# The Effects of Tax Incentives to Donate Wealth to Charity: Evidence from Qualified Charitable Distributions*

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July 7, 2025

**Abstract**

Can tax incentives encourage people to donate wealth to charity? Using regression discontinuity, I estimate the causal effects of tax rules that permit tax-free transfers of funds from retirement savings accounts to charities once individuals turn $70\frac{1}{2}$. These so-called qualified charitable distributions (QCDs) are excluded from taxable income and have additional tax benefits. I find that QCD eligibility significantly increased donations after the Tax Cuts and Jobs Act, which reduced incentives to itemize deductions and thus strengthened incentives to use QCDs to facilitate tax-advantaged giving. The increase occurred on the intensive margin and reflects increased likelihoods of donating large sums.

**Keywords:** Tax Policy, Charitable Giving, Qualified Charitable Distributions, Retirement Savings, Individual Retirement Accounts

**JEL codes:** H24, D64, D14, J26, J14

*I thank Daniel Hungerman for helpful conversations and comments.

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# 1 Introduction

The tax treatment of wealth might influence how people manage and consume their assets. In the U.S., tax-advantaged retirement savings accounts are a dominant asset. For instance, the Investment Company Institute (2025) estimates that about \$12.2 trillion are held in defined-contribution plans like 401(k)s and an additional \$16.8 trillion are held in Individual Retirement Accounts (IRAs). Typically, contributions to these accounts are tax-deductible, earnings within the accounts are not taxed, and then withdrawals from the accounts are taxed as regular income. However, special tax rules allow people to make tax-free withdrawals from IRAs if the distributed funds are used for a particular type of consumption: donating to charity. Do these tax incentives for donating retirement wealth to charity increase charitable giving? In this paper, I provide novel evidence on the answer to this question.

The tax rules that I study stipulate that IRA holders can make tax-free donations—known as IRA charitable rollovers or qualified charitable distributions (QCDs)—once they reach age $70\frac{1}{2}$. While donations to charity are in general tax-deductible for people who itemize their deductions, QCDs allow people who take the standard deduction to make tax-free donations as well. Moreover, QCDs have additional tax benefits. They do not count towards the maximum charitable deduction limit, which thus increases the amount of money that itemizers could potentially donate tax-free. They also do count towards required minimum distributions (mandated withdrawals from IRAs), and by reducing IRA balances they reduce future required distributions, which could be valuable for people looking to avoid tax implications of greater withdrawals later.

Using a regression discontinuity design and detailed survey data from the Health and Retirement Study, I estimate the causal effects of QCD eligibility on charitable giving decisions. My research design exploits the discontinuous nature of the policy for identification. The basic idea is to test for whether charitable giving changes discontinuously once people reach $70\frac{1}{2}$ and become eligible to make the tax-advantaged donations. Specifically, for a given tax year, I compare the charitable giving of IRA account holders who turn $70\frac{1}{2}$ before the end of the year, who are thus eligible to make QCDs, to otherwise-similar households who do not turn $70\frac{1}{2}$ until the start of the next year, who are thus ineligible to make QCDs.

I use this approach to document the effects of QCDs over two distinct time horizons, before and after the Tax Cuts and Jobs Act of 2018 (TCJA). This major tax reform had important implications for charitable giving and for QCD policy. Crucially, it increased the standard deduction, which increases the attractiveness of using QCDs to donate to charity.

The key insight is that IRA holders who itemize deductions can replicate an advantage of QCDs by withdrawing money from their IRA, donating the money to charity, and then claiming the charitable deduction. By substantially increasing the standard deduction and reducing incentives to itemize, TCJA eliminated the typical tax benefits from donating to charity for many. This change should therefore be expected to increase the use of QCDs.

