported nursing home risk excluding zeros. Thus, we consider those with above-median levels of such risk to be "high risk" individuals. We observe that the low and high risk groups have similar means for the outcome variables. The high risk group is also slightly older (76 versus 74), has lower financial literacy (29 versus 37 percent), is more likely to be widowed (33 versus 26 percent), and is more likely to have LTCI (20 versus 13 percent). On all other dimensions, the high and low risk groups appear comparable.

[6]Table A.2 shows the correlations between the key outcome and predictor variables.

Table 1: Summary Statistics

	Full Sample		Baseline (2006)			
	All Respondents		Low NH Risk NHR <0.2		High NH Risk NHR ≥ 0.2	
	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)
Outcomes:						
Any transfer to child?	0.33	0.47	0.35	0.48	0.35	0.48
Amount of transfer to child	0.40	1.27	0.42	1.29	0.43	1.26
Demographics:						
Age $\div$ 100	0.75	0.07	0.74	0.07	0.76	0.07
Female	0.58	0.49	0.57	0.50	0.59	0.49
Number of children	3.55	2.11	3.60	2.06	3.47	2.02
Years of Education	12.28	3.08	12.43	2.98	12.39	3.06
Financial Literacy†	0.32	0.47	0.37	0.48	0.29	0.46
Race: White	0.87	0.34	0.86	0.35	0.89	0.32
Race: Black	0.11	0.31	0.12	0.32	0.09	0.29
Race: Other	0.03	0.16	0.03	0.17	0.02	0.14
Ethnicity: Hispanic	0.06	0.24	0.07	0.26	0.05	0.22
Marital Status:						
Married/Coupled	0.62	0.49	0.62	0.49	0.57	0.50
Widowed	0.28	0.45	0.26	0.44	0.33	0.47
Divorced/Separated	0.08	0.27	0.09	0.29	0.08	0.27
Never married	0.00	0.07	0.01	0.07	0.00	0.07
Health Status:						
Number of ADLs	0.27	0.76	0.15	0.51	0.21	0.61
Number of Diseases	2.17	1.37	2.13	1.34	2.38	1.34
Medical Exp. (pre-2006)	0.26	0.43	0.23	0.39	0.25	0.35
Bad health?	2.86	1.08	2.70	1.04	2.98	1.02
Economic Controls:						
Wealth in MN (pre-2006)	0.51	0.76	0.52	0.78	0.56	0.79
Currently working?	0.19	0.39	0.22	0.42	0.17	0.37
Has LTC Insurance?‡	0.14	0.35	0.13	0.34	0.20	0.40
Observations	52,524		5,305		1,975	

Notes: All monetary variables except wealth are in units of \$10,000 and converted to 2012 dollars; wealth is in units of \$ million. Columns (1) and (2) show data from all respondent-years used in the regression; the remaining columns restrict to respondents in Wave 8 of the survey, which was conducted in 2006, to provide a measure of baseline information. $^{\dagger}N = 4,173$. $^{\ddagger}N = 51,873$.

EMPIRICAL METHODS

The main empirical strategy is a difference-in-differences (DD) analysis. We begin, however, by examining a first-difference model to estimate the impact of the DRA on asset transfer behaviors:

$$Y_{it} = \alpha + \beta \ Post_{it} + \gamma X_{it} + \lambda_t + \epsilon_{it}. \quad (1)$$

In this specification, the coefficient of interest is β, as the variable $Post$ is a binary variable indicating whether the observation is post-DRA (i.e., represents survey information collected in years 2008 or 2010). The estimate of β will be biased if it captures general time trends and misattributes these changes to the effect of the DRA.

In this model, and in the subsequent models, the vector X_{it} includes a number of demographic, health status, and economic variables that are known or hypothesized to impact asset holdings and transfers to the next generation. Demographic variables include the respondent's age, age squared, whether female, years of education, race (white, black, or other), ethnicity (whether Hispanic), and marital status (married/coupled, widowed, divorced/separated, or never married). Health status variables include whether the respondent indicates being in bad health, number of ADLs, number of diseases, and the mean level of pre-2006 medical expenditures.[7] Economic variables include the respondent's mean level of pre-2006 wealth, wealth squared, and whether the respondent is currently working. We show the staggered impact of these different sets of variables in our results.[8] The vector λ_t includes linear, squared, and cubed time trends to flexibly account for any time trends in the outcomes studied.

Since our dependent variables of interest are the probability and amount of transfers, we

[7] Prior research indicates that medical expenditures rise sharply at older ages making this variable relevant (Fahle, McGarry and Skinner 2016); the desire to become Medicaid-eligible is after all a function of expected medical expenses. Prior work also indicates that the prediction of such expenses require information on demographic, health status, and economic variables, hence we include these variables in our analysis (Frees, Gao and Rosenberg 2011).

[8] We do not control for long-term care insurance purchase as this may be endogenous.

estimate Probit and Tobit models throughout our analyses for these respective outcomes.

