The Effect of Required Minimum Distributions on Intergenerational Transfers*

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January 10, 2023

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.

Keywords: Retirement Policy, Tax Policy, Intergenerational Transfers
JEL codes: H24, D14, D64, J26, J14

*I thank participants at the public economics workshop at Clemson University, as well as Julie Cullen, Gordon Dahl, Itzik Fadlon, Alex Gelber, Gaurav Khanna, and Krislert Samphantharak for helpful conversations and comments.

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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. This major change has catalyzed research on the accumulation side of the lifecycle. An important literature studies the effects of tax-advantaged DC accounts on savings (e.g., Engen, Gale, and Scholz 1996, Poterba, Venti, and Wise 1996, Poterba, Venti, and Wise 2007, Gelber 2011, and Chetty et al. 2014). However, the shift to DC plans also has significant implications for the "other" side of the lifecycle—namely the decumulation phase. Standard DC accounts require households to decide when to draw down assets and how much to withdraw, which is in contrast to standard DB plans that pay out as annuities according to a previously defined structure.

Yet despite its importance for tax policy, 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. The goal of the tax-advantaged accounts is to help households achieve adequate income security in retirement; to analyze the overall efficacy of retirement savings 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.

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 retirement accounts and then to estimate the indirect effects on additional financial outcomes.

I focus on a particular set of policy-relevant outcomes: intergenerational transfers. 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 center of the regulations. Horneff, Maurer, and Mitchell (2021) point out that the regulations 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 Individual Retirement Accounts (IRAs) right as households reach RMD age. The RD estimates indicate that households are 37.3 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%. I also show a $4,279 increase in withdrawals from IRAs, which is quite sizable when compared to the baseline mean of $5,351. Establishing these estimates in my setting by using an RD design to quantify causal 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, and Stuart and Bryant 2021).[1] My results provide additional support to 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.

[1]For instance, although not using an RD framework like in my analysis, Poterba, Venti, and Wise (2013) use data from the HRS and the Survey of Income and Program Participation 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. Mortenson, Schramm, and Whitten (2019) likewise use tax data to show that withdrawals increase substantially after reaching RMD ages.

Next, I estimate the indirect effects of RMDs and document how the mandated decumulation of retirement savings impacts intergenerational transfers. I study primarily outcomes that capture inter vivos gifts and find that aging into RMD policy induces households to pass resources to the next generation. Specifically, I find a statistically significant 4.8 percentage point increase in the likelihood of making any inter vivos transfers to children or grandchildren, which represents a 10.2% increase when compared to the baseline mean. I also find an increase in the number of transfers made, which captures both intensive and extensive margin responses. Results for a noisier outcome variable on total transfer amounts in dollars are imprecise. I then study expectations about making future bequests, which are the other set of intergenerational transfer variables recorded in the HRS, and find no evidence of an impact.

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? Interestingly, unlike another policy that removes penalties on early withdrawals from IRAs upon reaching age $59\frac{1}{2}$, RMD policy does not lift a liquidity constraint. Households can access IRAs without penalty in the years preceding the RMD age threshold, so the discontinuous increase in transfers cannot be explained by increased access to funds. Furthermore, the requirement to take distributions can be fully anticipated, and the rules do not prohibit account holders from continuing to save the distributions elsewhere. Households who in the absence of the RMD regulations would not have taken a distribution from their IRA could continue to save the withdrawn assets in a non-retirement, 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 a 2009 suspension 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 that studies the decumulation of retirement assets. Several papers investigate trends in the drawdown of retirement wealth and document various factors associated with asset decumulation (e.g. Sabelhaus 2000, French et al. 2006, Coile and Milligan 2009, Poterba, Venti, and Wise 2011a, Poterba, Venti, and Wise 2013, Poterba, Venti, and Wise 2015, De Nardi, French, and Jones 2016, Siliciano and Wettstein

2021). Overall, an important empirical finding of this literature is that wealth decumulation in retirement appears to happen rather slowly, at least compared to trajectories from simple benchmark lifecycle models. Banks and Crawford (2022) provide a recent review of the literature, discussing research in both applied microeconomics and macroeconomics. They highlight how some work has shown that additions to standarad lifecycle models (such as bequest motives) can help explain trends in decumulation, whereas other work has shown that low levels of financial literacy and other behavioral factors can influence the drawdown of wealth in retirement.

Most similar to this paper, an emerging strand of the decumulation literature studies the effects of Required Minimum Distribution rules.[2] These papers mostly focus on the direct effects of RMDs on drawdown behavior. Poterba, Venti, and Wise (2011b) use data from the Survey of Income and Program Participation and the Health and Retirement Study and show that many households start to make withdrawals from retirement accounts only after reaching RMD ages. Brown, Poterba, and Richardson (2017) use data from a retirement services provider to study the 2009 suspension of RMDs and find that roughly one third of account holders suspended distributions. Mortenson, Schramm, and Whitten (2019) use tax data to show that around half of IRA holders would prefer to withdraw less than their required amounts. Three working papers build on these studies. Stuart and Bryant (2021) use tax data and a bunching analysis to show how RMDs impact the timing of withdrawals from IRAs, and they use a lifecycle model to show that alternative policies would increase welfare and tax remittances. Horneff, Maurer, and Mitchell (2021) use a lifecycle model to analyze how counterfactual RMD rules would influence consumption, income, and savings of households during both working life and retirement. Finally, Goodman (2019) uses tax data to show that RMD-induced withdrawals are only partially reallocated to other savings accounts.