I find clear evidence of a discontinuous increase in charitable donations at $70\frac{1}{2}$ after TCJA, in 2019. The increase occurred on the intensive margin. I find no evidence that QCDs impacted the extensive-margin decision about whether to give to charity at all. For people who did give to charity, the baseline estimate indicates that, on average, QCD eligibility increased total donations by $2,229. This estimate corresponds to a large, 53.9% increase when compared to the average donation amounts for people who gave to charity but were just-ineligible for QCDs, although it is modest when compared to the amount of wealth people hold in IRAs. In contrast, the evidence from earlier years suggests that QCDs had little to no effect on charitable giving decisions before TCJA. The point estimates for earlier years are generally smaller and not statistically different from zero.

I then show that the estimates are robust to specification checks and are not driven by confounding policies. A primary concern relates to required minimum distribution (RMD) rules. RMD rules require withdrawals from retirement accounts once account holders reach a specified age. While the RMD age has increased in recent years, during the time horizon of my study, required withdrawals from IRAs began when account holders reached the calendar year in which they turned $70\frac{1}{2}$. If the mandated withdrawal of assets from IRAs has its own, independent effect on charitable giving, then my estimates would capture the combination of this effect and that of QCDs. To investigate this threat to the interpretation of my results, I use pre-period data, when RMDs were in place but QCDs were not, to estimate the effects of reaching $70\frac{1}{2}$ on chartiable giving. I find clear evidence of increases in IRA withdrawals but no evidence of changes in donations, indicating that the main estimates are driven by QCD rules and their incentives, not by required withdrawals.

Finally, I conclude my analysis by looking at additional outcomes and subsamples that help to unpack the overall estimates and shed light on mechanisms. First, to better understand behaviors underlying the roughly-$2,200 increase in average donations, I estimate the effects on indicators for making donations of various sizes. I find considerable increases in the likelihood of donating large sums. For example, the estimates imply a doubling of the number of people who donated more than $10,000. (For comparison, mean donations for people with IRAs conditional on giving in 2019 were just under $5,000.) Second, I estimate separate effects for subsamples based on IRA balances. I find larger effects for people with larger IRA balances, which might suggest that people with stronger incentives to reduce future RMDs by lowering IRA balances were more likely to make a QCD.

My paper contributes primarily to the longstanding literature that studies charitable giving responses to tax incentives (e.g., Feldstein and Clotfelter, 1976; Clotfelter, 1980; Randolph, 1995; Auten, Sieg and Clotfelter, 2002; Fack and Landais, 2010; Bakija and Heim, 2011; Meer, 2014; Duquette, 2016; Almunia et al., 2020; Meer and Priday, 2020; Hungerman and Ottoni-Wilhelm, 2021; Hickey et al., 2023; Han, Hungerman and Ottoni-Wilhelm, 2024). Many papers in this area focus on estimating the after-tax price elasticity of giving, which informs optimal tax policy (Saez, 2004). One of the most common tax incentives studied in this literature is the tax-deductibility of charitable gifts for people who itemize, which papers often study by exploiting variation in the price of giving due to variation in marginal tax rates, either from changes in income or tax reforms. Existing estimates of the after-tax price elasticity vary across studies and settings. Two papers particularly relevant for my study's context are Meer and Priday (2020) and Han, Hungerman and Ottoni-Wilhelm (2024), which project and estimate, respectively, the overall effects of TCJA on charitable giving and find that this major tax reform substantially reduced donations. Moreover, as QCDs apply to retirement wealth, my study connects to recent evidence from Norway showing that indirect incentives to donate through wealth taxation (specifically the tax treatment of secondary homes) impacts charitable giving decisions (Ring and Thoresen, 2025).

I contribute to this literature by providing new evidence on the effects of qualified charitable distributions on giving. To the best of my knowledge, no other paper has estimated the effects of these important tax rules and incentives, despite the fact that the regulations have been around for almost two decades and apply to older people with assets, a group who may be particularly likely to give to charity (see List, 2011; Meer and Priday, 2021). My estimates on the effects of these tax rules provide unique evidence on how people respond to direct incentives to donate accumulated assets to charity.