Difference-in-Differences Estimation

Our main estimates come from DD models that compare changes in outcomes for individuals with low versus high nursing home risk. Specifically, we generate a variable $HighRisk_{it}$ that indicates whether respondent i reported an above-median expectation of nursing home risk (excluding zeros) in year t. From our data, this cutoff occurs at nursing home risk of 0.20, and we show in the robustness section that our estimates do not change with the specification choice of this variable.

The motivation for the DD model is that the DRA should impact financial transfer behaviors only for individuals with high nursing home risk. The regression specification is thus:

$$Y_{it} = \alpha + \beta_1 \ Post_{it} + \beta_2 \ HighRisk_{it} + \beta_3 \ Post_{it} \times HighRisk_{it} + \gamma X_{it} + \lambda_t + \epsilon_{it}, \qquad (2)$$

where the coefficient of interest is β_3. This coefficient informs us about how individuals with high nursing home risk differed in their transfer behaviors following the DRA compared to individuals at low nursing home risk. The term β_1 captures any overall changes in the post-DRA period, and the term β_2 captures the relationship of high nursing home risk and financial transfers. The vector X_{it} and the time controls captured by λ_t are defined as before.

Heterogeneity with Financial Literacy

Understanding the DRA and strategizing asset transfer behavior in accordance with the Act's new guidelines requires some level of financial literacy, hence we examine heterogeneity along this dimension. A priori, the directional impact of financial literacy is not clear. It could be that financially literate respondents understand the penalties associated with transfers deemed improper and thus take care to avoid any such transfers when penalties increase. Or, these individuals may shield assets in other ways or may not be sensitive to

Medicaid eligibility.

We analyze the impact of financial literacy in a triple differences framework (DDD) for respondent i in year t, following broadly the method in Tai-Seale, Freund and LoSasso (2001).[9] The hypothesis is that individuals with financial literacy received a different treatment from individuals with less financial literacy, and the regression specification is as follows:

$$\begin{aligned} Y_{it} = \alpha &+ \beta_1\ Post_{it} + \beta_2\ HighRisk_{it} + \beta_3\ FinLit_{it} \\ &+ \beta_4\ Post_{it} \times HighRisk_{it} + \beta_5\ Post_{it} \times FinLit_{it} + \beta_6\ HighRisk_{it} \times FinLit_{it} \\ &+ \beta_7\ Post_{it} \times HighRisk_{it} \times FinLit_{it} + \gamma X_{it} + \lambda_t + \epsilon_{it}. \end{aligned} \quad (3)$$

The variable $FinLit$ is binary and indicates whether the respondent has financial literacy, which we define as having answered all three of the financial literacy questions correctly. The coefficient of interest is β_7 as it captures the extent to which high-risk individuals with financial literacy differed in behavior relative to individuals with less financial literacy. The coefficient β_4 indicates the amount of response coming from individuals with high nursing home risk and with less financial literacy. The term β_5 in this regression captures the general "post" trend in financial literacy in predicting financial transfers, much like β_1 captures the general "post" trend for all respondents. As such, an additional assumption in the DDD model is that the outcomes for individuals with more versus less financial literacy would have evolved similarly after passage of the DRA. We examine this latter assumption through a placebo analysis in the robustness section.

The terms β_2, β_3, and β_6 in equation (3) control for the first-order and interacted impacts of high nursing home risk and financial literacy on transfer behaviors. As before, this regression also controls for other demographics, economic variables, and time trends, captured by the coefficient vectors γ and λ_t.

[9]Examining heterogeneity within a DD framework is identical to a DDD model, thus we use both terms in describing this analysis.

RESULTS

In this section, we present and discuss our results on the impact of the DRA on strategic asset transfers. We also show heterogeneity of these results by financial literacy.

Impact of DRA on Asset Transfers

Table 2 shows the main results, and each column contains a different set of covariates.[10] Column (1) includes the first difference model with all controls, and column (2) includes only the variables shown along with time trends. Moving from column (2) to column (5), variables are added sequentially as denoted until we obtain the fully saturated model in column (5). We observe that the first difference impact, captured by the coefficient on *Post*, is only marginally statistically significant in column (1) of Panel B. This coefficient is not statistically significant in other specifications.

The DD estimate is consistently significant, however. The estimate of $Post \times HighRisk$ is about -0.032 across columns (2) through (5) for the probability of transfer, and reduces slightly from -0.182 to -0.170 for the amount of transfer, indicating substantial stability with the inclusion of different sets of covariates. These estimates are strongly statistically significant ($p < 0.01$) in all specifications and represent practically meaningful quantities. The saturated models in column (5) of Table 2 indicate that the probability of transfer decreased by 3.2 percent for high risk individuals, representing an effect size of just under 10 percent since the mean incidence of transfers is about 33 percent. The total amount of transfer reduced by about \$1,700, which represents an effect size of about 40 percent given that the mean amount of transfer is about \$4,000.

We note that since the Tobit model already accounts for the large number of zeros in the transfer outcome, most of these effects are coming from the extensive margin. Specifically, we estimate that the partial effect conditional on any transfer is about \$460. This implies

[10] Our regressions contain 14 fewer observations than described in our summary statistics because of the use of "pweight", which weights the regressions by the probability of being sampled in the survey. 14 of our observations have weight equal to zero and are thus excluded from estimation.