I contribute by providing novel evidence on how RMDs impact intergenerational transfers. I use survey data to study these outcomes that are not present in administrative datasets analyzed by some of the other papers. Taking a broad view and documenting the effects on

[2]Another set of related papers study policies on early withdrawals from retirement accounts. In the U.S. context, Goda, Jones, and Ramnath (2022) use tax data to show large, sharp increases in withdrawals from IRAs upon the removal of the early withdrawal penalty at age $59\frac{1}{2}$, and Stuart and Bryant (2021) show that about 1.4% of IRA holders adjust their withdrawal behaviors because of the early withdrawal penalty. Amromin and Smith (2003) and Argento, Bryant, and Sabelhaus (2015) show that early withdrawals are correlated with adverse shocks, 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 becoming eligible to withdraw money from pension plans.

these outcomes is important for policy. First, the results can inform those administering the RMD regulations. The results suggest that policy makers might also 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 Act of 2019, which increased the age to 72. Second and more generally, my findings provide some insight into how households use tax-advantaged retirement accounts, an important issue to consider when evaluating the efficacy of tax policy pertaining to the accounts. The results point to some using IRAs to facilitate intergenerational transfers, but they also suggest that RMDs may curb tax-advantaged accumulation of wealth across generations, if it is the case that the inter vivos transfers upon aging into RMDs would have continued receiving beneficial tax treatment in IRAs until later conveyed as bequests.

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 Policy Environment

The U.S. government incentivizes saving for retirement through tax-advantaged retirement accounts. There are employer-sponsored plans, such as 401(k)s, and personal plans, called Individual Retirement Accounts (IRAs). This paper focuses on IRAs. There are two types of IRAs: traditional IRAs and Roth IRAs. Contributions to traditional IRAs can be deducted from taxable income, and then withdrawals are taxed as regular income. Contributions to Roth IRAs are not tax-deductible, but then withdrawals from Roth IRAs are not taxed.

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 personal 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 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 shows a typical RMD schedule. 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.

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,

[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.

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 whom the RMD rules are relevant, I study only those who 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 for whom the RMD rules are clearly relevant. 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 after reaching age $70\frac{1}{2}$.

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 who owned an IRA "earlier," that is, before reaching RMD age. This samples is less prone to endogeneity concerns, but a key drawback is that it can contain households who, by the time they reach RMD age, no longer own an IRA and are thus households for whom 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 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.

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.

The bequest outcome variables capture bequest expectations. An underlying survey question asks respondents to report the probability that they will leave a bequest of $10,000 or more. 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).

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 first calendar year for which a household's 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

$$Y_{ht} = \alpha + \beta \cdot RMD_{ht} + \gamma \cdot AGE_{ht} + \delta \cdot (AGE_{ht} \cdot RMD_{ht}) + \eta \cdot D_{ht} + \theta \cdot X_{ht} + \varepsilon_{ht}, \qquad (1)$$

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 estimating equation is completely standard except for the inclusion of D_{ht}, which is an indicator variable for being surveyed during the year that a household's very first RMD is due. I use this "donut" specification to prevent observations right at the cutoff from biasing my results, as I discuss in more detail below.

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 the RMD policy. In the baseline estimating equation, I use triangular weights and 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 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, and I use this bandwidth (87 months) to keep the underlying sample contributing to my estimates consistent across outcomes. Later I assess the robustness of my results to all of these specification choices.

The inclusion of D_{ht} in the regression specification is motivated by the RMD rules and the nature of the survey data. First, the rules stipulate that households must take an RMD-satisfying distribution for year τ at any point between January 1 of year τ and December 31 of year τ. This creates a blurred definition of "treatment" status (i.e. exposure to RMD rules) right at the cutoff. Those who are surveyed before reaching the cutoff are clearly in the control group, as they are not yet required to take an RMD. However, those surveyed on or right after the cutoff are harder to classify. Consider a household surveyed in March of the year that their first RMD is due. They are required to take an RMD in the year they are being surveyed, but they still have 9 months to do so. While they have aged into their RMD year, their behaviors are unlikely to capture the full effect of being exposed to RMDs.

Second, a grace period exists until April 1 of the subsequent calendar year for the first required distribution. Households with their first RMD due in December of year τ can take a distribution at any point between January 1 of year τ and April 1 of year $\tau + 1$. This extends the timing issue discussed above. Third, the biennial survey records outcome variables with look-back reference periods. The inter vivos transfer survey questions ask about transfers since the last interview, which is typically two years prior. As mentioned in Section 3, the questions about withdrawals ask about distributions since the last interview, but the variables are prorated to reflect the previous 12 months. These look-back periods can complicate the interpretation of the exact timing of reported behaviors as it relates to the age of the household at the time of the survey.

Therefore, in order to capture behaviors due to being fully exposed to RMD regulations, I use the donut specification. To be transparent, I include in my analysis standard RD graphs, which allow for a clear visualization of the design and which clearly illustrate the donut observations. The graphs for the direct effects of RMDs on withdrawals from IRAs suggest that the effect of being fully exposed to RMD rules is best quantified using the donut specification, 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 this could manifest itself as a discontinuity in the density of the running variable. I assess the density in Appendix Figure A.1. Graph (a) plots the histogram of the running variable for the analysis sample. There are cyclical spikes throughout the distribution due to interactions between birth dates and survey interview dates. Graph (b) plots a histogram of survey interview dates, highlighting the source of the spikes; the vast majority of surveys take place between March and July. Graph (c) plots a more coarse histogram of the running variable, using 12-month bins. Overall the density 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 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.1.)

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 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 RMDs. For instance, if the delayed retirement credit induces a jump in retirement, and if retirement has its own effect on inter vivos transfers, then this would influence my results. 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 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.2).[4]

5 The Effects of Aging into RMD Regulations

Here 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. In both cases, I begin with standard graphical analyses, which provide visual assessments 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, and I superimpose on these graphs regression lines from estimating separate linear trends in the running variable for observations on either side of the cutoff. I then turn to the regression analysis to formally quantify and assess the statistical significance of any discontinuities in outcomes.

5.1 The Direct Effects of RMDs on Distributions from IRAs

Figure 2 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 right 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.[5] Graph (b) depicts the impact of RMDs on the amount of dollars withdrawn from IRAs. The graph

[4]Guided by the 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).

[5]Why is the likelihood of taking a distribution not closer to 100%? 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 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.

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. The graphs provide strong 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 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, and they are answering survey questions about behaviors since the previous interview (two years prior). 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, which suggests that the effects of RMDs are not fully captured by these donut observations.