My research design and setting have three additional advantages worth emphasizing. One is that the identifying variation in incentives to donate is particularly clean, as it comes from an individual's age at the end of the year, and allows me to use a powerful regression discontinuity design. Two is that the nature of QCD rules allows me to study responses of people regardless of their itemization status, whereas previous work has tended to focus on people who itemize. Three is that I study both extensive and intensive margin responses, which is uncommon in the literature (Almunia et al., 2020).

My paper also connects to an emerging literature that studies the effects of tax rules governing the drawdown of retirement savings accounts. Understanding how drawdown rules impact people is increasingly important in light of recent and substantial growth in distributions from retirement accounts; total withdrawals from IRAs increased from about $295 billion in 2015 to just-under $500 billion in 2022 (IRS Statistics of Income, 2024). Existing evidence indicates that additional taxes on early withdrawals (Goda, Jones and Ramnath, 2022; Stuart and Bryant, 2024) and required minimum distributions (Poterba, Venti and Wise, 2013; Brown, Poterba and Richardson, 2017; Mortenson, Schramm and Whitten, 2019; Horneff, Maurer and Mitchell, 2023; Stuart and Bryant, 2024) strongly influence drawdown, but there is little causal evidence on how drawdown policies impact broader financial behaviors. One exception is Leganza (2024), which shows that aging into required minimum distributions increases inter vivos transfers to children. By showing that the ability to make tax-free distributions from IRAs if the funds are transferred to charity can increase charitable giving, my findings support the idea that tax rules that encourage people to use retirement accounts in specific ways can indeed influence household behaviors.[1]

## 2 Policy Environment

To understand qualified charitable distributions, one needs to understand the tax treatment of charitable gifts more generally, as well as the tax treatment of retirement savings accounts and required minimum distributions (a closely-related, yet distinct, set of tax rules). In this section, I discuss these relevant institutional details, provide more details on QCD rules, and overview the Tax Cuts and Jobs Act, which is also important for my study.

### 2.1 Typical Tax Treatment of Charitable Gifts

The U.S. government incentivizes gifts to charitable organizations through the tax code. Since 1917, individuals who itemize their deductions have been able to deduct contributions to qualifying charities from taxable income. This regulation encourages giving by reducing the effective price of donating to charity. For an individual who itemizes, each dollar donated to charity reduces their tax liability by their marginal tax rate. So, for example, an individual

[1]For examples of other behaviors the government might influence with tax rules that apply to the drawdown of retirement savings, consider the tax treatment of early withdrawals. Distributions from retirement accounts before age $59\frac{1}{2}$ are generally subject to income tax and an additional 10% tax, but this additional tax is waived—and thus funds are less costly to access—if, for example, the distribution is for qualified education expenses, a first-time home purchase, or expenses related to childbirth or adoption.

who faces a marginal tax rate of 32% can donate $1 to charity at a price of 68 cents. Importantly, this incentive does not apply to people who do not itemize and who instead take the standard deduction.

### 2.2 Typical Tax Treatment of Retirement Savings Accounts

The U.S. government incentivizes saving for retirement with tax-advantaged retirement savings accounts. Some retirement accounts like 401(k)s are sponsored by employers, whereas others, called Individual Retirement Accounts (IRAs), are not. Traditionally, contributions to these accounts are tax-deductible, earnings within the accounts are tax-free, and withdrawals from the accounts are taxed as regular income. In contrast, there are Roth accounts that are treated differently, with contributions that not tax-deductible, earnings that are tax-free, and withdrawals that are not taxed.

I focuses my analysis on IRAs because qualified charitable distribution policy applies to IRAs, not employer retirement accounts. Notably, many people accumulate funds in employer retirement accounts while working but then roll over the assets to IRAs later in life, which likely explains why IRA assets are greater than those in employer retirement plans in cross sectional data like those provided by Investment Company Institute (2025).