Table 2: Impact of the DRA on Parent-to-Child Transfers

	Parent-to-Child Financial Transfers				
	(1)	(2)	(3)	(4)	(5)
Panel A: Probability of Transfer (Probit models)					
Post	-0.011	-0.008	-0.004	-0.003	-0.002
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
Post × HighRisk		-0.032***	-0.030***	-0.030***	-0.032***
		(0.011)	(0.011)	(0.011)	(0.011)
HighRisk		0.025***	0.028***	0.030***	0.025***
		(0.007)	(0.007)	(0.007)	(0.007)
Observations	52,510	52,510	52,510	52,510	52,510
Pseudo R-squared	0.061	0.001	0.042	0.043	0.062
Panel B: Amount of Transfer (Tobit models)					
Post	-0.122*	-0.120	-0.092	-0.085	-0.075
	(0.073)	(0.080)	(0.079)	(0.079)	(0.077)
Post × HighRisk		-0.182**	-0.172**	-0.170**	-0.170**
		(0.078)	(0.076)	(0.076)	(0.073)
HighRisk		0.186***	0.183***	0.201***	0.139***
		(0.053)	(0.051)	(0.051)	(0.047)
Observations	52,510	52,510	52,510	52,510	52,510
Pseudo R-squared	0.052	0.001	0.026	0.027	0.052
Controls:					
Demographic	Y	N	Y	Y	Y
Health Status	Y	N	N	Y	Y
Economic	Y	N	N	N	Y

Notes: Table shows mean marginal effects. The variable "HighRisk" indicates that the nursing home risk is above-median, i.e., greater than or equal to 0.20. All columns control for linear, squared, and cubic time trends, and observations are weighted at the respondent-level. Robust standard errors are clustered at the household level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

that of the \$1,700 effect (unconditional) that we observe, about $\frac{460}{1,700} = 27\%$ comes from the intensive margin effect, and the rest comes from the extensive margin effect. Thus, we conclude from this analysis that high-risk individuals mostly altered transfers to children on the extensive margin.

We also observe that high risk individuals engage in significantly more transfers overall, as indicated by the positive and statistically significant coefficients on $HighRisk$, the treatment variable, in every specification. There are many possible sources of this relationship, and one reason could be financial transfers in exchange for informal care. For the purposes of the DD analysis, we focus only on interpreting the $Post \times HighRisk$ coefficients.

Effects of Financial Literacy

Having established that high risk individuals reduce assets in response to the DRA, we explore whether this behavior is heterogenous by the respondent's level of financial literacy. Table 3 shows the results of our analysis. Since the sample of respondents with financial literacy information is relatively small, we first replicate our earlier estimates on this sub-sample in columns (1) and (2) for the probability of any transfer and in columns (4) and (5) for the amount of transfer. The coefficient on the treatment variable $Post \times HighRisk$ in column (2) is not statistically significant, likely due to the reduction in sample size and underlying heterogeneity, though the point estimate of -0.037 is similar to those found in Table 2. The coefficient on this variable in column (4) is also not statistically significant, though the estimate is in the same direction as our earlier findings.

Column (3) of Table 3 contains the DDD estimates for predicting the probability of parent-to-child transfer. We observe that the coefficient on $Post \times HighRisk \times FinLit$ is positive and statistically significant ($p < 0.05$). This estimate reveals heterogeneity along financial literacy for individuals with high nursing home risk, though the total impact of financial literacy on asset transfers is not statistically significant: the total estimate would be the sum of the coefficients on $Post \times HighRisk \times FinLit$ and $Post \times HighRisk$, which is $-0.110 + 0.188 = 0.078$. Even though each of these estimates is statistically significant, the sum of these terms is not, so we cannot conclude that individuals with financial literacy alter their asset transfers in response to the DRA.[11] The coefficient on $Post \times HighRisk$ term is -0.110 and statistically significant ($p < 0.01$), however, indicating that the extensive margin reduction in parent-to-child transfers is driven by individuals with lower financial literacy. Overall, this analysis shows that as recently shown in Bitler, Gelbach and Hoynes

[11] The t-statistic for the sum of these terms is 1.25, and $p > 0.20$.

Table 3: Heterogeneity with Financial Literacy

	Parent-to-Child Financial Transfers					
	Any transfer?			Amount of Transfer		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.000	0.011	0.039	-0.104	-0.083	0.068
	(0.032)	(0.034)	(0.037)	(0.185)	(0.196)	(0.221)
Post × HighRisk		-0.037	-0.110***		-0.067	-0.342
		(0.035)	(0.042)		(0.207)	(0.269)
HighRisk		0.005	0.022		0.001	0.066
		(0.024)	(0.026)		(0.143)	(0.160)
FinLit			0.080***			0.450**
			(0.031)			(0.188)
Post × FinLit			-0.062			-0.329
			(0.041)			(0.240)
HighRisk × FinLit			-0.054			-0.187
			(0.053)			(0.321)
Post × HighRisk × FinLit			0.188**			0.648
			(0.075)			(0.438)
Model	Probit	Probit	Probit	Tobit	Tobit	Tobit
Observations	4,172	4,172	4,172	4,172	4,172	4,172
Pseudo R-squared	0.075	0.075	0.080	0.060	0.060	0.062

Notes: Table shows mean marginal effects. The variable "HighRisk" indicates that the nursing home risk is above-median, i.e., greater than or equal to 0.20. The variable "FinLit" indicates that the respondent answered all three financial literacy questions correctly. All columns control for linear, squared, and cubic time trends, as well as all demographic, health status, and economic controls. Observations are weighted at the respondent-level. Robust standard errors are clustered at the household level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(2017), it is important to consider heterogeneity as not all subgroups may exhibit responses to the treatment variable.

