The Effect of Required Minimum Distributions on Intergenerational Transfers*

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Abstract

How do households use retirement savings accounts in retirement? The answer to this question is important for tax policy pertaining to retirement savings. I shed light on this question by studying how households respond to Required Minimum Distribution (RMD) regulations, which mandate withdrawals from retirement accounts upon reaching a specified age. Using data from the Health and Retirement Study and a regression discontinuity design, I estimate the causal effects of aging into RMD regulations. First, I establish the direct effects of RMDs in my setting and show a sharp increase in withdrawals from Individual Retirement Accounts (IRAs). Next, I provide new evidence on the indirect effects of RMDs and show a concurrent, discontinuous increase in inter vivos transfers. The results indicate that some households ultimately use IRAs to facilitate intergenerational gifts, holding wealth in the tax-advantaged accounts until required to take distributions and then passing resources to children.

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1 Introduction

The transition from defined benefit (DB) retirement pensions to defined contribution (DC) retirement savings accounts has ushered in a new era of retirement saving. DC plans, including both employer-sponsored accounts such as 401(k)s and Individual Retirement Accounts (IRAs), have overtaken DB plans and now make up about 62% of total retirement assets in the U.S. (Investment Company Institute 2023). With the goal of helping households achieve adequate income security in retirement, the government incentivizes saving in these accounts through preferential treatment in the tax code. Maintaining these tax-based savings incentives has costs. The Joint Committee on Taxation (2022) estimates that tax expenditures for employer-sponsored DC plans and IRAs in 2023 will amount to just over $249 billion. To begin to assess the benefits, one needs to understand how households make use of tax-advantaged retirement savings accounts.

An important literature takes the first step and studies the effects of tax-advantaged retirement accounts on the accumulation of savings (e.g. Engen, Gale, and Scholz 1996; Poterba, Venti, and Wise 1996; Poterba, Venti, and Wise 2007; Gelber 2011; Chetty et al. 2014). Yet to analyze the overall efficacy of retirement accounts, one needs to understand not only how they might help households save during working life, but also how the accumulated savings are ultimately used in retirement. Despite its importance, less is known about how households draw down wealth in retirement accounts, and especially how these accounts may affect financial behaviors more generally in the decumulation phase.

Obtaining causal evidence on how the decumulation of retirement savings affects other retiree behaviors is challenging. One obstacle relates to identification. Correlations between retirement asset drawdown and outcomes of interest are unlikely to reflect causal relationships, as there could be unobservable factors that influence both the decumulation of retirement assets and the outcomes themselves. Another obstacle relates to data. Many survey datasets do not contain information on the decumulation of retirement accounts, and while administrative data from sources such as the Internal Revenue Service or a retirement plan provider allow for detailed analyses of drawdown, these data can be more limited in scope and may not contain information on other important financial outcomes.

In this paper, I confront these challenges by using a regression discontinuity (RD) design and detailed data from the Health and Retirement Study (HRS) to analyze how households respond to Required Minimum Distribution (RMD) regulations. RMD regulations mandate the decumulation of most tax-qualified retirement plans once account holders reach a specified age and are thus advantageous from an identification perspective. Over the time period that I study, the regulations state that account holders must begin taking annual distributions from their plans after reaching the calendar year that they turn $70\frac{1}{2}$. I leverage the discontinuous nature of the policy and use an RD design to estimate the causal effects of aging into mandated drawdown. I leverage the breadth of the HRS survey data to show the direct effects of the policy on withdrawals from IRAs and then to estimate the indirect effects on additional financial outcomes.

I focus my analysis of indirect effects on one key set of outcomes: intergenerational transfers. Understanding intergenerational transfers is important. They are quite common, and the amount of resources transferred from parents to children is substantial. For instance, Gale and Scholz (1994) argue that inter vivos giving (transfers when the parent is alive) can account for at least 20 percent of wealth accumulation in the U.S., with bequests (transfers after the death of the parent) accounting for an additional 31 percent. Moreover, intergenerational transfers are particularly relevant for RMD regulations. RMDs were put into place because contributions to traditional retirement accounts, as well as gains within the accounts, are exempt from taxation until withdrawn, when distributions are then taxed as income. RMD policy aims to increase withdrawals and limit the deferral of taxation until very late into retirement or death. There are thus natural intergenerational considerations at the heart of the regulations. Horneff, Maurer, and Mitchell (2021) point out that RMDs prevent account holders from avoiding income taxes on retirement savings for their entire lives and then passing the money to their children. Similarly, Warshawsky (1998) reviews the background and intent of the regulations and notes how they "specifically limit the use of retirement arrangements as a tax-advantaged means of accumulating assets to pass across generations to children, grandchildren and other young beneficiaries." Against this backdrop, I investigate whether aging into RMDs influences family transfers.

I begin by showing a large and discontinuous increase in withdrawals from IRAs right as households reach RMD age. The RD estimates indicate that households are 37.6 percentage points more likely to take a distribution from an IRA after aging into the policy, which represents a large increase off a baseline mean of 26%. Establishing these estimates in my setting by using an RD design to quantify the effects complements existing work that has shown using a variety of datasets and other strategies that RMDs induce drawdown from retirement accounts (Poterba, Venti, and Wise 2013, Brown, Poterba, and Richardson 2017; Mortenson, Schramm, and Whitten 2019; Horneff, Maurer, and Mitchell 2021; Stuart and Bryant 2021).[1] My results support conclusions from the literature that RMDs lead households to draw down assets that otherwise would not have been drawn down and that many households hold wealth in IRAs until they are required to take distributions.

Next, I provide new estimates on the indirect effects of RMDs and show how the mandated decumulation of retirement savings impacts intergenerational transfers. I find that aging into RMD policy induces households to pass resources to the next generation. Specifically, I find a statistically significant 4.7 percentage point increase in the likelihood of making any inter vivos transfers to children or grandchildren, which represents a 10% increase when compared to the baseline mean. I also find an increase in the number of transfers made, which can reflect both extensive margin responses about whether to transfer any resources as well as intensive margin responses about how many transfers to make.

Taken together, my findings indicate that some households ultimately use IRAs to transfer resources to the next generation, holding on to savings in the accounts and then passing resources to children when induced to draw down assets. What can explain these results? Importantly, RMD policy does not lift a liquidity constraint, as households can access IRAs without penalty in the years preceding RMD ages, so the increase in transfers cannot be explained by increased access to funds. Furthermore, RMD requirements can be anticipated and do not prohibit account holders from continuing to save the distributions elsewhere, so households could continue to save the withdrawn assets in a taxable savings account. Later, I discuss a few potential underlying explanations. It could be that households increase inter vivos gifts due to a change in the marginal return to saving. It could also be that aging into RMDs leads to increased awareness of funds or salience of information related to asset decumulation and spending. Indeed, in their analyses of drawdown behaviors, Mortenson, Schramm, and Whitten (2019) show evidence of optimization frictions in the context of the regulations and Brown, Poterba, and Richardson (2017) show that many people report viewing RMDs as a consumption guide.

This paper relates generally to the literature on the decumulation of retirement assets. Banks and Crawford (2022) review the existing evidence and call for more research in this area. Previous empirical work mostly investigates trends in asset drawdown and documents factors associated with withdrawals from retirement accounts (e.g. Sabelhaus 2000; Amromin

[1]For instance, although not using an RD framework like in my analysis, Poterba, Venti, and Wise (2013) use data from the Survey of Income and Program Participation and the HRS to investigate the age profile of withdrawals from retirement accounts and find clear increases in withdrawals as households age into their 70's and reach RMD ages, whereas Mortenson, Schramm, and Whitten (2019) and Stuart and Bryant (2021) likewise use tax data to show that withdrawals increase substantially after reaching RMD ages.

and Smith 2003; French et al. 2006; Coile and Milligan 2009; Poterba, Venti, and Wise 2011a; Poterba, Venti, and Wise 2013; Argento, Bryant, and Sabelhaus 2015; Poterba, Venti, and Wise 2015; De Nardi, French, and Jones 2016; Siliciano and Wettstein 2021). Overall, a key broad finding that sets the stage for much of the work in this literature is that the decumulation of retirement assets appears to occur rather slowly compared to predictions from benchmark lifecycle models.

My analysis relates most closely to an emerging strand of the decumulation literature that also studies the effects of Required Minimum Distribution regulations.[2] Most papers focus on the direct effects of RMDs on the drawdown of retirement accounts (Poterba, Venti, and Wise 2011b; Brown, Poterba, and Richardson 2017; Mortenson, Schramm, and Whitten 2019; Stuart and Bryant 2021). I contribute by providing some of the first reduced-form causal evidence on the indirect effects of RMDs on other financial outcomes. To my knowledge, the only other paper to estimate indirect effects using an empirical approach similar to mine is Goodman (2019), a working paper that provides complementary evidence by using tax data to estimate the effects on taxable savings. Two other papers, Stuart and Bryant (2021) and Horneff, Maurer, and Mitchell (2021) take a different approach and provide insights on indirect effects by using lifecycle models to predict how counterfactual RMD policies would impact consumption, savings, tax payments, and other outcomes. None of these other papers study the effects of RMDs on inter vivos transfers, which is the focus of this paper. In using survey data to study outcomes that are not present in administrative datasets analyzed by some of the other papers, my analysis takes a broad view and documents responses that are relevant for policy. For instance, my results suggest that policy makers are likely to influence the timing of intergenerational gifts when making changes to the RMD threshold age, as was recently done by the Setting Every Community Up for Retirement Enhancement (SECURE) Act of 2019 (which increased the age to 72) and again by the SECURE 2.0 Act of 2022 (which further increased the age to 73 starting in 2023).

The rest of this paper is organized as follows. Section 2 overviews the policy environment. Section 3 describes the data. Section 4 lays out the identification strategy. Section 5 presents the results. Section 6 discusses potential mechanisms. I conclude in Section 7.