### 2.3 Required Minimum Distributions

A key set of rules related to QCDs are called required minimum distributions, which apply to retirement savings accounts and form the backdrop to QCD policy. RMD rules require households to begin making withdrawals from IRAs once account holders reach a specified age.[2] Traditionally, the RMD age was $70\frac{1}{2}$, and this age is the relevant one for the time horizon of my analysis. However, the RMD age was recently increased by the Setting Every Community Up for Retirement Enhancement (SECURE) Act of 2019 and then again by the SECURE 2.0 Act of 2022. RMDs aim to limit revenue losses from IRAs and apply to traditional IRAs, but not Roth IRAs, since contributions to Roth IRAs are made on an after-tax basis.

The amount that an account holder is required to withdraw depends on the balances of their accounts. For a given IRA, the RMD for is calculated by dividing the balance of the account on December 31 of the previous year by a distribution period taken from IRS life

[2] A different set of rules apply to early withdrawals from IRAs. To discourage withdrawals before retirement, account holders are required to pay an additional 10% tax on withdrawals made before $59\frac{1}{2}$, with some exceptions.

expectancy tables. If a person owns multiple IRAs, their total RMD is the sum of their RMDs for each account. Required distributions typically start at roughly 4% of the IRA balance and increase to about 5.5% after 10 years.

While RMDs begin when the account holder turns $70\frac{1}{2}$, the first required withdrawal 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, and the penalty for not taking an RMD is a 50% tax on the required-but-undistributed amount.

It is important to note that these regulations coincide almost perfectly with QCD regulations, described in more detail below. They therefore constitute a confounding policy that I must take into consideration when implementing my regression discontinuity design and interpreting the resulting estimates. If RMD policy has its own impact on charitable giving, then my estimates would reflect a combination of RMD and QCD regulations. Crucially, QCDs came into place long after RMDs were implemented, which allows me to use data from years when RMDs were in place but QCDs were not to test whether RMDs have their own impact on charitable giving. I describe this test in more detail later, when assessing threats to the validity of my research design, and I find no evidence that RMDs impact charitable giving, which lends support to the interpretation of my main estimates as being driven by QCD eligibility only.

### 2.4 Qualified Charitable Distributions

Part of the Pension Protection Act of 2006 established QCDs. The regulations allow people who have reached age $70\frac{1}{2}$ to exclude IRA withdrawals given directly to a qualified charity from taxable income. The maximum QCD for an individual is $100,000, but each member of a couple filing jointly can make a QCD. In addition, QCDs do not apply to the overall charitable deduction limit, which is typically 60% of adjusted gross income, and they count towards any RMDs the individual needs to take.

For a donation to qualify as a QCD, several conditions must be met. The person making the donation must be older than $70\frac{1}{2}$ when the donation is made, the funds must come from a traditional IRA, and the funds must have been otherwise included in taxable income (some IRAs include deductible and non-deductible contributions). Moreover, the distribution must be a trustee-to-trustee transfer of funds directly from the IRA to the receiving charity, and the charity must be eligible to receive tax-deductible charitable distributions.

The original legislation created QCDs on a temporary basis: people could make QCDs in tax years 2006 and 2007. However, several acts extended the policy in two-year increments so that it was in place through 2014. Finally, the Protecting Americans from Tax Hikes Act of 2015 made QCDs permanent.

QCDs provide several tax benefits that encourage people to donate. Perhaps most importantly, they allow people who take the standard deduction to make tax-advantaged gifts. In the absence of QCDs, IRA holders at advanced ages would need to itemize in order to deduct their charitable gifts. People who itemize can benefit from QCDs as well though. Without QCDs, these individuals could still make a tax-advantaged gift by withdrawing funds from their IRA, donating the funds to a charity, and then taking a deduction for the gift. However, QCDs allow people who itemize to make greater tax-free donations because QCDs do not count towards the charitable deduction limit. For both groups of people, the fact that QCDs count towards RMDs provides some additional incentives to give: donating required distributions reduces tax liability today and reduces IRA balances and thus also reduces future RMDs.