In column (6) of Table 3 we examine whether the DDD specification yields insights on heterogeneity by financial literacy in the prediction of parent-to-child transfer amounts, but we do not uncover any statistically significant relationships.

Other Heterogeneity

The HRS also has information on other variables that plausibly interact with high nursing home risk in determining post-DRA financial transfer behaviors. Specifically, we might expect that individuals who have already purchased LTCI will respond less to the DRA because they have already insured long-term care expenses. We might also expect that individuals who have already qualified for Medicaid (about 6 percent of the sample) at the time of the Act's passage should not be sensitive to the DRA's new regulations. We explored heterogeneity along these two dimensions, but our analysis did not reveal any statistically significant results on the triple-differenced interactions. These results are in Table A.1.

ROBUSTNESS CHECKS

In this section, we provide evidence in support of the parallel trends assumptions required by the DD analysis. We also provide robustness checks to our specification of nursing home risk, timing of the DRA's passage, and age subgroups studied.

Plausibility of the Parallel Trends Assumption

For the DD estimation, our identifying assumption is that parent-to-child financial transfer behaviors evolved similarly for individuals with low versus high expectations of nursing home risk. While we cannot provide direct evidence on this parallel trends assumption, we can show that the DRA and its interaction with nursing home risk did not impact a set of "placebo" outcomes. For this analysis, we examine child-to-parent financial transfers; these results are in Table 4. Column (1) examines the impact of the DRA on whether the respondent received any financial transfers from children, and column (2) layers on the interaction with nursing home risk in predicting this outcome. For the models in which we consider heterogeneity with financial literacy, we require that such transfer behaviors evolved similarly for individuals with more versus less financial literacy. We thus test this DDD specification in predicting our placebo outcomes in columns (3) and (6). We observe that no variable is a statistically significant predictor. Columns (4) to (6) examine the same variables to predict the *amount* of child-to-parent financial transfers, and we continue to observe no statistically significant relationships.

This analysis yields two observations that provide some comfort in the validity of our parallel trends assumptions. First, since none of the coefficients are statistically significant, there is unlikely to be a strong underlying relationship between the covariates of interest

Table 4: Impact of DRA on Placebo Outcomes

	Child-to-Parent Financial Transfers					
	Any Transfer?			Amount of Transfer		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.003	0.002	0.025	0.043	0.041	0.212
	(0.005)	(0.005)	(0.020)	(0.051)	(0.054)	(0.150)
Post × HighRisk		0.002	-0.015		0.009	-0.068
		(0.005)	(0.021)		(0.049)	(0.159)
HighRisk		-0.001	-0.005		-0.013	-0.041
		(0.003)	(0.013)		(0.032)	(0.105)
FinLit			0.012			0.090
			(0.016)			(0.126)
Post × FinLit			-0.024			-0.196
			(0.022)			(0.173)
HighRisk × FinLit			-0.005			0.010
			(0.028)			(0.234)
Post × HighRisk × FinLit			0.033			0.208
			(0.041)			(0.316)
Model	Probit	Probit	Probit	Tobit	Tobit	Tobit
Mean of dep. var.	0.05	0.05	0.06	0.02	0.02	0.02
Observations	52,449	52,449	4,169	52,449	52,449	4,169
Pseudo R-squared	0.074	0.074	0.126	0.064	0.064	0.116

Notes: Table shows mean marginal effects. The variable "HighRisk" indicates that the nursing home risk is above-median, i.e., greater than or equal to 0.20. The variable "FinLit" indicates that the respondent answered all three financial literacy questions correctly. All columns control for linear, squared, and cubic time trends, as well as all demographic, health status, and economic controls. Observations are weighted at the respondent-level. Robust standard errors are clustered at the household level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and the placebo outcomes. (Note, however, that we do not estimate precise zeros, so we cannot preclude the possibility that our regressions are underpowered.) Second, the point estimates of the coefficients are small, so to the extent that we can interpret coefficients that are not statistically significant, we can rule out very large effects. For example, in column (2), the coefficient on $Post \times HighRisk$ is 0.002 with a standard error of 0.005, so we can rule out that this interaction had effects much greater than one percent on the probability of child-to-parent transfers. Our confidence interval on the DDD coefficient is larger and has a wider standard error, however.

Taken together with our analysis on the year-by-year effects of the DRA (described later in this section and shown in Table 4), which simulates a placebo timing of the law, we believe that the parallel trends assumptions are likely to hold in our setting.