[2]Other related work studies responses to policies on early withdrawal penalties. In the U.S. context, Goda, Jones, and Ramnath (2022) and Stuart and Bryant (2021) show that the removal of penalties on early withdrawals from IRAs at age $59\frac{1}{2}$ influences drawdown, and Coyne, Fadlon, and Porzio (2022) use penalized withdrawals to study how households value liquidity. In the context of Singapore, Agarwal, Pan, and Qian (2020) show that withdrawals and consumption increase after individuals become eligible to withdraw money from pension plans.

2 Policy Environment

The U.S. government incentivizes saving for retirement through tax-advantaged defined contribution retirement accounts. Generally, accounts can be categorized as either "traditional" or "Roth" accounts. Contributions to traditional accounts are typically tax deductible, and then withdrawals are taxed as regular income. In contrast, contributions to Roth accounts are not tax-deductible, but then withdrawals from the accounts are not taxed. Some retirement accounts are sponsored by employers, such as 401(k)s, whereas others are personal accounts, called Individual Retirement Accounts (IRAs). This paper focuses on IRAs, an important savings vehicle for many households. In the fourth quarter of 2022, assets in IRAs amounted to about \$11.5 trillion, whereas assets in employer-sponsored defined contribution accounts amounted to about \$9.3 trillion (Investment Company Institute 2023).

Two key pieces of regulation govern the drawdown of IRAs. First, an early withdrawal penalty states that account holders must pay a penalty on withdrawals made before reaching age $59\frac{1}{2}$. The purpose of this rule is to discourage withdrawals before reaching retirement. The penalty applies to withdrawals from traditional IRAs, with exceptions for qualified events such as disability or first-time-buyer home purchases. The penalty applies only to withdrawals from Roth IRAs that exceed contributions, as contributions to Roth accounts are made after taxes and can thus be withdrawn penalty-free.

Second, Required Minimum Distribution (RMD) rules state that account holders must begin withdrawing assets once they reach a specified age. The purpose of RMD regulations is to limit revenue losses associated with tax-advantaged retirement savings. The regulations mandate that account holders of most tax-advantaged retirement accounts start taking yearly distributions beginning in the calendar year during which the account holder turns $70\frac{1}{2}$. The rules apply to traditional IRAs, but not Roth IRAs, since contributions to Roth IRAs are made after tax. The rules also apply to employer-sponsored plans such as 401(k)s, but here I focus on the rules governing the drawdown of IRAs, because I am able to study IRAs with my data.[3] Note that employer plans may be rolled over to IRAs upon retirement or separation from employment.

The RMD rules mandate a distribution amount to be taken each year based on the balance of the account. For each IRA an individual owns, the RMD for that IRA is calculated by dividing the balance of the account on December 31 of the previous year by a distribution

[3] RMD rules apply generally to both traditional and Roth 401(k) plans. The rules for employer-sponsored plans are similar to those regarding traditional IRAs, except that individuals still working can usually delay taking RMDs from their plans sponsored by their current employer until after retirement.

period, which is a number taken from IRS life expectancy tables. Typically, the number comes from the Uniform Lifetime table, but account holders whose spouse is the only beneficiary of the account and more than 10 years younger than the account holder must use the Joint Life and Last Survivor Expectancy table. Owners of multiple IRAs total their RMDs from each IRA and can take that amount from any combination of their accounts. Figure 1 plots a typical RMD schedule derived from the Uniform Life table. The rules are rather modest, with initial required distributions starting at just shy of 4% of the IRA balance and only increasing to about 5.5% of the balance after 10 years. To give these percentages more meaning, note that Mortenson et al. (2019) use tax data to show that the average IRA balance for individuals 60 and older amounts to just under $185,000 (in 2014 dollars).

The first RMD for an account holder, that is, the distribution required for the year during which the account holder turns $70\frac{1}{2}$, is subject to a grace period and due by April 1 of the next calendar year. All other RMDs are due by December 31 of the calendar year to which the RMD applies. The penalty for not taking an RMD is a 50% tax on the required-but-undistributed amount.

3 Data

To study empirically the effects of the RMD rules, I use data from the Health and Retirement Study (HRS). The HRS is a biennial survey dataset on older households in the U.S. that contains detailed information on financial behaviors. It is well-suited for my analysis, as it has a relatively large number of households around the RMD threshold age and information on both IRA ownership and drawdown. Moreover, the survey nature of the data means that there is information on intergenerational transfers that is absent from typical administrative datasets. I use the HRS datasets produced by the RAND Center for the Study of Aging, which contain cleaned-and-processed versions of HRS variables. Specifically, I merge the RAND HRS Longitudinal File 2016 (Bugliari et al. 2019b) with the RAND HRS Detailed Imputations File 2016 (Bugliari et al. 2019a) and the RAND HRS Family Data 2014 (Bugliari et al. 2018).

3.1 Analysis Sample

To construct the analysis sample, I start with the merged RAND HRS datasets and implement five restrictions. First, I keep only survey waves 5 through 12, which correspond to years 2000 through 2014, because it is for these waves that the information on both

IRA withdrawals and intergenerational transfers is available. Second, because both IRA ownership and inter vivos transfer variables are defined at the household level, I conduct a household level analysis by keeping only observations of individuals who are designated as the financial respondent for their household. Third, I keep only observations of households with children or step-children, so that I can study intergenerational transfers. Fourth, I keep only observations with non-missing information on outcome variables (discussed below) and demographics (gender, marital status, race, and education). Fifth, to study households for which the RMD rules are relevant, I study only those that have an IRA.

The restriction to IRA holders is natural but warrants more discussion. It has advantages and disadvantages. The key advantage is that it allows me to study a sample of households that can be subject to the RMD rules. The disadvantage is that, in the context of my RD design, studying only IRA holders could potentially be problematic if aging into RMD regulations impacts the likelihood of owning an IRA. That is, IRA ownership could itself be considered an outcome variable. Indeed, Mortenson, Schramm, and Whitten (2019) study how RMDs impact decumulation behavior and document in their large-scale administrative tax data an increase in the likelihood of closing accounts for those with lower account balances.[4]

I address potential problems with this sample restriction in two ways. First, I directly investigate IRA ownership as an outcome in the HRS data using my RD design, and I do not find evidence of a discontinuous change in my sample. Second, as a robustness check nonetheless, I study an alternative sample of households that owned an IRA earlier, that is, before reaching RMD age. This sample is less prone to endogeneity concerns, but a key drawback is that it can contain households that, by the time they reach RMD age, no longer own an IRA and are thus households for which the RMD rules are no longer relevant. Therefore, I use as my baseline sample households with IRAs, but I show later that results are similar when using the alternative sample.

3.2 Key Variables

I make use of two main sets of outcome variables for the analysis. First, I study withdrawals from IRAs. While IRA ownership is recorded at the household (i.e. respondent and spouse) level, information on withdrawals from IRAs is recorded at the individual level. I thus study as the main drawdown variables withdrawals made by financial respondents, who make up the

[4] For instance, using a logistic regression model, they show that the first year of being subject to RMDs is associated with a 6 percentage point increase in the likelihood of closing an account for people in each of the bottom two ventiles of the account balance distribution.

analysis sample. The withdrawal variables capture distributions from IRAs in the previous year. (The survey asks about distributions "since last interview," but the RAND-processed variables prorate responses to reflect a 12-month period.) The primary drawdown outcomes are an indicator variable for taking a distribution from an IRA and a variable that records the total amount of dollars withdrawn. I winsorize the dollar amount variable at the 95th percentile to limit the influence of outliers and express it in 2010 dollars.

Second, I study intergenerational transfers. The data contain both information on inter vivos transfers and bequest expectations. The primary inter vivos transfer outcome variable is a household-level indicator variable for making any inter vivos transfer. The underlying survey question asks whether respondents or their spouses provided financial help or other gifts, amounting to $500 or more, to children (or grandchildren). I also study the total number of transfers, normalized by the number of children, which can capture both potential extensive margin responses about whether to make any inter vivos transfers at all, as well as potential intensive margin responses about how many transfers to make. Additionally, I study total inter vivos transfer amounts in dollars, also winsorized at the 95th percentile to limit the influence of outliers and expressed in 2010 dollars.

The bequest outcome variables capture bequest expectations. A survey question asks respondents to report the chances that they will leave a bequest of $10,000 or more (and responses are recorded as percentages between 0 and 100). If that probability is greater than 0, then they are asked the same question about a bequest of $100,000 or more. If that probability is greater than 0, then they are asked about a bequest of $500,000. I study three separate outcome variables, one for each bequest amount, where the outcomes are the self-reported probabilities of leaving a future bequest greater than or equal to the specified amount. I note that the variable covering the largest bequests is not available for survey wave 5.

Finally, I make use of several other variables to conduct my analysis. As control variables, I use information on gender, race, marital status, and college education. To construct the running variable for my RD analysis, I use information on birth date (birth month and birth year) as well as the survey interview date (the month and year that the interview is completed).

For reference, Appendix Table A.1 displays summary statistics and highlights how the characteristics of my analysis sample compare to other similar-aged households in the HRS data. The first two columns report means and standard deviations of variables for 69 year-old households in my analysis sample, those that have children and an IRA. The second two columns correspond to 69 year-old households that have children but that do not have an IRA. The financial respondents of households with IRAs are more likely to be male, married, and white, and they are more likely to have attended some college. Households with IRAs are also more likely to make inter vivos transfers, and they report greater likelihoods of leaving future bequests.

4 Identification Strategy

4.1 Regression Discontinuity Design

To estimate causal effects, I derive identification from the age-based discontinuous exposure to RMD rules. I track the evolution of outcomes as a function of household age and estimate discontinuous jumps in outcome variables as households age into RMD policy.

RMD rules require distributions beginning in the calendar year that an account holder turns $70\frac{1}{2}$. For those born during the first half of the year, this calendar year corresponds to the year during which they turn 70 on their birthday. For those born during the second half of the year, this calendar year corresponds to the year during which they turn 71 on their birthday. In my RD framework, I define January of the calendar year for which a household's first RMD is due as the cutoff, and I use household age at the time they are surveyed to define the running variable as the distance to this cutoff. The idea is to compare households interviewed before their first RMD year starts, when they are not subject to the regulations, to households interviewed after, as they age into the regulations.