Moreover, I note that QCDs may lead to reductions in tax liability for people who would have itemized in the absence of the rules, but who instead choose to use QCDs and take the standard deduction because of the rules. For example, suppose a single individual faces a standard deduction of $12,000, wants to donate $20,000 to charity, and this gift would be their only tax deduction. Without being able to make a QCD, this person would itemize and thus reduce their taxable income by $20,000. With QCDs though, this person could make a $20,000 QCD and then take the standard deduction, which would together reduce their taxable income by $32,000. This type of incentive means that QCDs might impact itemization status.

### 2.5 The Tax Cuts and Jobs Act

TCJA was passed in December of 2017 and was implemented in 2018. This major tax reform had important implications for charitable giving in general (Meer and Priday, 2020; Han, Hungerman and Ottoni-Wilhelm, 2024). The most prominent change brought about by TCJA as it relates to charitable giving is the increase in the standard deduction. In the years before TCJA, the standard deductions for single taxpayers and those who are married filing jointly were roughly $6,000 and $12,000, respectively. After TCJA, those standard deductions were increased to $12,000 and $24,000, respectively (in 2018) and $12,200 and $24,400 (in 2019, the post-TCJA year that my data cover). Moreover, TCJA limited deductions for state and local taxes and for mortgage interest payments.

These key changes resulted in a large shift in the share of people who take the standard deduction. The fraction of tax returns with itemized deductions fell abruptly after TCJA from over 30% to under 10% (Tax Policy Center, 2024). Meer and Priday (2020) and Han, Hungerman and Ottoni-Wilhelm (2024) study the effects of TCJA on charitable giving and provide in depth discussions of how TCJA and the increase in the standard deduction could theoretically impact donations. On the one hand, the increase in the standard deduction removes the typical incentive for itemizers to donate because their donations will no longer be tax-deductible. On the other hand, the increase in the standard deduction can also represent a positive income effect, which could induce some people to donate more.

My focus is not on estimating the effects of TCJA, but rather on the effects of QCDs both before and after TCJA is implemented. The key insight for my analysis is that QCDs should become more attractive after TCJA. Before TCJA, when the standard deduction was lower, many older people with IRAs could make tax-free donations by itemizing and deducting their charitable gifts. After TCJA, the increase in the standard deduction limits that route to tax-free giving, but older people with IRAs who no longer find it advantageous to itemize can instead use QCDs to make tax-free donations. Moreover, to the extent that income effects from an increase in the standard deduction induce people to donate more, the fact that QCDs allow people to make greater amounts of tax-free gifts should also make giving through QCDs more attractive.

### 2.6 Summary of Incentives and Time Horizons

Becoming eligible for QCDs should be expected to increase charitable giving. Both itemizers and non-itemizers who own IRAs experience additional tax incentives to give once they reach $70\frac{1}{2}$. My analysis thus focuses on estimating changes in giving once people age into eligibility. Because TCJA created major changes, both to the charitable giving environment in general and to the relative benefits of using QCDs, I estimate the year-by-year impacts of aging into QCD eligibility and group responses into two distinct periods: post-TCJA and pre-TCJA.

## 3 Data

I use data from the Health and Retirement Study (HRS), a biennial survey of older households in the U.S.[3] The data contain detailed information on household finances and consist of reasonably large samples of people around the QCD-eligibility age. The data are thus

[3]The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan.

well-suited for my study.

To conduct my analysis, I use the HRS datasets produced by the RAND Center for the Study of Aging (Bugliari et al., 2023). These datasets provide researchers with processed versions of the HRS data. Specifically, I use the RAND HRS Longitudinal File 2020 V2 and the RAND Fat Files. The RAND HRS Longitudinal File contains cleaned demographic and economic variables for every individual to appear in the HRS data and thus forms the base of my analysis data. The RAND Fat Files are versions of the raw HRS data and contain variables absent from the Longitudinal File that are necessary for my analysis: the charitable giving outcomes and variables that allow me to determine which individuals within coupled households own an IRA.