Regression Specification and Sample Definition Checks

We conduct a variety of robustness checks to explore the stability of our results. First, we examine different specifications for "HighRisk", which is a binary indicator for whether the probability of nursing home risk within five years is greater than or equal to 0.20. These results are in Table 5. We find that the main result we document is robust to whether we instead consider this covariate as a continuous variable taking values between 0 and 1, or if we make the cutoff 0.25 or 0.50. For perspective, among respondents reporting nonzero nursing home risk, 0.25 is about the 60^{th} percentile and 0.50 is about the 90^{th} percentile of nursing home risk.

The continuous variable specification in column (1) suggests that the propensity to transfer assets to children reduces by 7.6 percent as the probability goes from 0 to 1, which is consistent with the effects we observed earlier. We also observe in columns (2) and (3) that the effect of nursing home risk is monotonic in predicting the probability of transfers. All the coefficients of interest remain statistically significant ($p < 0.01$). Columns (4) to (6) of Table 5 indicate similar findings for the amount of transfers: the effects are monotonic with respect to nursing home risk, and the interaction of interest is statistically significant ($p < 0.01$) in every specification. The coefficient in column (4) implies a reduction in transfer of \$4,470 as nursing home risk changes from 0 to 1, again consistent with our main findings of a \$1,700 reduction for above-median nursing home risk.[12]

Next, to deal with concerns about transfer behaviors in anticipation of the law, we examine the year-by-year effects of the DRA. This test is also informative about a placebo test regarding the timing of the DRA's passage. The results of this analysis are in Table 6. Columns (1) and (3) are the analogs of our specification with only "Post" (and all other con-

[12]We do not expect this estimate to be exactly double our earlier one because we defined above-median nursing home risk after excluding zeros.

Table 5: Robustness to Specification of Nursing Home Risk

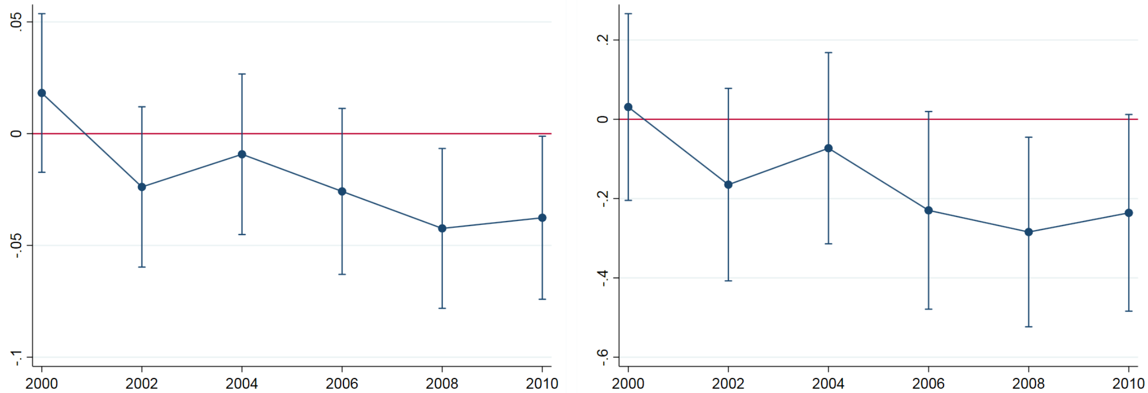
	Parent-to-Child Financial Transfers					
	Any transfer?			Amount of Transfer		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.000	-0.003	-0.004	-0.062	-0.082	-0.083
	(0.012)	(0.012)	(0.012)	(0.077)	(0.076)	(0.074)
Post × NHR	-0.076***			-0.447***		
	(0.023)			(0.158)		
NHR	0.059***			0.362***		
	(0.015)			(0.105)		
Post × NHR $\geq$ 0.25		-0.036***			-0.183**	
		(0.012)			(0.079)	
NHR $\geq$ 0.25		0.029***			0.159***	
		(0.007)			(0.050)	
Post × NHR $\geq$ 0.50			-0.046***			-0.285***
			(0.014)			(0.092)
NHR $\geq$ 0.50			0.029***			0.182***
			(0.008)			(0.056)
Model	Probit	Probit	Probit	Tobit	Tobit	Tobit
Observations	52,510	52,510	52,510	52,510	52,510	52,510
Pseudo R-squared	0.062	0.062	0.062	0.052	0.052	0.052

Notes: Table shows mean marginal effects. NHR denotes Nursing Home Risk and takes values between 0 and 1; it is entered as a continuous variable in columns (1) and (4). All columns control for linear, squared, and cubic time trends, as well as all demographic, health status, and economic controls. Observations are weighted at the respondent-level. Robust standard errors are clustered at the household level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

trols) to estimate the year-by-year effects, and columns (2) and (4) layer on the interacted $HighRisk \times Year$ controls. We observe that these interacted terms are only statistically significant ($p < 0.01$) in predicting the probability and amount of transfers for years 2008 and 2010, which are both post-DRA.[13] We do not find any effect on the interaction term with 2006 or prior years, indicating that the DRA was not sufficiently anticipated to impact financial transfers prior to the Act's passage. This finding is consistent with the Google Trends data shown in Figure 3 and provides robustness to our definition of *Post* in the main analyses. We plot the coefficients of interest in Figure 4 to illustrate the presence of statistically significant results only in the two post-DRA observation years, 2008 and 2010.