To make these comparisons, I estimate

$$Y_{ht} = \alpha + \beta RMD_{ht} + \gamma AGE_{ht} + \delta(AGE_{ht} \times RMD_{ht}) + \theta X_{ht} + \varepsilon_{ht}, \tag{1}$$

where Y_{ht} is an outcome variable for household h during survey wave t, AGE_{ht} is the age in months of the household financial respondent at the time of the survey and defined relative to their age in January of the calendar year during which they turn $70\frac{1}{2}$, RMD_{ht} is an indicator for being surveyed after reaching the January cutoff, X_{ht} is a vector of control variables, and ε_{ht} is an error term. The coefficient of interest is β, the "RD estimate." It captures the discontinuity in the outcome of interest at the age threshold and represents the reduced-form effect of aging into RMD policy.

In the baseline regression specification, I use triangular weights, I cluster standard errors at the household level, and I include as control variables a dummy for gender, a dummy for being white, a dummy for having attended at least some college, a dummy for being married, and survey wave fixed effects. To choose a leading bandwidth, I treat the running variable as a continuous variable and use the procedure from Calonico, Cattaneo, and Titiunik (2014) to select the optimal bandwidth for my main outcome variable of interest, an indicator for any inter vivos transfers. I then use this bandwidth (87 months) throughout my analysis to keep the underlying sample contributing to my estimates consistent. Later, I assess the robustness of my results to all of these specification choices.

An important point regarding the policy regulations is that people can take their required distributions at any point during the calendar year that their RMD is due. The rules stipulate that households must take RMD-satisfying distributions for year τ at some point between January 1 of year τ—the cutoff date in the RD framework—and December 31 of year τ. This setup creates a blurred definition of treatment status (i.e. exposure to RMD rules) right at the cutoff. Those surveyed before reaching the cutoff are clearly in the control group, as they are not yet subject to RMDs. However, those surveyed on or immediately after the cutoff are harder to classify. Consider a household surveyed in February of the year that their first RMD is due. This household is required to take an RMD in the year it is being surveyed, but if it has not yet taken an RMD-satisfying distribution, it still has 10 months to do so. (Moreover, the grace period for initial RMDs would allow for late distributions up until April 1 of the subsequent year.) While this household would have aged into their first RMD year, its behaviors as of the time that it is surveyed are unlikely to capture the full effect of being exposed to RMDs.

Therefore, in order to quantify the effects of being fully exposed to the regulations, I use a donut approach. Specifically, I exclude observations of households during the calendar year that they turn $70\frac{1}{2}$ from the regressions. To be transparent, I include in my analysis standard RD graphs, which allow for a clear visualization of the design and which highlight the donut observations. The graphical analysis for the direct effects of RMDs on withdrawals from IRAs show that the effect of being fully exposed to RMD rules is best quantified by excluding the donut observations, but I assess the sensitivity of my results to this choice in the robustness section.

4.2 Threats to Validity

The identifying assumption underlying the RD design is that other factors that influence outcome variables do so smoothly as households age into exposure to the RMD rules. To interpret any estimated jumps in outcome variables as causal, one needs to assume that, in the absence of the RMD rules, outcomes would have evolved smoothly as households age through the calendar year during which they turn $70\frac{1}{2}$. To gauge the relevance of threats to this assumption, I undertake several validity checks.

First, I examine the density of the running variable. Because the running variable is a household's monthly age at the time of their survey, manipulation in the classical sense is unlikely. However, my leading estimates come from a sample of IRA owners, and if IRA ownership changes at the cutoff, then there could be a discontinuous change in the number of individuals observed around the threshold. Therefore, in the spirit of McCrary (2008), I plot a histogram of the running variable in Figure 2.[5] The density of the running variable appears to evolve smoothly through the threshold. A formal density test as proposed by Cattaneo, Jansson, and Ma (2020) results in a p-value of 0.767, so I conclude that there is no evidence of a discontinuity in the density of the running variable at the cutoff. Moreover, in the robustness section later, I directly investigate whether IRA ownership changes discontinuously in the full sample of households (that is, without imposing the IRA ownership restriction), and I do not find any evidence of such a change.

Next, to provide another check on the validity of the design, I estimate equation (1) using control variables as outcome variables. Control variables should not change discontinuously as households age into RMD exposure. Indeed, point estimates are small and statistically indistinguishable from zero (see Appendix Table A.2.)

Finally, there is a potential issue regarding a confounding policy. Social Security's delayed retirement credit increases monthly retirement benefits for those who claim after their Full Retirement Age, but these increases stop at age 70. This policy could threaten the interpretation of my estimates as being driven by RMDs, if the ending of the delayed retirement credit at age 70 leads to discontinuities in outcomes right around the time that households age into RMD policy. For instance, if the delayed retirement credit policy induces a jump in retirement, and if retirement has its own effect on inter vivos transfers, then my estimates could reflect changes in transfers due to retirement, and not RMDs. Fortunately, I am able to investigate the relevance of this threat, as the HRS data contain information on retirement benefits and labor supply. Appendix Figure A.2 plots RD graphs for these outcomes, which appear to evolve smoothly through the RMD cutoff. Graph (a) indicates an increasing trend in the likelihood of receiving benefits as households age through Social Security eligibility

[5] The histogram uses 12-month bins. Appendix Figure A.1 plots a histogram of survey interview months. The graph shows how the vast majority of surveys take place between March and July, whereas relatively few surveys take place in other months. This pattern means that, within each 12-month bin, relatively few observations will correspond to the earliest and latest months of the year.

ages, but almost all households claim benefits before age 70, and so benefit receipt ultimately evolves smoothly through the cutoff. Graph (b) shows a declining trend in the likelihood of having positive earnings as households age, but labor supply also ultimately evolves smoothly through the cutoff. The corresponding regression estimates show no evidence of any effects (see Appendix Table A.3).[6]

5 The Effects of Aging into RMD Regulations

In this section, I present the results, which document the causal effects of aging into RMD regulations. I first establish the direct effects of RMDs on the drawdown of IRAs. I then document the indirect effects of RMDs on intergenerational transfers.

5.1 The Direct Effects of RMDs on Distributions from IRAs

I begin with a standard RD graphical analysis, which provides a visual assessment of the effects. Specifically, I plot binned means of outcome variables against the running variable—age at the time of survey interview—for those around the cutoff. I then superimpose on these graphs regression lines from estimating separate linear trends in the running variable for observations on either side of the cutoff.

Figure 3 illustrates the direct effects of RMDs on the drawdown of IRAs. Graph (a) depicts the impact of aging into RMD policy on the likelihood on taking a distribution from an IRA. The graph shows a large and discontinuous jump in the taking of distributions as households age into RMD exposure. Before reaching the year during which the first RMD is due, only between 20 to 30 percent of households take distributions, but after aging into the rules, the likelihood of taking a distribution rises to around 70 to 80 percent. This pattern is completely consistent with the findings of Poterba, Venti, and Wise (2013); while they do not employ an RD design, they use over a decade of Survey of Income and Program Participation data (but also one year of HRS data) to show clear increases in the probability of withdrawals from retirement accounts as households age into their 70's. The magnitude of the increase that I show here is very similar to what they document.[7] Mortenson, Schramm,

[6]Guided by the striking pattern of means in graph (a) of Appendix Figure A.2, the regression for Social Security benefit receipt includes separate quadratic polynomials in the running variable on either side of the cutoff (as opposed to linear polynomials). I note that the procedure from Pei, Lee, Card, and Weber (2022) that can help with polynomial order selection also calls for a quadratic specification for this outcome.

[7]Why is the likelihood of taking a distribution not closer to 100% after reaching RMD ages? There are several possibilities, which are discussed by Poterba, Venti, and Wise (2013). First, the outcome is withdrawals made by the financial respondent, so it could be that for some households all IRAs are owned

and Whitten (2019) find similar patterns in the tax data for the years 2008 and 2010 (there was a suspension of the rules in 2009), although the likelihood of taking a withdrawal in their data jumps up even more, to around 90%, in the years after reaching age 70.

Graph (b) depicts the impact of RMDs on the amount of dollars withdrawn from IRAs. The graph provides additional evidence of a large and discontinuous change in drawdown behavior, and it provides insight into the amount of the dollars being withdrawn. In my sample, average distributions were just under \$6,000 right before aging into the rules but then jump to just over \$10,000 after. Together, the graphs provide clear visual evidence that RMD regulations induce withdrawals from IRAs.

The graphs also highlight how the donut specification will be implemented. The hollow gray dot in each graph plots the binned mean of the outcome variable for the observations of households being surveyed between January and December of the calendar year for which their first RMD is due. Recall that these households are partially exposed to RMD rules, in the sense that they are surveyed in the year for which their first RMD is due, but they may still have several months before they must take the required distribution. The hollow dots are clearly higher than the dots to the left of the cutoff, but they are also clearly much lower than the dots more to the right of the cutoff, consistent with the policy not binding until the end of the time period. These observations will be dropped from the regressions when estimating the baseline specification.

I turn to the regression analysis to formally quantify and assess the statistical significance of any discontinuities in outcomes. Table 1 reports the results. The RD estimate in column (1) indicates that households are 37.6 percentage points more likely to take a distribution as they age into the RMD rules, which is a 145% increase when compared to the mean of 26% (the fraction of households within the leading bandwidth to the left of the cutoff who take a distribution). The RD estimate in column (2) indicates that there is a \$4,309 increase in the amount of dollars withdrawn from IRAs.

Overall, the results in this section complement existing work and provide additional evidence that RMDs induce withdrawals from IRAs that would otherwise not have occurred. The results also establish a strong sort of first stage that can be used to analyze how the mandated decumulation of retirement accounts may impact other financial outcomes.