Table 1 reports results from the regression analysis. The RD estimate in column (1) indicates that households are 37.3 percentage points more likely to take a distribution as they age into the RMD rules, which is a 143% 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 \$4,279 increase in the amount of dollars withdrawn from IRAs.

Overall, the results in this section complement existing work and provide evidence that RMD regulations at $70\frac{1}{2}$ 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.

5.2 The Indirect Effects of RMDs on Intergenerational Transfers

I begin by analyzing inter vivos transfers. Figure 3 presents the graphical evidence. 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 donut dot is elevated compared to binned means for observations 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 and grandchildren. Graph (c) is for total inter vivos transfer amounts in dollars. There is no visual evidence of a discontinuity, although these data are naturally more noisy, and the confidence intervals on the regression lines give some indication that it is unlikely that I will be able to detect or rule out meaningful effect sizes. Overall, the graphs provide evidence that aging into RMDs leads to increases in inter vivos transfers and suggest that some of the RMD-induced distributions from IRAs are being passed to the next generation.

The regression results for inter vivos transfers are reported in columns (1), (2), and (3) of Table 2. Column (1) indicates that aging into the RMD rules increases the likelihood of making an inter vivos transfer by 4.8 percentage points. This point estimate is statistically significant at the 5% level, and it represents an increase of 10.2%. Column (2) indicates that RMDs lead households to make a statistically significant 0.40 more transfers per child. Column (3) reports a point estimate that would suggest that total transfer amounts increase by $206, but this estimate is not statistically significant.

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 IRAs. However, there is reason to be cautious when doing so. The issue is that 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 retirement plans are rolled over to IRAs after retirement, it is possible that some households in the sample age into the RMD regulations, withdraw money directly from a 401(k), and pass along some of the funds to their children, but without reporting a required distribution from an IRA. To the extent that this occurs, the straightforward scaling exercise would understate the magnitude of a conceptual first stage defined as any withdrawals from any retirement accounts. 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, I analyze bequest expectations, the other set of intergenerational transfer variables available in the HRS. I find no evidence that aging into RMDs impacts self-assessed probabilities of leaving future bequests. Figure 4 presents the graphical evidence, and columns (3), (4), and (5) of Table 2 report the corresponding RD estimates. There is no evidence of a discontinuity in any of the outcomes, which are the probabilities households assign to leaving future bequests of various sizes. It may be worth cautiously speculating on the interpretation of the lack of evidence supporting changes in these outcomes. On the one hand, perhaps it is unsurprising that *expectations* appear to evolve smoothly across the RMD age threshold that can be anticipated by households. On the other hand, if it is the case that inter vivos transfers and future bequests are substitutes, then perhaps it would not have been surprising to see bequest expectations drop as actual inter vivos transfers increase.

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 5 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 the other outcome variables, inter vivos transfer amounts and bequest expectations, are statistically indistinguishable from zero across the entire range of bandwidths considered (see Appendix Figure A.3).

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. 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 then estimates equation (1) including the donut observations. 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.

Third, I address potential issues from studying IRA holders. Selecting the sample on IRA 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.4). Second, I study an alternative analysis sample, exploiting the longitudinal nature of the data to study households who are "early IRA holders." That is, I study those who 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 F 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 74% of its baseline estimate, and the point estimate for making an inter vivos transfer is about 77% 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 discontinuous increase in inter vivos transfers upon reaching RMD age? To help with interpreting the results, it is useful to consider any economic incentives, or lack thereof, created by the RMD regulations.

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 such 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 the impact of Required Minimum Distributions (RMDs) on 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 4.8 percentage point increase in the likelihood of making an inter vivos transfer as households age into the RMD regulations and withdraw assets from Individual Retirement Accounts (IRAs).

My findings have implications for policy. Most directly, the results suggest that reforms that move the RMD threshold age might also change the timing of intergenerational transfers. 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. The results indicate that some households appear to use IRAs to facilitate transfers of resources to their descendants.

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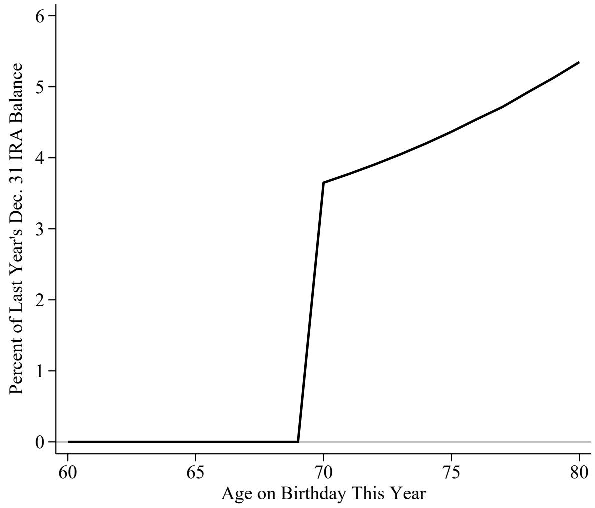
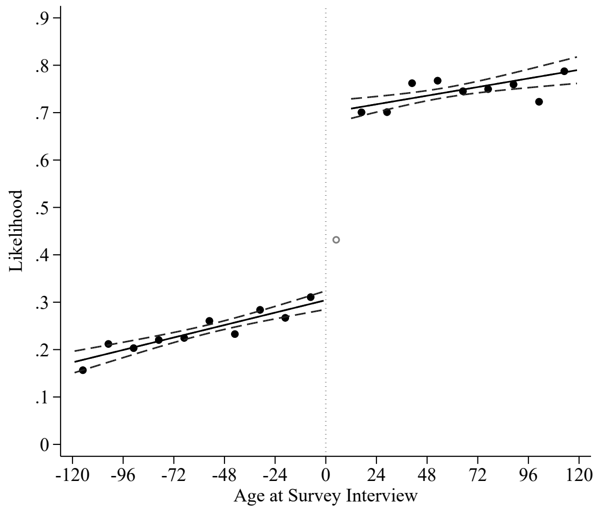
Figure 1: Typical Required Minimum Distribution Schedule