[13] Recall that the HRS asks questions about the two years prior, so the 2008 survey represents information from 2006 and 2007.

Figure 4: Coefficient Plots of Treatment Interactions



Panel A: Probability of Transfer *Panel B: Amount of Transfer*

Notes: Figure shows the coefficients and 95 percent confidence intervals associated with the $Year \times HighRisk$ interactions shown in columns (2) and (4) of Table 4, in which $HighRisk$ indicates that the nursing home risk is above-median, i.e., greater than or equal to 0.20. The two post-DRA observation years are 2008 and 2010.

Finally, we restrict the sample to different age groups to test whether our results are different for older subgroups as their nursing home needs are more imminent. We replicate our main findings on the probability and amount of parent-to-child transfers for individuals aged 70+ and 75+; these results are in Table 7. We observe that the estimate on the treatment variable, $Post \times HighRisk$, is stable across these two groups, with the effect demonstrating some monotonicity with increased age.

Table 6: Year-by-Year Impacts of the DRA on Asset Transfers

	Parent-to-Child Financial Transfers			
	Any transfer?		Amount of Transfer	
	(1)	(2)	(3)	(4)
HighRisk × 2000		0.018		0.031
		(0.018)		(0.120)
HighRisk × 2002		-0.024		-0.165
		(0.018)		(0.124)
HighRisk × 2004		-0.009		-0.073
		(0.018)		(0.123)
HighRisk × 2006		-0.026		-0.230*
		(0.019)		(0.127)
HighRisk × 2008		-0.042**		-0.284**
		(0.018)		(0.122)
HighRisk × 2010		-0.038**		-0.236*
		(0.019)		(0.127)
2000	0.032***	0.025***	0.226***	0.207***
	(0.008)	(0.010)	(0.058)	(0.069)
2002	0.007	0.013	0.027	0.068
	(0.009)	(0.010)	(0.060)	(0.070)
2004	0.017*	0.018*	-0.000	0.013
	(0.009)	(0.010)	(0.061)	(0.071)
2006	0.032***	0.038***	0.107*	0.167**
	(0.009)	(0.011)	(0.062)	(0.072)
2008	0.024**	0.035***	-0.014	0.064
	(0.009)	(0.011)	(0.062)	(0.071)
2010	0.034***	0.044***	0.102	0.165**
	(0.010)	(0.011)	(0.065)	(0.075)
HighRisk		0.033**		0.227**
		(0.014)		(0.095)
Model	Probit	Probit	Tobit	Tobit
Observations	52,510	52,510	52,510	52,510
Pseudo R-squared	0.062	0.062	0.052	0.052

Notes: Table shows mean marginal effects. The variable "High-Risk" indicates that the nursing home risk is above-median, i.e., greater than or equal to 0.20. All columns control all demographic, health status, and economic controls, and observations are weighted at the respondent-level. Robust standard errors are clustered at the household level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Robustness to Age Subgroups

	Parent-to-Child Financial Transfers			
	Any transfer?		Amount of Transfer	
Sample	Age 70+ (1)	Age 75+ (2)	Age 70+ (3)	Age 75+ (4)
Post	0.005	-0.010	-0.070	-0.153
	(0.014)	(0.016)	(0.096)	(0.120)
Post × HighRisk	-0.039***	-0.042***	-0.191**	-0.258**
	(0.012)	(0.015)	(0.090)	(0.110)
HighRisk	0.028***	0.031***	0.162***	0.193***
	(0.008)	(0.009)	(0.059)	(0.071)
Model	Probit	Probit	Tobit	Tobit
Mean of dep. var.	0.32	0.31	0.42	0.41
Observations	34,981	23,560	34,981	23,560
Pseudo R-squared	0.065	0.069	0.054	0.054

Notes: Table shows mean marginal effects. The variable "High-Risk" indicates that the nursing home risk is above-median, i.e., greater than or equal to 0.20. All columns control for linear, squared, and cubic time trends, as well as all demographic, health status, and economic controls. Observations are weighted at the respondent-level. Robust standard errors are clustered at the household level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

CONCLUSION

In this paper, we investigated the extent to which asset transfers change in response to Medicaid eligibility rules. We used variation from the Deficit Reduction Act of 2005, which increased the look-back period on asset transfers by two years and increased the penalties associated with such transfers by delaying Medicaid eligibility at the time of application. We found that individuals who report being at above-median levels of nursing home risk (high risk) exhibited statistically significant and meaningful reductions in both the probability and the amount of financial transfers to children. Individuals with high nursing home risk were 10 percent less likely to transfer any money to their children, corresponding to a 40 percent reduction in transfer amounts. These results suggest that by penalizing parent-to-child financial transfers, a key mechanism by which individuals could reduce their countable assets, the DRA was effective in limiting strategic behaviors.