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by a spouse younger than the financial respondent. Second, some households could own only Roth IRAs, which are not subject to RMDs and which I cannot distinguish from traditional IRAs in these data. Third, some households could fail to report withdrawals in the survey. Fourth, some households could fail to comply with the policy. Mortenson, Schramm, and Whitten (2019) discuss the issue of noncompliance in more detail and show that even in administrative tax data the likelihood of withdrawals after reaching RMD age is not at 100 percent for traditional IRA holders.

5.2 The Indirect Effects of RMDs on Intergenerational Transfers

Figure 4 presents the graphical evidence for the effects of RMDs on inter vivos transfers. Graph (a) analyzes the main extensive-margin binary outcome that captures the likelihood of making any inter vivos transfers to children (or grandchildren). The graph provides visual evidence that households are discontinuously more likely to make inter vivos transfers right as they age into RMDs. The likelihood is in general declining with age, and the rate of this decline appears constant on either side of the cutoff, but there is a jump right as households age into the rules. (Consistent with the drawdown graphs, the hollow donut dot is elevated compared to the dots to the left of the cutoff.) Graph (b) shows a similar pattern for the outcome variable that captures both extensive and intensive margin responses. The graph shows a discontinuous increase in the number of inter vivos transfers that households make to their children, where I normalize the number of transfers by the number of children.

I also study transfer amounts, although these data are more noisy. Graph (a) of Appendix Figure A.3 shows no clear evidence of a discontinuity in total transfer amounts in dollars, but the confidence intervals indicate that it is unlikely that I will be able to detect or rule out meaningful effect sizes here. However, Figure 5 provides a different look at transfer amounts. Each graph shows results for an indicator variable that corresponds to making transfers of a particular size. Specifically, I analyze the likelihood of making inter vivos transfers that total to either less than or greater than the gift tax annual exclusion amount. In general, transfers to children are considered taxable gifts at the federal level, but gifts that are less than the annual exclusion amount are an exception. I use the annual exclusion amounts during my sample period, which vary from \$10,000 to \$14,000 depending on the year, to categorize the dollar amount of transfers made.[8] Graph (a) of Figure 5 shows a discontinuous increase in the likelihood of making inter vivos transfers that total to less than the annual exclusion. Graph (b) shows no evidence of an increase in the likelihood of making transfers that total to more than the annual exclusion. This dichotomy shows that the increase in inter vivos transfers induced by RMDs appears to be driven by gifts that are not large enough to be included in any potential gift tax calculation.

Overall, the graphical evidence indicates that aging into RMDs leads to increases in inter vivos transfers and that some of the RMD-induced distributions from IRAs are being passed to the next generation. Table 2 reports the corresponding regression results. Column (1) indicates that aging into the RMD rules increases the likelihood of making an inter vivos

[8]Note that the annual exclusion applies to each gift, whereas I observe total transfer amounts across all gifts made. Nonetheless, the annual exclusion amounts provide a useful benchmark for this exercise.

transfer by 4.7 percentage points. This point estimate is statistically significant at the 5% level, and it represents an increase of 10% when compared to the mean. Column (2) indicates that RMDs lead households to make a statistically significant 0.038 more transfers per child. Column (3) reports a point estimate that would suggest that total transfer amounts increase by $202, but this estimate is not statistically significant. Column (4) shows that the increase in transfers is driven by a 4.3 percentage point increase in the likelihood of making transfers that are less than the gift tax annual exclusion, whereas column (5) shows no statistical evidence of an increase in the likelihood of making much larger transfers.

The magnitude of the main effect on any inter vivos transfers is sizable when compared to its baseline mean. In principle, it would be helpful to also compare the magnitude to the estimates capturing drawdown. That is, one could scale the increase in the likelihood of passing resources to children by the increase in the likelihood of withdrawing money from an IRA. However, there is reason to be somewhat cautious when doing so. Other accounts, such as 401(k)s, can be subject to RMD regulations as well, but I do not observe withdrawals from these accounts. Even though many employer plans are rolled over to IRAs after retirement, there could be an issue for the scaling exercise if some households in my sample of IRA holders have both types of accounts but take required distributions only from their employer accounts and not from their IRAs. To the extent that this behavior occurs, my estimate on distributions from IRAs would understate the magnitude of a conceptual first stage defined as the impact of RMDs on any distributions from any type of retirement account. (Note that households in my sample with both types of accounts that take required distributions from both accounts do not present such an issue, as my estimate on distributions from IRAs would capture the fact that these households withdrew money from a retirement account.) Nonetheless and with this caveat in mind, taking the RD estimates at face value and scaling them would suggest that for every 100 households induced to take a distribution from an IRA due to the RMD rules, about 13 pass along some funds to children or grandchildren.

Next, for completeness, I analyze bequest expectations, which are the other set of intergenerational transfer variables available in the HRS data. I find no evidence that aging into RMD regulations impacts self-assessed probabilities of leaving future bequests of various sizes. Appendix Figure A.3 presents the graphical evidence, and columns (6), (7), and (8) of Table 2 report the RD estimates. It is perhaps unsurprising to see no evidence of an impact on these outcomes that reflect household *expectations*, as RMD policy mandates relatively modest withdrawals and can in principle be fully anticipated.

Taken together, the results indicate that some households hold on to wealth in IRAs until government policy mandates distributions and induces them to draw down assets, at which point they pass along resources to their children. Before discussing potential explanations for these findings, I first carry out several robustness checks.

5.3 Robustness Checks

First, I conduct a bandwidth sensitivity analysis. Figure 6 illustrates how the key estimates change with different bandwidths. Graphs (a) and (b) correspond to the drawdown outcomes, whereas graphs (c) and (d) correspond to the main inter vivos transfer outcomes. Each graph plots RD estimates and 95% confidence intervals as I vary the bandwidth from 36 months to 120 months. The vertical dashed lines denote the leading estimates that come from using the baseline bandwidth. Overall, the results appear stable. The point estimates for the inter vivos transfer outcomes fluctuate across the smallest bandwidths, but then the estimates stabilize and remain statistically significant. The estimates for other outcome variables, inter vivos transfer amounts in dollars and bequest expectations, are statistically indistinguishable from zero across the entire range of bandwidths (see Appendix Figure A.4).

Second, I probe the robustness of my estimates to various regression specification checks. Table 3 reports the results for drawdown and inter vivos transfer outcomes.[9] The columns of the table correspond to different outcome variables. The rows of the table describe the various robustness checks. Row A reproduces the baseline estimates, for ease of comparison. Row B drops the control variables from the regressions. Row C drops the triangular weights. Row D clusters the standard errors at the running variable level, rather than at the household level. The results are robust to all of these standard specification checks. Row E uses a quadratic polynomial in the running variable, rather than a linear polynomial. The point estimates for any inter vivos transfers and for the number of transfers are larger than, but within the confidence intervals of, the baseline estimates. Rows F and G then address the donut approach. Row F includes the donut observations in the regressions, instead of excluding them. The point estimates, as expected based on the graphs, are smaller, but each estimate that is statistically significant in the baseline specification remains statistically significant in this specification. Row G uses a wider donut to account for the grace period on initial RMDs until April 1 of the subsequent calendar year. That is, it excludes observations from the calendar year that one turns $70\frac{1}{2}$, plus observations in January, February, and March of the next calendar year. The estimates are similar to those from the baseline specification.

Third, I address potential issues from studying IRA holders. Selecting the sample on IRA

[9] Appendix Table A.4 reports the results for bequest expectations.

ownership could bias the results if some households drop out of the sample due to closing IRAs as they age into the rules, and if that propensity to drop out is not as good as random as it relates to the outcome variables. I assess the relevance of this threat in two ways. First, I note that there does not appear to be a discontinuous change in IRA ownership around the cutoff in the unrestricted sample of households (see Appendix Figure A.5). Second, I study an alternative analysis sample, exploiting the longitudinal nature of the data to study households that are early IRA holders. That is, I study those that held an IRA at some point before the cutoff—so that the RMD rules are likely relevant—but I avoid selecting on IRA ownership after the cutoff. Row H of Table 3 analyzes those observed with an IRA at any point before age 69. The main estimates are smaller for this alternative sample, but they are statistically significant and similar in relative magnitudes. The point estimate for taking an IRA distribution is about 73% of its baseline estimate, and the point estimate for making an inter vivos transfer is about 74% of its baseline estimate. Overall, these results indicate that the baseline estimates are unlikely to be driven by problematic sample selection.

6 Discussion on Mechanisms

What can explain the increase in inter vivos transfers upon aging into RMDs? First, I note that unlike the lift of the tax penalty on early withdrawals from IRAs before age $59\frac{1}{2}$, RMD regulations do not represent an increase in liquidity. Households can access the funds in their IRAs penalty-free before reaching the RMD age. If a household's children needed, as the survey asks about, "financial help," or if the households themselves had a preference for providing their children with monetary gifts, they could have used assets in IRAs to facilitate inter vivos transfers even before reaching RMD age. The increase in transfers is thus not explained by increased access to funds.

Furthermore, while RMD regulations mandate distributions, they do not mandate consumption. Consider an account holder who, in the absence of the RMD regulations, would not have taken a distribution from their IRA. While the regulations would lead to increases in withdrawals for this person, they would not mechanically lead to increases in consumption expenditures or inter vivos gifts. The person could reinvest the withdrawn amount in a non-retirement savings account if they so desired.

To consider the decision-making of an account holder more carefully, a useful benchmark to have in mind is that of a simple lifecycle model. Brown, Poterba, and Richardson (2017) lay out a standard setup and discuss how RMD rules compare and contrast with optimal consumption paths. Most important for my findings, they point out that, if retirement accounts earn some rate of return of r but taxable accounts earn some smaller return $(1-\tau)r$, then RMDs can affect the consumption path by influencing the marginal return to saving. It could be that this decline in the marginal return to saving as households age into the rules is underlying some of the increase in transfers.