I use data from survey waves 5 through 15, which correspond to surveys taking place during the even-numbered years between 2000 and 2020. This time horizon allows me to look at donations (i) over several pre-period years before QCD policy was enacted in 2006, (ii) over several years after QCDs were introduced but before TCJA, and (iii) in one year after TCJA.

### 3.1 Key Variables

My outcome variables capture charitable giving behaviors. The HRS survey asks respondents if either they or their spouse donated more than \$500 of money, property, or possessions to charity in the last calendar year. The survey also asks for the approximate value of total donations. To prevent my analysis from being affected by outliers, I winsorize the donation amounts variable at the 99.5th percentile. Using these variables, I define three outcomes: (i) an indicator for donating to charity, (ii) donation amounts (including zeros for people who do not donate), and (iii) donation amounts conditional on giving. I express donation amounts in 2019 U.S. dollars.

These charitable giving variables capture total donations. I do not have information on QCDs themselves, which means that I cannot separately track QCDs and other donations. However, I emphasize that total charitable giving is the primary outcome of interest, as my goal is to study whether the incentives from QCD rules cause people to donate more to charity than they otherwise would have. Moreover, the total donations variables capture any potentially-unintended additional effects of QCDs on donations that are important to account for, such as, for instance, learning about a particular charity because of the rules and then donating to that charity out of normal income throughout the year.

It is also important to note that the timing of the outcome variables means that the charitable giving behaviors reported are for the calendar year before the survey year. For example, wave 15 of the survey corresponds to 2020, so the charitable giving outcome variables for that wave reflect donations in 2019. I therefore define a new variable, tax year, which is equal to the year before the survey year.

I use several other variables to define my sample and implement my RD design. To define the analysis sample, I use variables on IRA ownership. Using the RAND Fat Files, I define an individual-level variable that takes the value of one if the individual owns an IRA.[4] To construct the running variable in my RD design, which is age as of December in the tax year defined relative to age $70\frac{1}{2}$, I use individual-level variables for birth year and birth month. For additional outcomes analyzed when assessing the validity of the RD design, I use indicator variables for whether an individual receives Social Security retirement benefits, for whether an individual is retired, defined as having zero earned income, and for whether the individual withdrew money from an IRA. Finally, for potential control variables, I use information on gender, race, marital status, and college education.

### 3.2 Analysis Sample

To construct my main analysis dataset, I merge the RAND HRS Longitudinal File with the variables extracted from the RAND Fat Files (charitable giving outcomes and an individual-level indicator for owning an IRA). I then make three sample restrictions. First, I keep observations from survey waves 5 through 15, which correspond to survey interview years 2000 through 2020 and tax years 1999 through 2019. Second, I keep individuals who own an IRA because QCD policy applies to these individuals. Third, and finally, I drop observations with missing values for charitable giving outcomes. Appendix Table A.1 documents the impact of these sample restrictions on the number of observations and unique individuals in my analysis sample. My main analysis sample contains 49,963 observations on 13,180 unique individuals who own IRAs.

For reference, Table 1 displays summary statistics for my analysis sample and for a comparison group of people in households without IRAs. For each group, the first two

[4] The survey asks respondents whether they or their spouse own an IRA and, if so, how many IRAs they own. The survey then asks about the ownership of the largest account, the second-largest account, and then finally the third account or all other accounts. I define a person to own an IRA if they own any of the household IRAs. However, in wave 5 of the data (tax year 1999), the survey only asks about ownership of the largest account, so that for that one pre-period year individual-level ownership is defined based solely on the largest account. The cleaned-and-processed Longitudinal File contains a variable that captures household-level IRA balances, and I use this variable to define a placebo sample of individuals within households where neither individual owns an IRA, defined as a household-level IRA balance of $0.

columns report means and standard deviations of variables, and the third column reports the number of person-survey-wave observations underlying these calculations. My analysis sample of IRA holders are more likely to be male, married, and white compared to those without IRAs. They are also much more likely to have attended at least some college. On average, they are more likely to donate to charity, and they donate more money to charity conditional on donating.