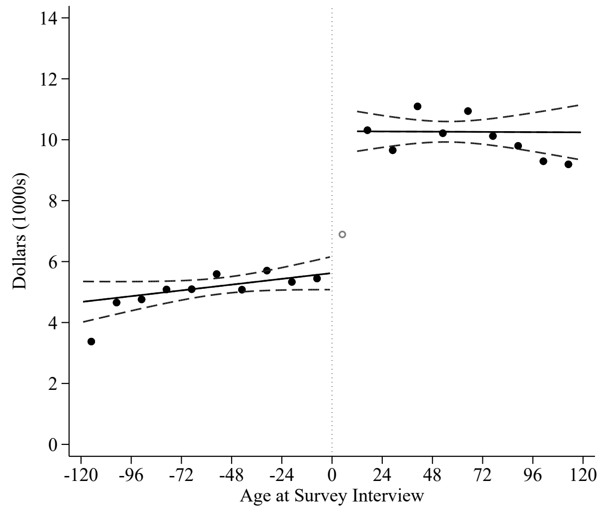
Notes: This figure plots the minimum amount of distributions that must be taken for the years during which RMD rules apply. The RMD amount is equal to the account balance on December 31 of the previous year divided by a life expectancy factor, which depends on the account holder's age. This particular 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: Direct Effects of Required Minimum Distributions on Drawdown of Individual Retirement Accounts

(a) Any Distribution from an IRA



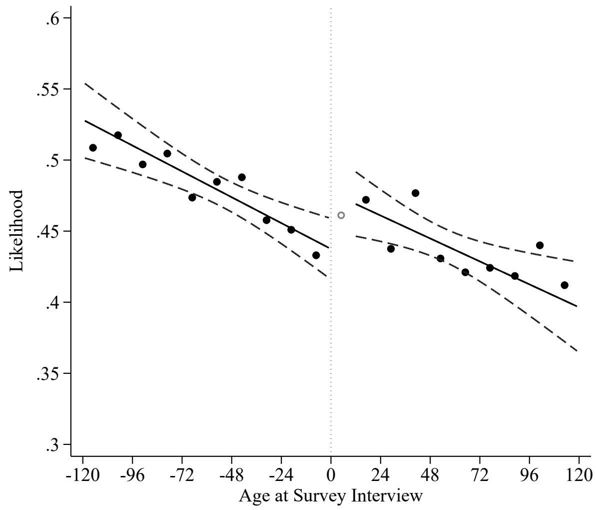
(b) Total IRA Distribution Amounts



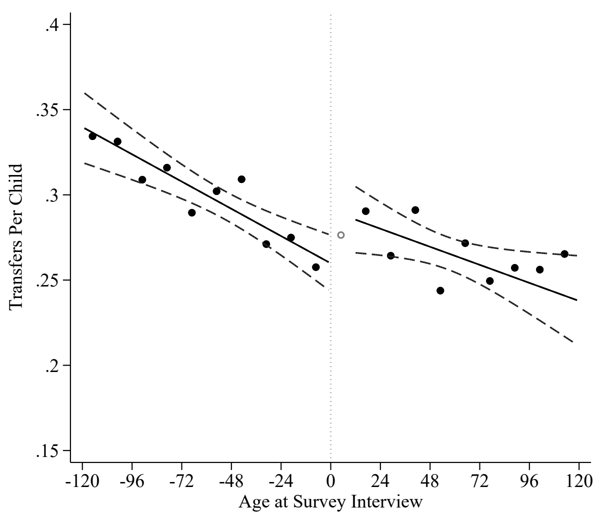
Notes: This figure illustrates the direct effects of aging into Required Minimum Distribution regulations on the drawdown of Individual Retirement Accounts (IRAs). Graph (a) illustrates the impact on an indicator variable for taking a distribution from an IRA. Graph (b) illustrates the impact on the total amount of dollars withdrawn. Each graph is constructed as follows. The running variable along the horizontal axis is household age, in months, at the time of their 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 3: Indirect Effects of Required Minimum Distributions on Inter Vivos Transfers