Still there could be other explanations. Mortenson, Schramm, and Whitten (2019) show evidence of optimization frictions such as inattention among account holders responding to a 2009 suspension of the RMD regulations. If there is inattention more generally associated with RMDs, then perhaps aging into the regulations could increase, for instance, awareness of available funds and thus increase inter vivos gifts. Moreover, direct survey evidence from Brown, Poterba, and Richardson (2017) indicate that many see RMDs as a good guide for consumption spending. It could be that, even though RMDs can in principle be fully anticipated, aging into the regulations makes this perceived guidance more salient, which could then lead to increases in consumption spending and inter vivos transfers for some.

7 Conclusion

In this paper, I provide new evidence on how Required Minimum Distributions (RMDs) impact intergenerational transfers. Using data from the Health and Retirement Study and a regression discontinuity design, I estimate the casual effects of aging into RMD regulations. I find a 4.7 percentage point increase in the likelihood of making an inter vivos transfer as households age into the regulations and begin to draw down assets from Individual Retirement Accounts (IRAs).

My findings have implications for policy. First, in a quite direct sense, the results can inform policy makers administering the RMD regulations. These major regulations are one of the most important set of rules that govern the drawdown of retirement savings accounts in the U.S. They have recently been, and continue to be, the subject of policy discussions related to retirement reform. Policy makers increased the RMD threshold age to 72 in 2019 as a part of the Setting Every Community Up for Retirement Enhancement (SECURE) Act, and they increased the age again to 73 in 2023 as a part of the SECURE 2.0 Act. To have a better understanding of how changes to RMD ages will impact retirement-aged households overall, one needs to understand not only the direct effects of the policy on withdrawals from retirement accounts, but also the indirect effects of the policy on broader financial outcomes. My study makes progress in this area and shows that older households transfer resources to children when RMDs require withdrawals from tax-advantaged retirement accounts. This result indicates that as policy makers increase the RMD threshold age, they are likely to delay not only withdrawals and corresponding tax revenue, but also some intergenerational gifts.

Second and more generally, in leveraging the RMD policy environment to study how households respond to mandated retirement asset drawdown, my study sheds light on the question of how households ultimately use retirement accounts in retirement. Answering this question is crucial for evaluating the overall efficacy of tax policy pertaining to retirement accounts. My findings provide evidence that some households appear to ultimately use tax-advantaged IRAs to facilitate transfers of resources to their descendants. However, my findings also suggest that RMDs may curb the tax-advantaged accumulation of wealth across generations, if it is the case that the inter vivos transfers upon aging into RMD policy would have continued receiving beneficial tax treatment in IRAs until later conveyed as bequests.

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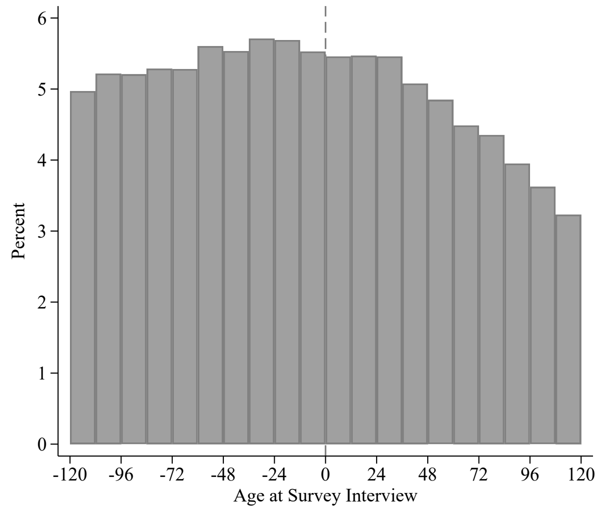
Figure 1: Typical Required Minimum Distribution Schedule

Notes: This figure plots the minimum amount of distributions that must be taken for the years during which RMD rules apply. The RMD amount is equal to the account balance on December 31 of the previous year divided by a life expectancy factor, which depends on the account holder's age. This particular schedule is derived from the IRS's Uniform Lifetime table, which is used by most IRA holders. Some account holders—those whose spouse is (i) the only beneficiary of the account and (ii) more than 10 years younger than the account holder—must use the Joint Life and Last Survivor Expectancy table.

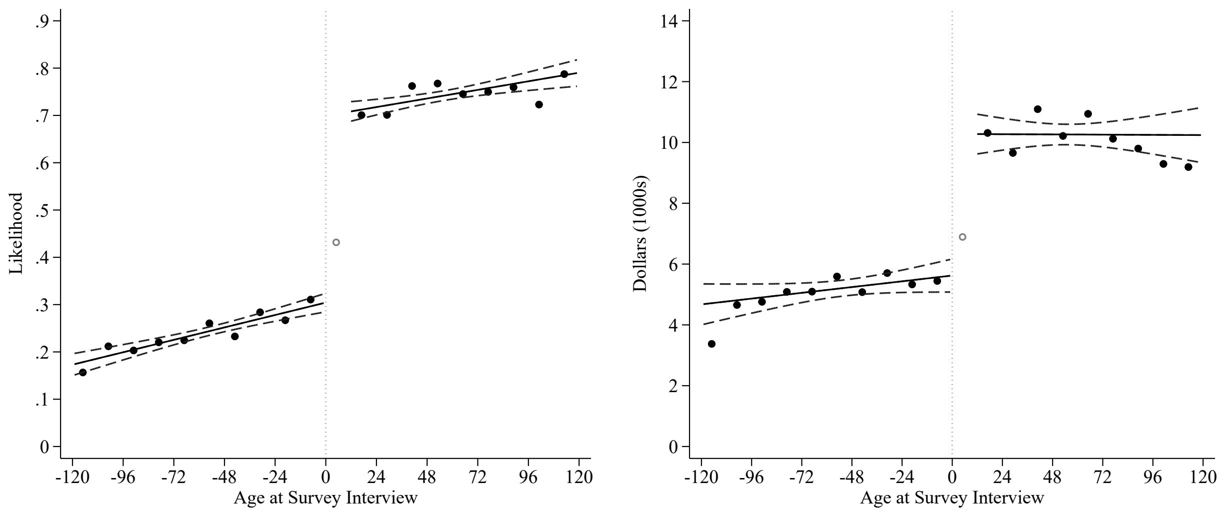
Figure 2: Histogram of the Running Variable



Notes: This figure plots a histogram of the running variable, monthly age at the time of the survey interview (defined relative to January of the calendar year during which the household turns $70\frac{1}{2}$).

Figure 3: Direct Effects of Required Minimum Distributions on Drawdown of Individual Retirement Accounts

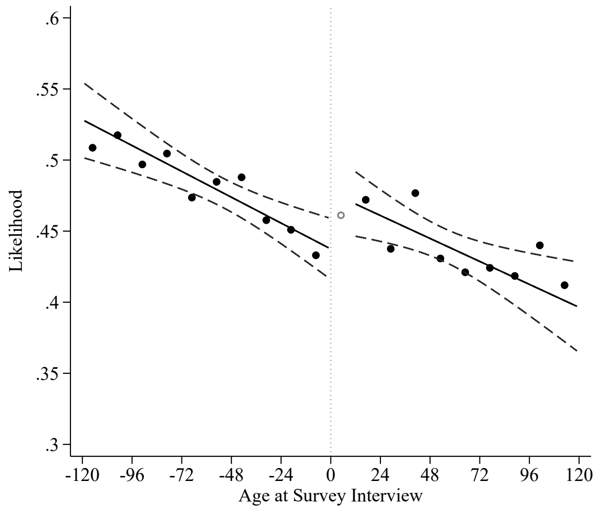
(a) Any Distribution from an IRA **(b) Total IRA Distribution Amounts**



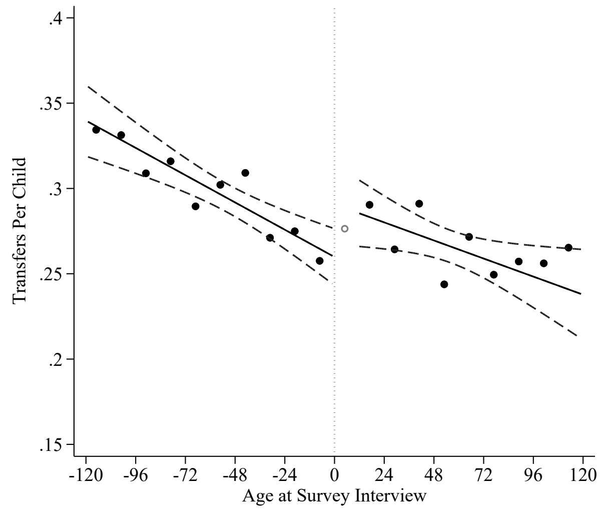
Notes: This figure illustrates the direct effects of aging into Required Minimum Distribution regulations on the drawdown of Individual Retirement Accounts (IRAs). Graph (a) illustrates the impact on an indicator variable for taking a distribution from an IRA. Graph (b) illustrates the impact on the total amount of dollars withdrawn. Each graph is constructed as follows. The running variable along the horizontal axis is household monthly age at the time of the survey interview, expressed in terms of distance from the cutoff. The cutoff is defined as January of the calendar year during which the household's first RMD is due, and it is denoted by the dotted vertical line. The dots are average outcomes in 12-month bins. The superimposed regression lines and 95-percent confidence intervals are based on the underlying unbinned data.