Given the policy concerns about "Medicaid planning", we also examined heterogeneity by financial literacy. Our measure of financial literacy was whether the respondent could answer all three questions correctly on a widely used module developed by Lusardi and Mitchell (2011). Using a triple-differences framework in which individuals with high nursing home risk and financial literacy are hypothesized to be treated differently than their counterparts, we find that the reductions in transfers come from individuals *with low* financial literacy. This result may stem from the fact that individuals with financial literacy already had alternative mechanisms to circumvent eligibility requirements such as investments in other types of non-countable assets such as home equity, trusts, or certain long-term care insurance products. These other mechanisms to shield assets are generally preferable because asset transfers to children result in loss of control over those savings.

Our results are robust to different specifications of nursing home risk, year-by-year effects, and different age groups. We also provide some evidence of the parallel trends assumptions required by our analyses by showing that the covariates of interest are not statistically significantly linked with a placebo outcome, child-to-parent transfers. Still, our analysis has several limitations. First, we only examine one outcome—parent-to-child financial transfers—as an indicator of changes in asset holdings. While this measure is useful because it is easily manipulable and a chief source of concern for Medicaid officials, there are other dimensions on which individuals can alter their asset holdings to strategize eligibility. Second, we examine interactions with self-reported nursing home risk which may be noisy, though these probabilities likely dictate the behaviors of interest and we control for other measures of health status. Third, Medicaid is a joint federal and state program with substantial differences across states, but we do not observe this level of geographic variation in the data.

The long-term care insurance offered by Medicaid is of paramount importance in an era of increasing life expectancies combined with greater financial inequities. Our analysis sheds some light on the actions that individuals undertake to protect or enhance their eligibility in the vulnerable period of old age, but further work is needed to better understand the gaps in long-term care coverage for the country's aging population.

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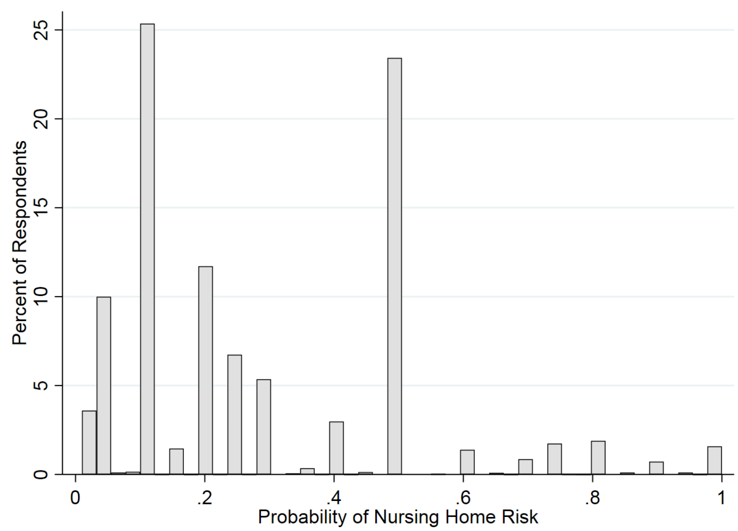
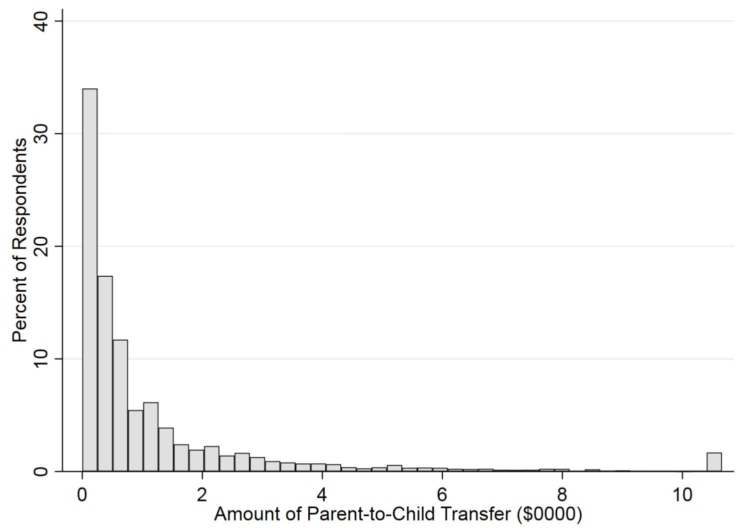
APPENDIX

Figure A.1: Distribution of Expected Nursing Home Risk



Notes: Figure shows the histogram of self-assessed probabilities of requiring nursing home care, for respondents indicating a non-zero probability. $N = 25{,}415$ respondent-year observations. We define *HighRisk* to indicate probability of such need ≥ 0.20, as this is the median value among respondents reporting non-zero probabilities.

Figure A.2: Distribution of Parent-to-Child Transfers



Notes: Figure shows the histogram of (non-zero) parent-to-child transfers, measured in $0000. N = 17,405 respondent-year observations.