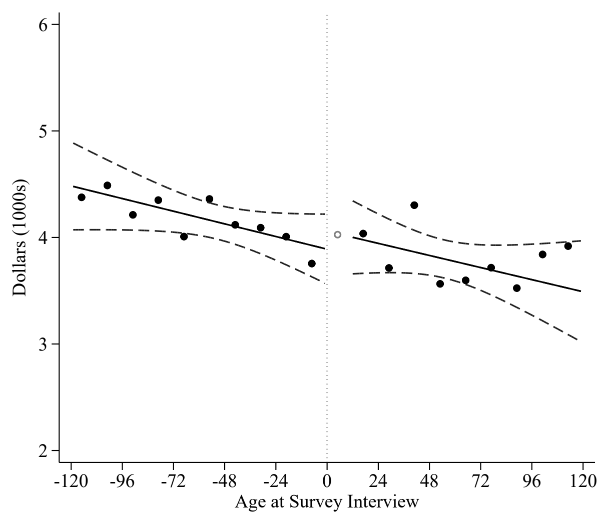
(a) Any Inter Vivos Transfers



(b) Number of Transfers per Child



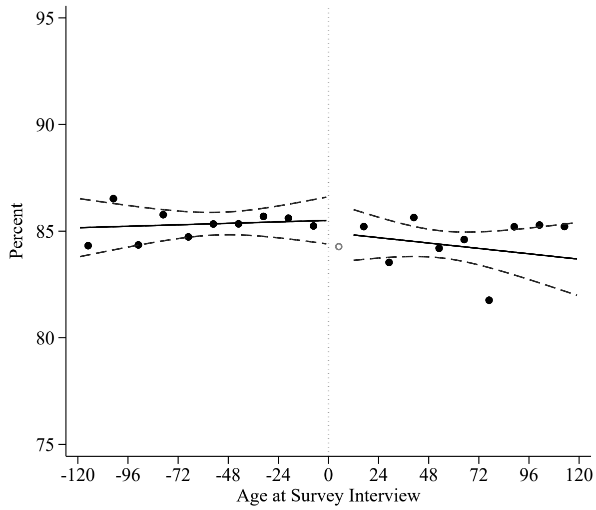
(c) Total Transfer Amounts



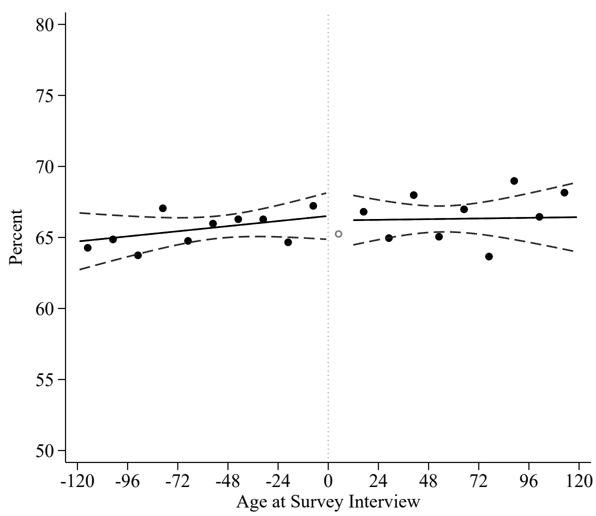
Notes: This figure illustrates the indirect effects of aging into Required Minimum Distribution regulations on inter vivos transfers. Graph (a) illustrates the impact on an indicator variable for making any inter vivos transfers. Graph (b) illustrates the impact on the number of inter vivos transfers made. Graph (c) illustrates the impact on the total amount of dollars transferred. See the notes of Figure 2 for more details on how each graph is constructed.

Figure 4: Indirect Effects of Required Minimum Distributions on Expectations of Leaving a Future Bequest

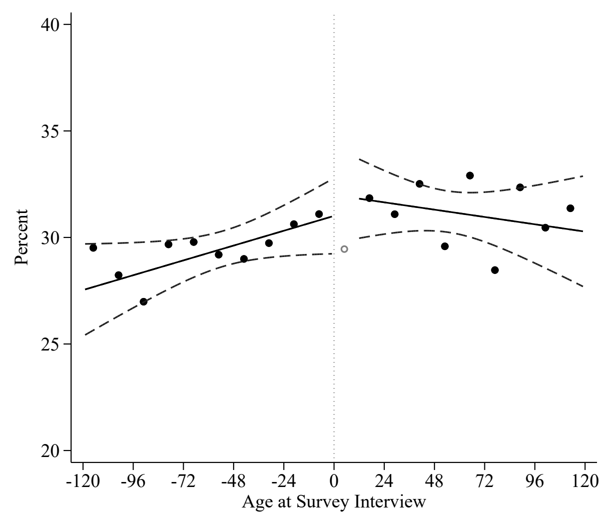
(a) Prob. of Making a $10,000 Bequest



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



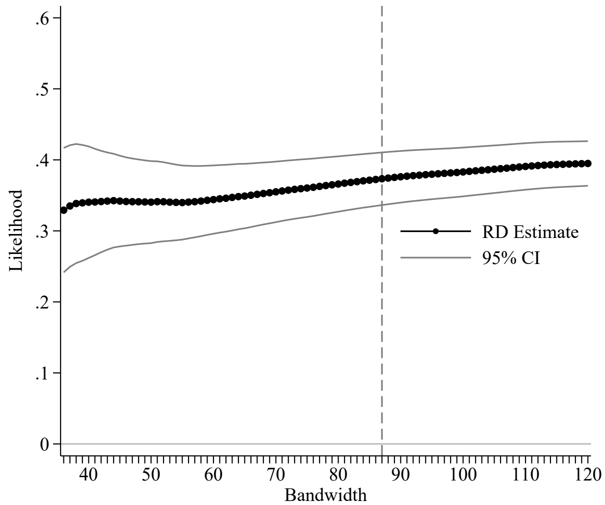
(c) Prob. of Making a $500,000 Bequest



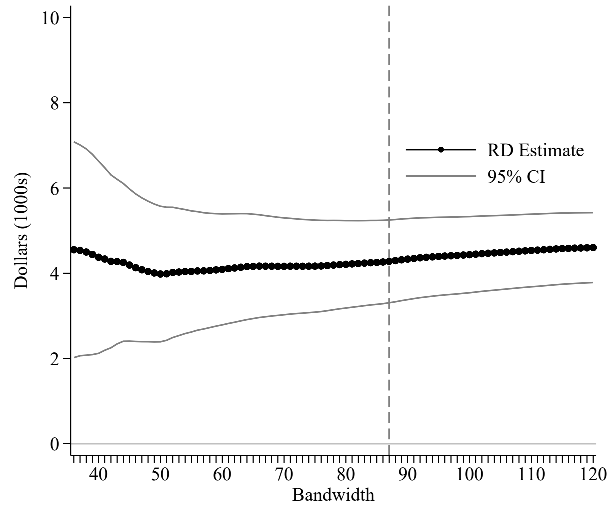
Notes: This figure illustrates the indirect effects of aging into Required Minimum Distribution regulations on bequest expectations. Graph (a) illustrates the impact on the self-assessed probability of leaving a future bequest of $10,000 or more. Graph (b) illustrates the same for a future bequest of $100,000 or more. Graph (c) illustrates the same for a future bequest of $500,000 or more. Note that graph (c) does not use data from survey wave 5, as the corresponding survey question was not asked during that wave. See the notes of Figure 2 for more details on how each graph is constructed.