Figure 4: Indirect Effects of Required Minimum Distributions on Inter Vivos Transfers

(a) Any Inter Vivos Transfers



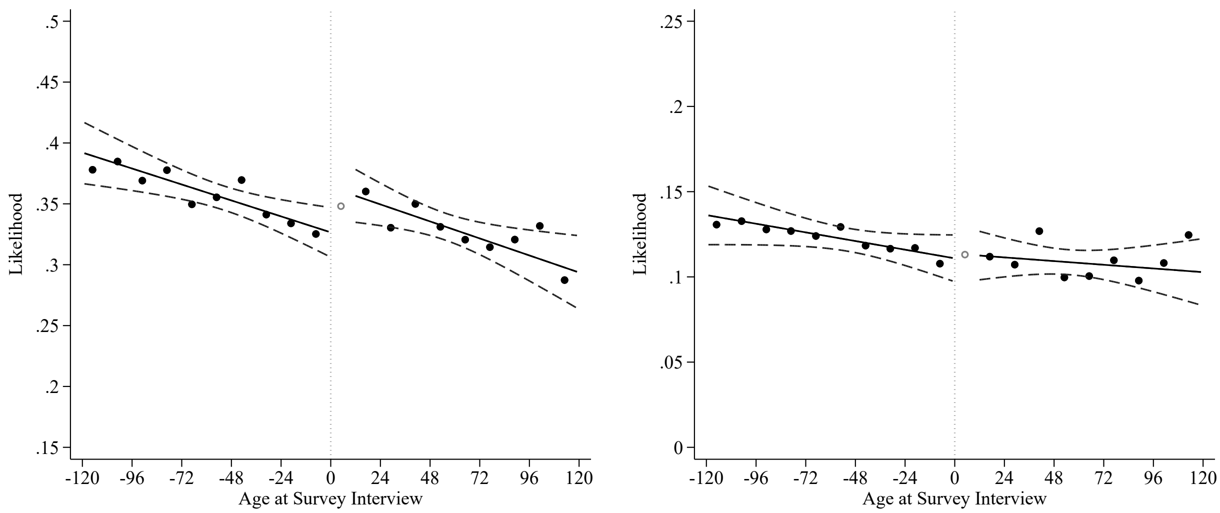
(b) Number of Transfers per Child



Notes: This figure illustrates the indirect effects of aging into Required Minimum Distribution regulations on inter vivos transfers. Graph (a) illustrates the impact on an indicator variable for making any inter vivos transfers. Graph (b) illustrates the impact on the number of inter vivos transfers made. See the notes of Figure 3 for more details on how each graph is constructed.

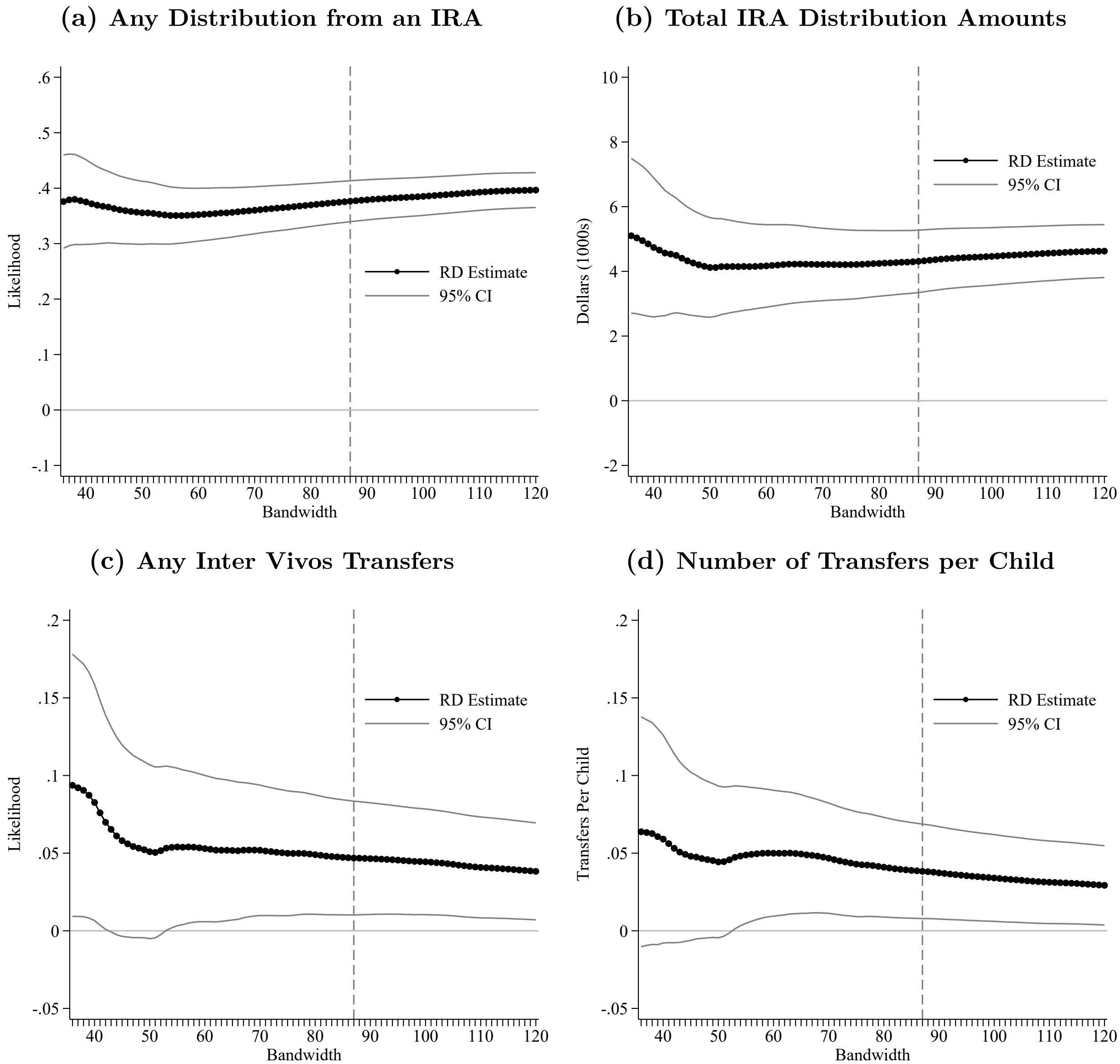
Figure 5: Indirect Effects of Required Minimum Distributions on Inter Vivos Transfer Amounts

(a) Transfers Less than Gift Tax Annual Exclusion **(b) Transfers More than Gift Tax Annual Exclusion**



Notes: This figure illustrates the indirect effects of aging into Required Minimum Distribution regulations on inter vivos transfers, using indicator variables for transfer amounts as outcomes. Graph (a) illustrates the impact on an indicator variable for making inter vivos transfers that amount to less than the gift tax annual exclusion amount. Graph (b) illustrates the impact on an indicator variable for making inter vivos transfers that amount to more than the gift tax annual exclusion amount. The gift tax annual exclusion amounts were $10,000 for 2000 and 2001, $11,000 for 2002 through 2005, $12,000 for 2006 through 2008, $13,000 for 2009 through 2012, and $14,000 for 2013 and 2014. See the notes of Figure 3 for more details on how each graph is constructed.

Figure 6: Robustness of Main Estimates to Bandwidth Selection



Notes: This figure illustrates the robustness of the main estimates to varying the bandwidth. Each graph plots the RD estimates and 95% confidence intervals for a different key outcome variable against bandwidths ranging from 36 months to 120 months. The vertical dashed lines denote the leading bandwidth of 87 months.

Table 1: Regression Discontinuity Estimates for Drawdown of Individual Retirement Accounts

	Any IRA Distribution (1)	IRA Distribution Amounts (2)
RD Estimate	0.376***	4,309***
	(0.019)	(492)
Mean	0.26	5,351
Clusters	4,810	4,810
Observations	12,906	12,906

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into Required Minimum Distribution regulations on distributions from Individual Retirement Accounts (IRAs). The RD estimates come from estimating equation (1). Standard errors clustered at the household level are in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

Table 2: Regression Discontinuity Estimates for Intergenerational Transfers

	Inter Vivos Transfers					Bequest Expectations		
	Any Transfers (1)	Number of Transfers per Child (2)	Total Transfer Amounts (3)	Transfers Less than Annual Exclusion (4)	Transfers More than Annual Exclusion (5)	Prob. of \$10,000 Bequest (6)	Prob. of \$100,000 Bequest (7)	Prob. of \$500,000 Bequest (8)
RD Estimate	0.047**	0.038**	202	0.043**	0.004	-0.301	-0.010	1.203
	(0.019)	(0.016)	(279)	(0.019)	(0.012)	(0.985)	(1.298)	(1.289)
Mean	0.47	0.29	4,118	0.35	0.12	85	66	30
Clusters	4,810	4,810	4,810	4,810	4,810	4,810	4,810	4,345
Observations	12,906	12,906	12,906	12,906	12,906	12,906	12,906	11,168

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into Required Minimum Distribution regulations on intergenerational transfers. The RD estimates come from estimating equation (1). Standard errors clustered at the household level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

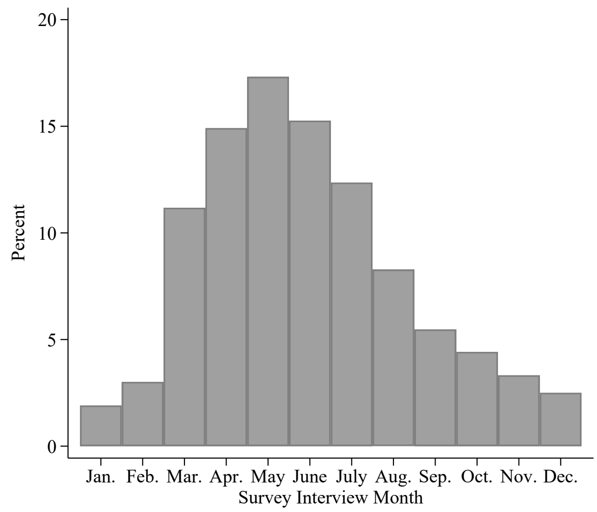
Table 3: Robustness of Estimates to Specification Checks and Sample Selection