Table A.1: Heterogeneity with LTCI and Medicaid

	Parent-to-Child Financial Transfers					
	Any Transfer?			Amount of Transfer		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Heterogeneity with LTCI						
Post	-0.011	-0.002	-0.003	-0.122*	-0.075	-0.093
	(0.011)	(0.012)	(0.012)	(0.073)	(0.077)	(0.079)
Post × HighRisk		-0.032***	-0.034***		-0.170**	-0.187**
		(0.011)	(0.013)		(0.073)	(0.082)
HighRisk		0.025***	0.023***		0.139***	0.142**
		(0.007)	(0.008)		(0.047)	(0.056)
LTCI			0.024*			0.135
			(0.014)			(0.094)
Post × LTCI			-0.026			-0.156
			(0.019)			(0.127)
HighRisk × LTCI			0.002			-0.041
			(0.020)			(0.139)
Post × HighRisk × LTCI			0.017			0.140
			(0.029)			(0.201)
Model	Probit	Probit	Probit	Tobit	Tobit	Tobit
Observations	52,510	52,510	44,655	52,510	52,510	44,655
Pseudo R-squared	0.061	0.062	0.059	0.052	0.052	0.051
Panel B: Heterogeneity with Medicaid						
Post	-0.011	-0.002	-0.005	-0.122*	-0.075	-0.104
	(0.011)	(0.012)	(0.012)	(0.073)	(0.077)	(0.078)
Post × HighRisk		-0.032***	-0.032***		-0.170**	-0.171**
		(0.011)	(0.012)		(0.073)	(0.077)
HighRisk		0.025***	0.024***		0.139***	0.139***
		(0.007)	(0.008)		(0.047)	(0.053)
Medicaid			-0.155***			-0.867***
			(0.021)			(0.151)
Post × Medicaid			-0.015			-0.148
			(0.030)			(0.197)
HighRisk × Medicaid			-0.016			-0.222
			(0.036)			(0.233)
Post × HighRisk × Medicaid			-0.067			-0.447
			(0.061)			(0.394)
Model	Probit	Probit	Probit	Tobit	Tobit	Tobit
Observations	52,510	52,510	44,942	52,510	52,510	44,942
Pseudo R-squared	0.061	0.062	0.063	0.052	0.052	0.052

Notes: Table shows mean marginal effects. The variable "HighRisk" indicates that the nursing home risk is above-median, i.e., greater than or equal to 0.20. The variable LTCI indicates whether the respondent had long-term care insurance in 2006, and the variable Medicaid indicates whether the respondent had Medicaid in 2006. All columns control for linear, squared, and cubic time trends, as well as all demographic, health status, and economic controls. Observations are weighted at the respondent-level. Robust standard errors are clustered at the household level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Correlations between Key Outcome and Explanatory Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Any Transfer?	1.00																	
2. Transfer Amt.	0.45	1.00																
3. Prob. NH	0.01	0.02	1.00															
4. LTCI	0.08	0.07	0.06	1.00														
5. Wealth	0.21	0.32	0.01	0.16	1.00													
6. Bad health	-0.08	-0.06	0.12	-0.10	-0.19	1.00												
7. ADLs	-0.04	-0.02	0.09	-0.05	-0.09	0.34	1.00											
8. Diseases	-0.03	-0.04	0.10	-0.05	-0.12	0.43	0.25	1.00										
9. Med.Exp.	0.03	0.03	0.03	0.02	0.05	0.08	0.05	0.10	1.00									
10. Educ. Years.	0.20	0.16	0.02	0.17	0.32	-0.24	-0.13	-0.09	0.04	1.00								
11. Fin. Literacy	0.15	0.11	-0.02	0.13	0.17	-0.15	-0.11	-0.01	-0.00	0.23	1.00							
12. Age $\div$ 100	-0.06	0.01	0.15	-0.02	-0.02	0.10	0.15	0.12	0.02	-0.06	-0.12	1.00						
13. Female	-0.07	-0.04	0.04	-0.00	-0.08	0.01	0.05	0.01	0.01	-0.06	-0.17	0.02	1.00					
14. Couple	0.08	0.04	-0.05	0.07	0.20	-0.10	-0.11	-0.08	0.00	0.13	0.14	-0.24	-0.30	1.00				
15. NChildren	-0.05	-0.03	-0.05	-0.05	-0.07	0.03	0.03	0.04	-0.02	-0.16	-0.06	-0.08	-0.02	0.04	1.00			
16. White	0.06	0.07	0.02	0.08	0.18	-0.11	-0.06	-0.03	0.02	0.17	0.15	0.08	-0.03	0.12	-0.12	1.00		
17. Hispanic	-0.07	-0.05	-0.02	-0.07	-0.11	0.10	0.06	-0.03	-0.03	-0.31	-0.07	-0.05	-0.00	-0.01	0.09	-0.05	1.00	
18. Working	0.07	0.03	-0.06	0.02	0.06	-0.17	-0.11	-0.14	-0.00	0.11	0.07	-0.24	-0.11	0.08	0.02	-0.01	-0.03	1.00

Notes: Table reports correlations between key outcome and explanatory variables. Transfer amounts and medical expenditures are measured in \$10,000 and are calculated as pre-2006 means. Wealth is measured in \$ million and is also calculated as a pre-2006 mean.