# 4 Identification Strategy

## 4.1 Regression Discontinuity Design

I use a regression discontinuity (RD) design to estimate the causal effects of QCD eligibility. The idea is to derive identification from the policy-induced discontinuity at $70\frac{1}{2}$. My RD design tracks the evolution of outcomes as a function of age and estimates discontinuous jumps in those outcomes as people age into eligibility for QCDs.

The tax regulations allow people to make tax-free donations to charities once they reach age $70\frac{1}{2}$. These regulations mean that, for any given tax year, $t$, people face different incentives to give depending on when they were born. People born in June of year $t-70$ turn $70\frac{1}{2}$ in December of year $t$ and can thus make a QCD in that year. In contrast, people born in July of year $t-70$ do not turn $70\frac{1}{2}$ until January of year $t+1$, making them just-ineligible for QCDs in year $t$.

My approach is to compare the charitable giving behavior in a given year for people who turn $70\frac{1}{2}$ before the end of the year to otherwise-similar people who turn $70\frac{1}{2}$ at the start of the next year. I thus define the running variable in my RD design to be a person's age in December of the relevant tax year for the donations reported in the survey, and I define the cutoff to be $70\frac{1}{2}$.

To implement my RD design, I estimate separate regressions of the following form for each tax year:

$$y_i = \alpha + \beta \cdot 1[x_i \geq c] + \gamma \cdot x_i + \delta \cdot x_i \cdot 1[x_i \geq c] + \varepsilon_i, \tag{1}$$

where $y_i$ is a charitable giving outcome variable for person $i$ (such as an indicator for giving to charity), $x_i$ is the running variable, monthly age in December of the tax year, defined relative to age $70\frac{1}{2}$, $c$ is the cutoff, and $\varepsilon_i$ is an error term. The coefficient of interest is $\beta$, which I refer to as the "RD estimate." It is an estimate of the discontinuity in the outcome variable at the cutoff and represents the reduced-form effect of aging into QCD eligibility.

My biennial data means that I can estimate the effects in each odd-numbered tax year between 2007 (one year after QCDs were implemented) and 2019 (one year after TCJA). In the baseline specifications, I use triangular weights and cluster standard errors at the household level because two individuals from the same household can both be in the analysis sample if each owns an IRA. I also use the procedure from Calonico, Cattaneo and Titiunik (2014) to select a data-driven optimal bandwidth for each regression (that is, for each outcome-year combination). Later, I assess the robustness of my estimates to these choices.

### 4.2 Threats to Validity

To interpret the RD estimates as causal, the identifying assumption is that the other factors that influence charitable giving do so smoothly as people age into QCD eligibility. I carry out several validity checks to assess the relevance of threats to this assumption.

First, I assess the classical threat to the validity of RD designs, namely manipulation of the running variable. As the running variable in my design is age, which cannot be manipulated, typical problems associated with this threat are unlikely. However, my analysis sample consists of IRA holders, so if the propensity to own an IRA changes at the cutoff, then my sample would be differentially selected on either side of the cutoff. Therefore, following the logic of McCrary (2008) but using more-recent methods from Cattaneo, Jansson and Ma (2020), I test for discontinuities in the density of the running variable. If IRA ownership changes at the cutoff, then I would expect to see differences in the number of people on either side of the cutoff and a non-smooth density. Figure 1 plots a histogram of the running variable for 2019, the most recent tax year in my data. The density appears to evolve smoothly through the cutoff, and the p-value from the formal density test is 0.696. There is no evidence of a discontinuity in the density at the cutoff. Appendix Figure A.1 plots the histograms for the earlier years, and Appendix Table A.2 reports the t-statistics and p-values from density tests for each year. There is little to no evidence of problematic discontinuities in the density of the running variable, although I note that one of the p-values (for the test in 2017), is 0.092.