		Drawdown of IRAs		Inter Vivos Transfers		
		Any IRA Distribution (1)	IRA Distribution Amounts (2)	Any Transfers (3)	Number of Transfers per Child (4)	Total Transfer Amounts (5)
A.	Baseline	0.376***	4,309***	0.047**	0.038**	202
		(0.019)	(492)	(0.019)	(0.016)	(279)
B.	No Control Variables	0.376***	4,333***	0.048**	0.039**	218
		(0.019)	(498)	(0.019)	(0.016)	(281)
C.	No Triangular Weights	0.401***	4,646***	0.040**	0.029**	173
		(0.017)	(455)	(0.018)	(0.014)	(268)
D.	Cluster on Running Variable	0.376***	4,309***	0.047**	0.038**	202
		(0.017)	(435)	(0.021)	(0.018)	(287)
E.	Quadratic Polynomial	0.324***	3,979***	0.062*	0.061**	-18
		(0.035)	(970)	(0.035)	(0.031)	(533)
F.	Include Donut Observations	0.202***	2,296***	0.037**	0.028**	204
		(0.016)	(411)	(0.016)	(0.012)	(241)
G.	Use a Wider Donut	0.378***	4,407***	0.043**	0.043**	354
		(0.020)	(510)	(0.020)	(0.017)	(292)
H.	IRA Holder Before Age 69	0.274***	2,849***	0.035*	0.025*	-95
		(0.019)	(391)	(0.018)	(0.014)	(238)

Notes: This table reports results from assessing the sensitivity of the RD estimates to various specification checks and an alternative analysis sample definition. Each column corresponds to a different main outcome variable. Each row indicates the specification choice or alternative analysis sample. Row A reproduces baseline estimates for ease of comparison. Row B drops control variables from the regressions. Row C drops the triangular weights. Row D clusters standard errors on the running variable. Row E uses a quadratic polynomial in the running variable. Row F includes the donut observations. Row G uses a wider donut to account for the policy grace period. Row H studies an alternative analysis sample of early IRA holders, defined as those observed holding an IRA at some point before age 69. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$

Appendix A Additional Figures and Tables

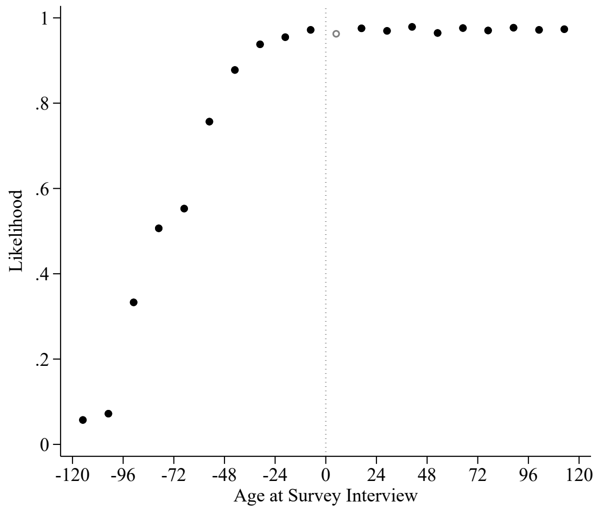
Figure A.1: Histogram of Survey Interview Months



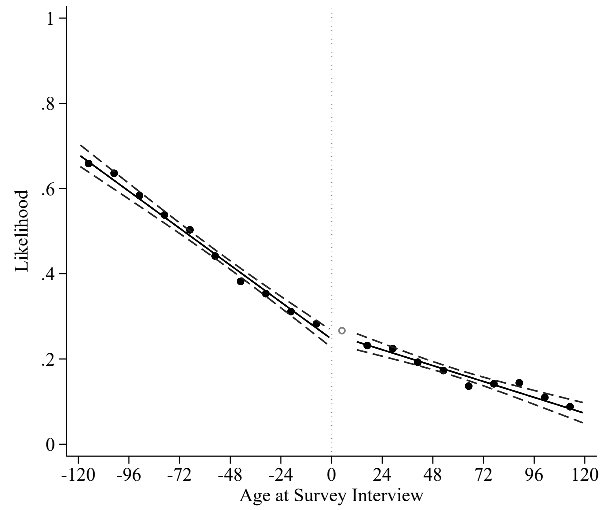
Notes: This figure plots a histogram of survey interview months. The vast majority of surveys take place between March and July, whereas few surveys take place in, for instance, January and December.

Figure A.2: Social Security Benefit Receipt and Labor Supply Around the Cutoff

(a) Any Social Security Benefits



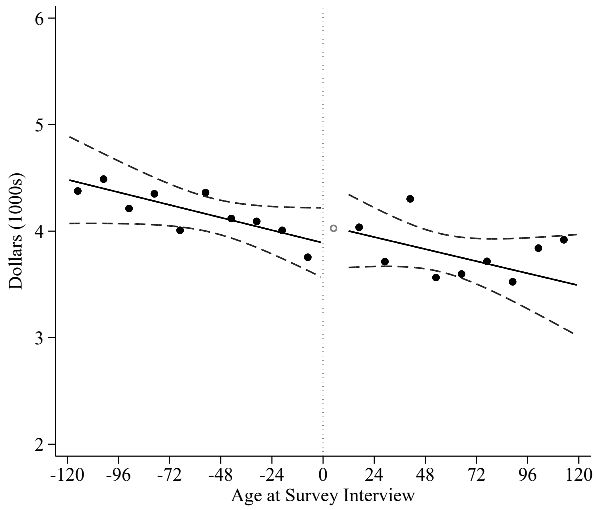
(b) Any Labor Market Earnings



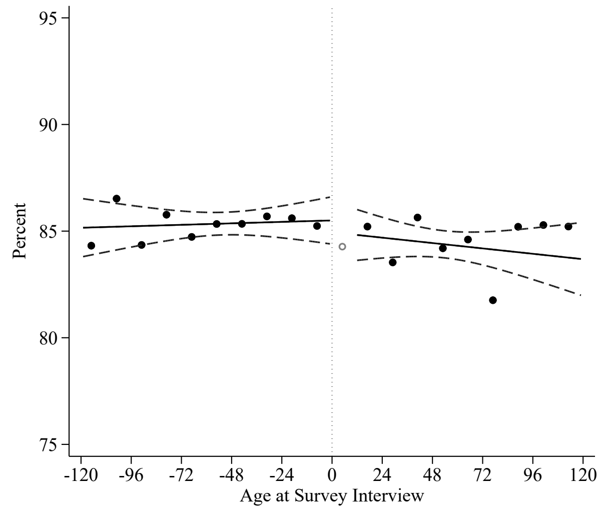
Notes: This figure illustrates how outcomes related to the ending of Social Security's Delayed Retirement Credit evolve as households age into Required Minimum Distribution regulations. Graph (a) analyzes an indicator variable for receiving Social Security retirement benefits. Graph (b) analyzes an indicator variable for having positive earnings. See the notes of Figure 3 for more details on how each graph is constructed.

Figure A.3: Indirect Effects of Required Minimum Distributions on Additional Outcomes

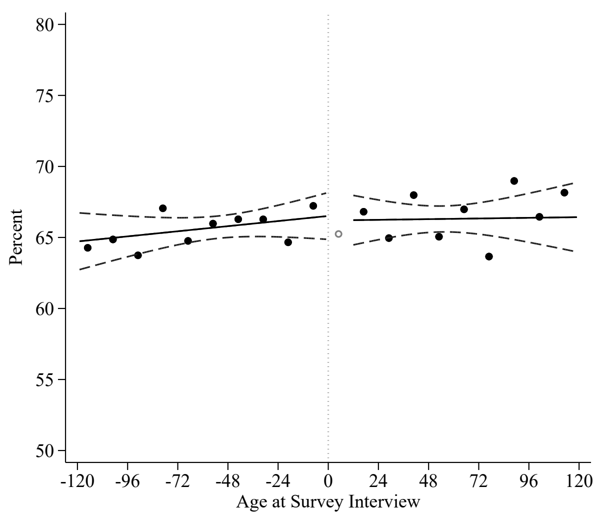
(a) Total Inter Vivos Transfer Amounts



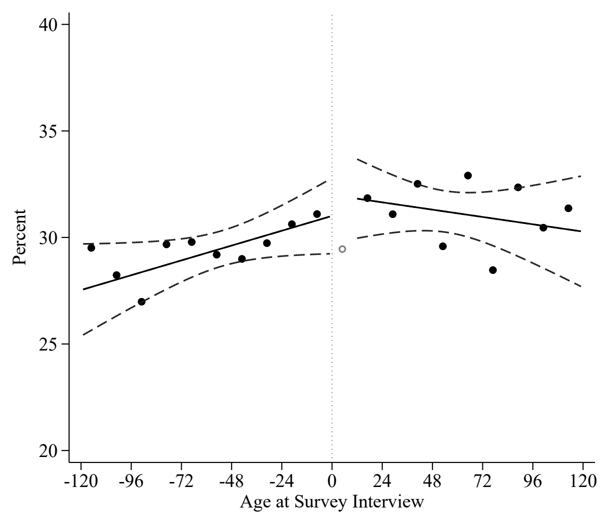
(b) Prob. of Making a $10,000 Bequest



(c) Prob. of Making a $100,000 Bequest



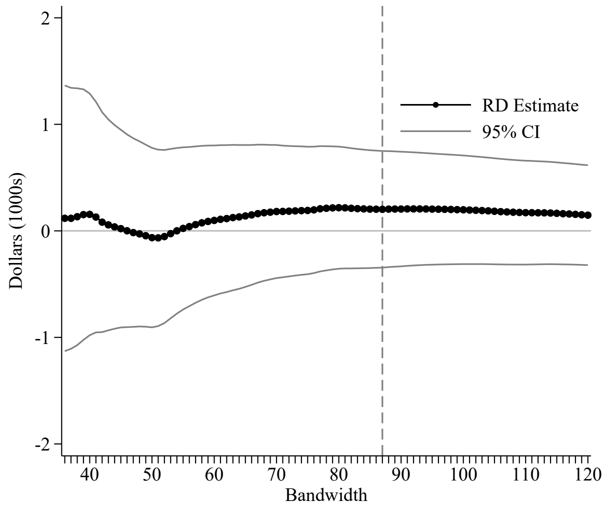
(d) Prob. of Making a $500,000 Bequest



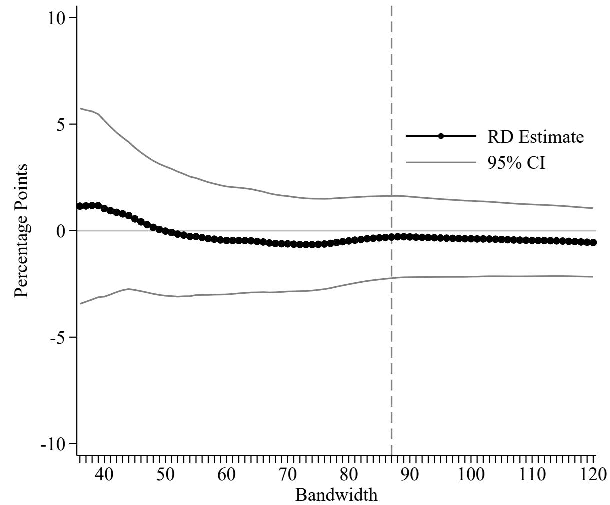
Notes: This figure illustrates the indirect effects of aging into Required Minimum Distribution regulations on additional outcomes. Graph (a) illustrates the impact on the total amount of inter vivos transfers in dollars. Graph (b) illustrates the impact on the self-assessed probability of leaving a future bequest of $10,000 or more. Graph (c) illustrates the same for a future bequest of $100,000 or more. Graph (d) illustrates the same for a future bequest of $500,000 or more. Note that graph (d) does not use data from survey wave 5, as the corresponding survey question was not asked during that wave. See the notes of Figure 3 for more details on how each graph is constructed.