Figure 5: Robustness of Main Estimates to Bandwidth Selection

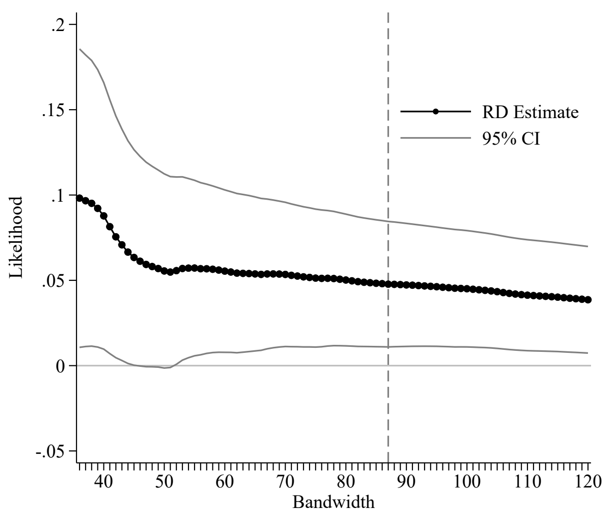
(a) Any Distribution from an IRA



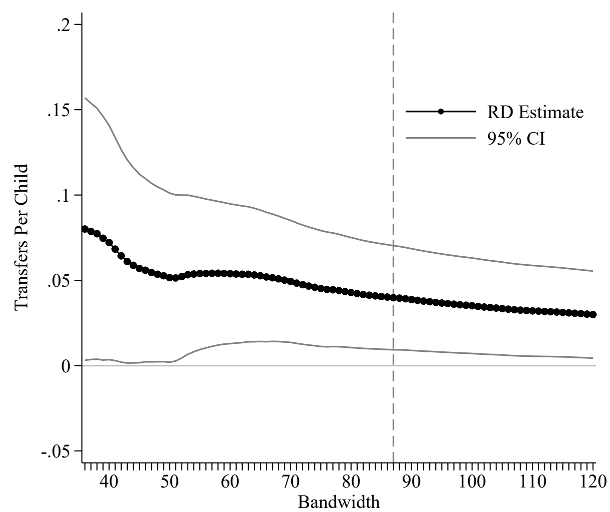
(b) Total IRA Distribution Amounts



(c) Any Inter Vivos Transfers



(d) Number of Transfers per Child



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	0.373***	4,279***
	(0.019)	(496)
Mean	0.26	5,351
Clusters	4,862	4,862
Observations	13,923	13,923

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)	Prob. of \$10,000 Bequest (4)	Prob. of \$100,000 Bequest (5)	Prob. of \$500,000 Bequest (6)
RD Estimate	0.048**	0.040**	206	-0.391	-0.160	1.039
	(0.019)	(0.016)	(280)	(0.986)	(1.302)	(1.296)
Mean	0.47	0.29	4,118	85	66	30
Clusters	4,862	4,862	4,862	4,862	4,862	4,398
Observations	13,923	13,923	13,923	13,923	13,923	12,077

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

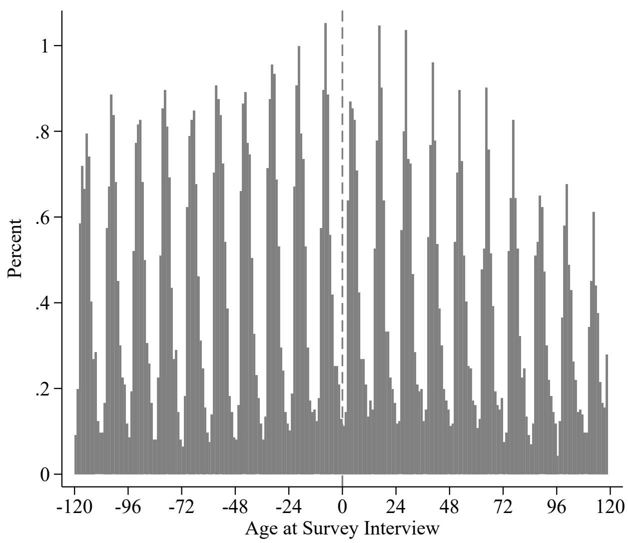
		Drawdown of IRAs		Inter Vivos Transfers		
		Any IRA Distribution (1)	IRA Distribution Amounts (2)	Any Transfers (3)	Number of Transfers per Child (4)	Total Transfer Amounts (5)
A.	Baseline	0.373***	4,279***	0.048**	0.040**	206
		(0.019)	(496)	(0.019)	(0.016)	(280)
B.	No Control Variables	0.372***	4,288***	0.048**	0.040**	213
		(0.019)	(502)	(0.019)	(0.016)	(282)
C.	No Triangular Weights	0.399***	4,627***	0.040**	0.030**	175
		(0.017)	(456)	(0.018)	(0.014)	(268)
D.	Cluster on Running Variable	0.373***	4,279***	0.048**	0.040**	206
		(0.017)	(434)	(0.021)	(0.018)	(287)
E.	Include Donut Observations	0.202***	2,296***	0.037**	0.028**	204
		(0.016)	(411)	(0.016)	(0.012)	(241)
F.	IRA Holder Before Age 69	0.275***	2,918***	0.037**	0.028*	-48
		(0.019)	(394)	(0.018)	(0.014)	(240)

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 includes the donut observations. Row F studies an alternative analysis sample of "early IRA holders," defined as those observed holding an IRA at some point before age 69. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$

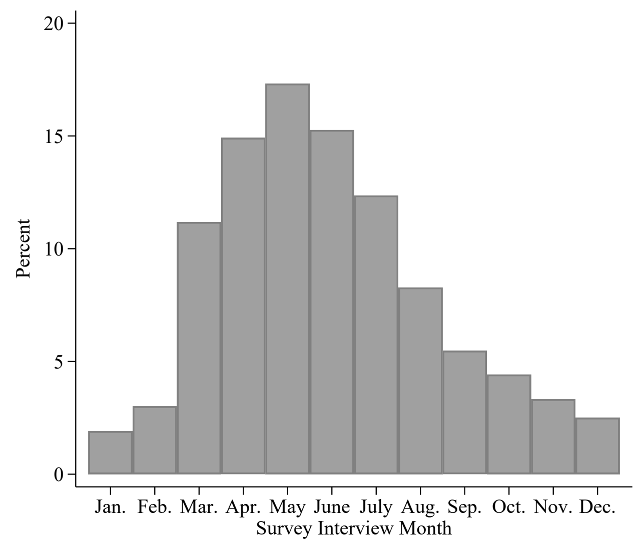
Appendix A Additional Figures and Tables