Figure A.4: Robustness of Additional Estimates to Bandwidth Selection

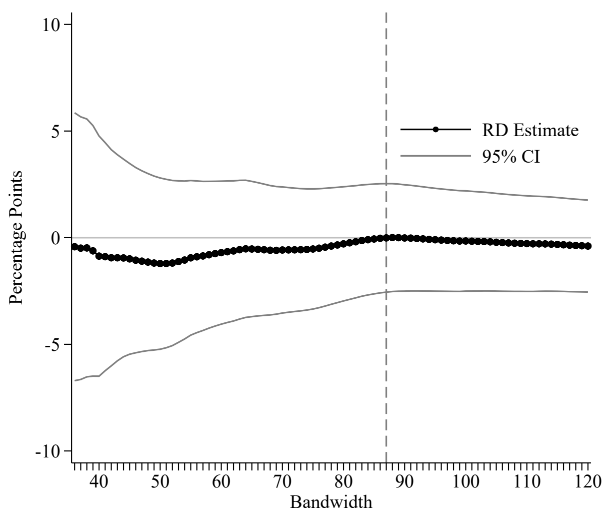
(a) Total Inter Vivos Transfer Amounts



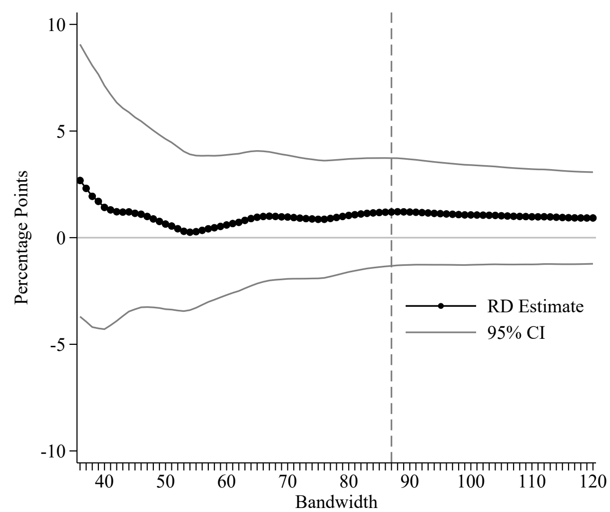
(b) Prob. of Making a $10,000 Bequest



(c) Prob. of Making a $100,000 Bequest

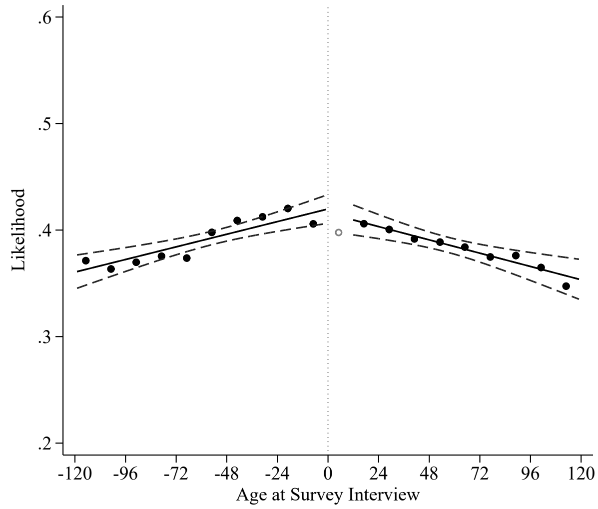


(d) Prob. of Making a $500,000 Bequest



Notes: This figure illustrates the robustness of the estimates to varying the bandwidth. Each graph plots the RD estimates and 95% confidence intervals for a different outcome variable against bandwidths ranging from 36 months to 120 months. The vertical dashed lines denote the leading bandwidth of 87 months.

Figure A.5: Individual Retirement Account Ownership Around the Cutoff



Notes: This figure illustrates how IRA ownership evolves as households age into the calendar years that correspond to Required Minimum Distribution regulations. The underlying sample is constructed just as the analysis sample described in Section 3, except without the restriction to households that own an IRA. The graph analyzes IRA ownership as the outcome variable and is constructed as follows. The running variable along the horizontal axis is household monthly age at the time of the survey interview, expressed in terms of distance from the cutoff. The cutoff is defined as January of the calendar year during which the household's first RMD is due (for households that do own an IRA), or during which the household's first RMD would be due if it did own an IRA (for households that do not own an IRA), and it is denoted by the dotted vertical line. The dots are average outcomes in 12-month bins. The superimposed regression lines and 95-percent confidence intervals are based on the underlying unbinned data.

Table A.1: Summary Statistics at Age 69

	Households with an IRA		Households without an IRA	
	Mean (1)	SD (2)	Mean (3)	SD (4)
Male	0.53	0.50	0.39	0.49
Married	0.70	0.46	0.43	0.50
White	0.91	0.28	0.70	0.46
Some College	0.57	0.49	0.30	0.46
Number of Children	3.20	1.67	3.86	2.21
IRA Balances ($)	214,334	626,628	–	–
Any Inter Vivos Transfers	0.43	0.50	0.28	0.45
Number of Inter Vivos Transfers (per Child)	0.25	0.37	0.14	0.29
Total Inter Vivos Transfer Amounts ($)	4,632	12,884	1,876	7,078
Probability of Leaving a $10,000 Bequest (%)	85	26	53	43
Probability of Leaving a $100,000 Bequest (%)	67	38	28	40
Probability of Leaving a $500,000 Bequest (%)	30	38	9	24
Observations	1,079		1,518	

Notes: This table reports summary statistics for two groups of 69 year-old households with children. The first two columns report means and standard deviations for households with an IRA. The second two columns report means and standard deviations for households without an IRA. Monetary values are expressed in 2010 dollars.

Table A.2: Regression Discontinuity Estimates Using Control Variables as Outcomes

	Male (1)	Married (2)	White (3)	College (4)
RD Estimate	0.006	0.008	0.002	0.005
	(0.013)	(0.014)	(0.008)	(0.013)
Mean	0.54	0.71	0.90	0.60
Clusters	4,810	4,810	4,810	4,810
Observations	12,906	12,906	12,906	12,906

Notes: This table reports regression discontinuity (RD) estimates when using control variables as outcome variables. The RD estimates come from estimating equation (1). Standard errors clustered at the household level are in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

Table A.3: Regression Discontinuity Estimates for Social Security Benefit Receipt and Labor Supply

	Any Social Security Benefits (1)	Any Labor Market Earnings (2)
RD Estimate	0.017	0.013
	(0.011)	(0.015)
Mean	0.80	0.40
Clusters	4,810	4,810
Observations	12,906	12,906

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into Required Minimum Distribution regulations on Social Security benefit receipt and labor supply. The RD estimates come from estimating equation (1), except that the regression for Social Security benefit receipt includes separate quadratic polynomials in the running variable on either side of the cutoff (as opposed to linear polynomials). Standard errors clustered at the household level are in parentheses. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$

Table A.4: Robustness of Bequest Expectation Estimates to Specification Checks and Sample Selection

		Bequest Expectations		
		Prob. of \$10,000 Bequest (1)	Prob. of \$100,000 Bequest (2)	Prob. of \$500,000 Bequest (3)
A.	Baseline	-0.301	-0.010	1.203
		(0.985)	(1.298)	(1.289)
B.	No Controls	-0.207	0.164	1.314
		(1.000)	(1.340)	(1.325)
C.	No Triangular Weights	0.068	0.474	1.406
		(0.917)	(1.224)	(1.225)
D.	Cluster on Running Variable	-0.301	-0.010	1.203
		(1.086)	(1.838)	(1.407)
E.	Quadratic Polynomial	-0.914	-1.961	0.346
		(1.930)	(2.541)	(2.517)
F.	Include Donut Observations	-0.808	-0.755	-0.503
		(0.857)	(1.140)	(1.161)
G.	Use a Wider Donut	0.032	1.209	1.163
		(1.007)	(1.337)	(1.353)
H.	IRA Holder Before Age 69	-0.386	-0.144	0.138
		(1.048)	(1.255)	(1.125)

Notes: This table reports results from assessing the sensitivity of the RD estimates to various specification checks and an alternative analysis sample definition. Each column corresponds to a different main outcome variable. Each row indicates the specification choice or alternative analysis sample. Row A reproduces baseline estimates for ease of comparison. Row B drops control variables from the regressions. Row C drops the triangular weights. Row D clusters standard errors on the running variable. Row E uses a quadratic polynomial in the running variable. Row F includes the donut observations. Row G uses a wider donut to account for the policy grace period. Row H studies an alternative analysis sample of early IRA holders, defined as those observed holding an IRA at some point before age 69. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$