Figure A.1: Density of the Running Variable

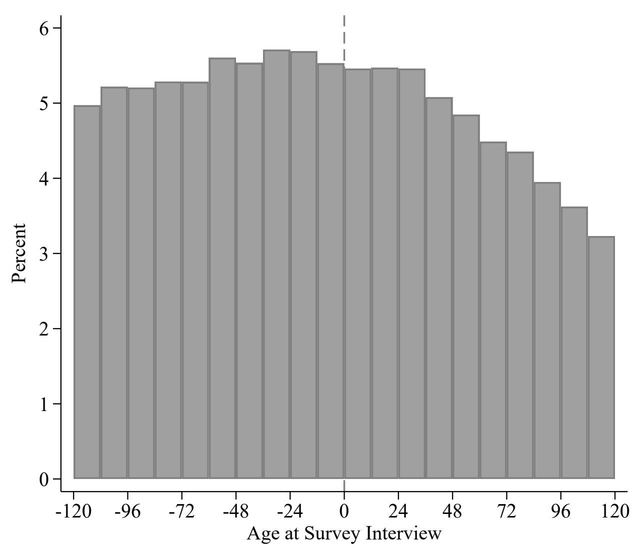
(a) Age at Survey Interview



(b) Survey Interview Month

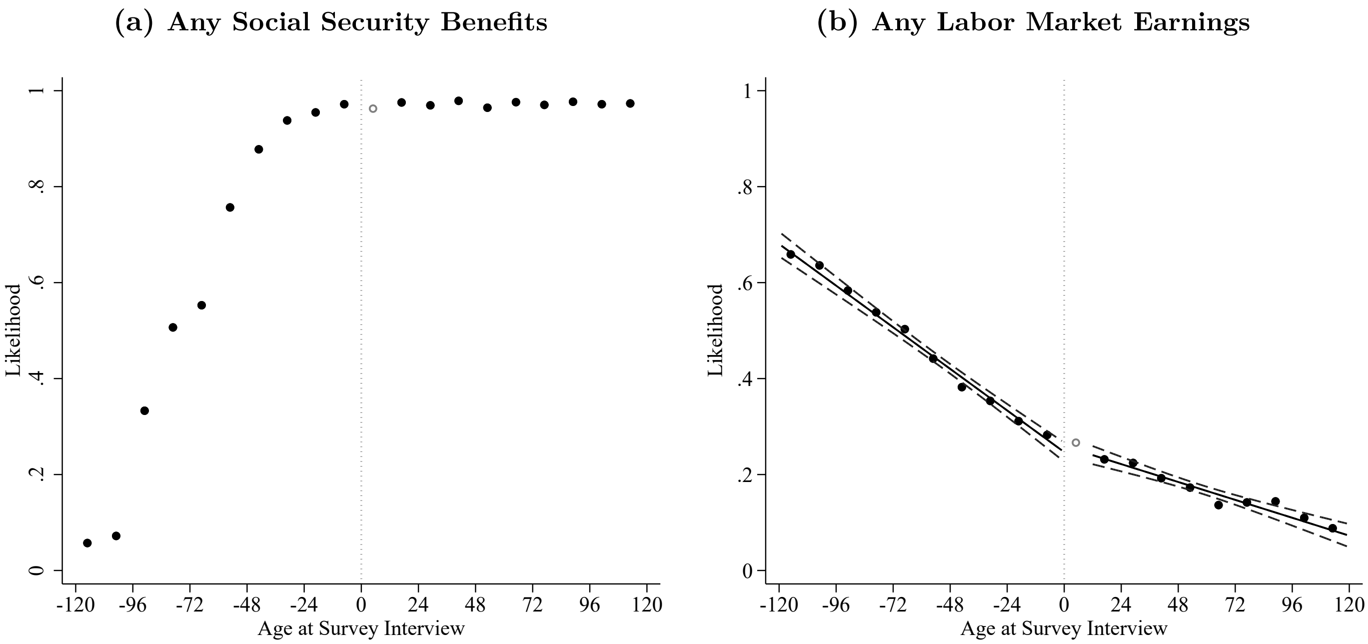


(c) Age at Survey Interview (Wider Bins)



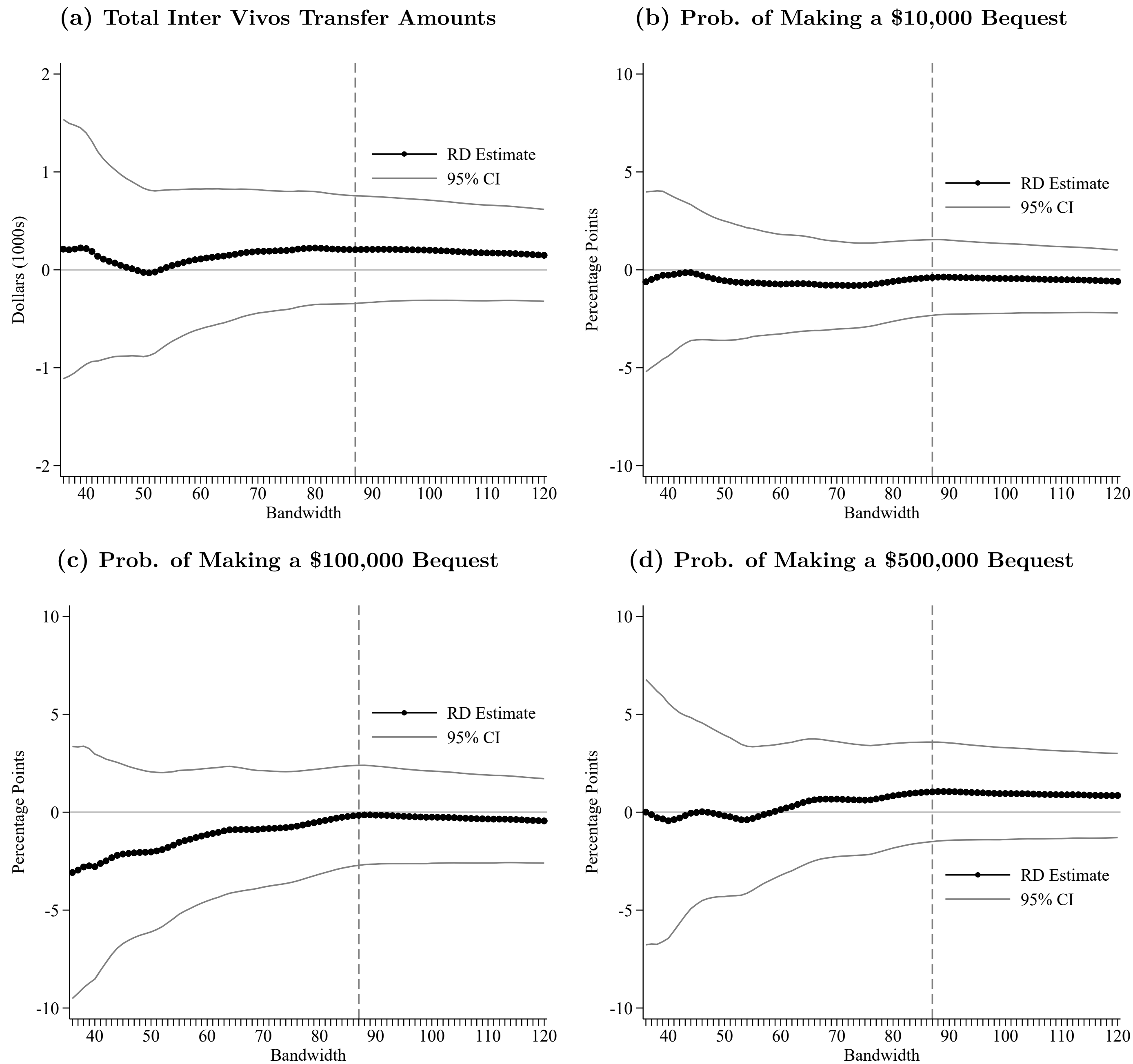
Notes: This figure graphically assesses the density of the running variable. Graph (a) plots the histogram. There are large spikes throughout due to interactions between birth dates and survey interview dates. Graph (b) plots a histogram of survey interview dates, which highlights the source of the spikes in graph (a). The vast majority of surveys take place between March and July. Graph (c) plots the histogram of the running variable using 12-month bins. The p-value from the formal density test proposed by Cattaneo, Jansson, and Ma (2020) is 0.767.

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



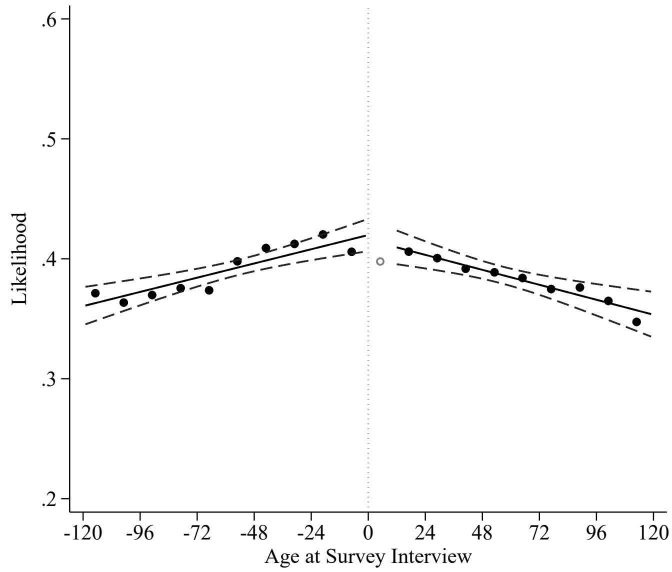
Notes: This figure illustrates how outcomes related to the ending of Social Security's Delayed Retirement Credit evolve as households age into Required Minimum Distribution regulations. Graph (a) analyzes an indicator variable for receiving Social Security retirement benefits. Graph (b) analyzes an indicator variable for having positive earnings. See the notes of Figure 2 for more details on how each graph is constructed.

Figure A.3: Robustness of Other Outcomes to Bandwidth Selection



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.4: 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 age, in months, at the time of their 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 who do own an IRA), or during which the household's first RMD would be due if they did own an IRA (for households who 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: Regression Discontinuity Estimates Using Control Variables as Outcomes

	Male (1)	Married (2)	White (3)	College (4)
RD Estimate	0.005	0.009	0.002	0.002
	(0.014)	(0.014)	(0.008)	(0.014)
Mean	0.54	0.71	0.90	0.60
Clusters	4,862	4,862	4,862	4,862
Observations	13,923	13,923	13,923	13,923

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.2: Regression Discontinuity Estimates for Social Security Benefit Receipt and Labor Supply

	Any Social Security Benefits (1)	Any Labor Market Earnings (2)
RD Estimate	0.015	0.012
	(0.012)	(0.015)
Mean	0.80	0.40
Clusters	4,862	4,862
Observations	13,923	13,923

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). Standard errors clustered at the household level are in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

Table A.3: 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	-0.391	-0.160	1.039
		(0.986)	(1.302)	(1.296)
B.	No Controls	-0.327	-0.025	1.157
		(1.001)	(1.344)	(1.333)
C.	No Triangular Weights	0.026	0.410	1.336
		(0.917)	(1.224)	(1.224)
D.	Cluster on Running Variable	-0.391	-0.160	1.039
		(1.091)	(1.845)	(1.422)
E.	Include Donut Observations	-0.808	-0.755	-0.503
		(0.857)	(1.140)	(1.161)
F.	IRA Holder Before Age 69	-0.348	-0.191	0.216
		(1.053)	(1.262)	(1.138)

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 includes the donut observations. Row F studies an alternative analysis sample of "early IRA holders," defined as those observed holding an IRA at some point before age 69. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$