Second, I conduct another standard check for RD designs, testing for discontinuities in control variables at the cutoff. It would be concerning if there were differences in covariates for people who turn $70\frac{1}{2}$ just before the end of the year compared to those who turn $70\frac{1}{2}$ just after the end of the year. To test for this possibility, I estimate my RD regression using control variables as outcomes. Appendix Table A.3 reports the results. Reassuringly, only one of the twenty-eight estimates is statistically different from zero at the 10-percent level. All other estimates are statistically indistinguishable from zero at conventional levels (including those in 2017) and are mostly small in magnitude.

Third, I investigate the relevance of confounding policies, which is another key threat to RD designs. If something else is changing discontinuously at the same cutoff, then any estimated discontinuities could be the result of QCD rules or the confounding factor. To my knowledge, there are two confounding policies to consider. The first is, as mentioned earlier, RMD policy. During my analysis time horizon, RMDs began at age $70\frac{1}{2}$. These regulations influence the drawdown of retirement assets (Poterba, Venti and Wise, 2013; Brown, Poterba and Richardson, 2017; Mortenson, Schramm and Whitten, 2019; Horneff, Maurer and Mitchell, 2023; Stuart and Bryant, 2024), and Leganza (2024) shows that aging into RMDs causes people to make inter vivos transfers to their children. It is possible that requiring people to draw down assets in IRAs also induces them to donate money to charity (although I emphasize that the rules do not require people to consume the assets; they could continue to save the funds in non-retirement accounts). If RMDs have their own independent impact on charitable giving, then my RD estimates that capture discontinuous changes in giving would reflect the combined effects of QCDs and RMDs.

Fortunately, I can test whether RMDs have their own impact on giving because I have data that cover years for which RMDs were in place but QCDs were not. Specifically, I use my RD design to estimate discontinuities in outcomes in pre-QCD tax years 1999 through 2005. I first confirm that RMDs impact drawdown: Appendix Figure A.2 plots standard-style RD graphs for IRA withdrawals in these years and, as expected, shows that there is a large discontinuous increase in the likelihood of withdrawing money at $70\frac{1}{2}$. However, Appendix Figure A.3 plots the RD graphs for all three of my main charitable giving outcomes in each of these pre-period years and shows no graphical evidence of an impact. Appendix Table A.4 presents the corresponding point estimates and also reveals a lack of evidence that RMDs have their own impact on donations. None of the point estimates are statistically different from zero and the sign of the estimates is not consistently positive or negative. Even so, one might consider taking the magnitudes of these not-statistically-significant estimates into consideration when interpreting the main results later. The idea would be to use the pre-period estimates to difference out any pure RMD effects from the effects of QCDs. Taking the pre-period point estimates at face value and simply averaging them would suggest a modest \$177 increase in donations and a \$173 increase in donations conditional on giving due to RMDs, a point that I revisit below, when presenting the main estimates.

The second confounding policy is Social Security's delayed retirement credit. In general, people who delay claiming their Social Security benefits past their Full Retirement Age receive an increase in their monthly benefit amount, up until age 70. The fact that this delayed retirement credit policy creates a cutoff close to $70\frac{1}{2}$ could be problematic for my design if it has its own impact on charitable giving. The concern is that the delayed retirement credits induce discontinuous changes in benefit receipt or retirement at 70, which could then impact donations. Again, my data allow me to investigate the relevance of this threat. Appendix Figures A.4 and A.5 present graphical evidence on the effects of reaching $70\frac{1}{2}$ during the main years of my analysis on the likelihood of receiving retirement benefits from Social Security and on the likelihood of being retired, respectively. Appendix Table A.5 presents the corresponding point estimates. The estimates are not consistent in sign and only one out of fourteen estimates is statistically different from zero. Neither benefit claiming nor retirement appears to change discontinuously at $70\frac{1}{2}$. Notably, benefit receipt increases rapidly as people age through Social Security eligibility (which begins at 62), but few people delay their claiming as late as 70, which likely contributes to the smooth evolution of these outcomes.

In sum, the density of the running variable is smooth, there is little to no evidence that covariates change at the cutoff, and while there are two potential confounding policies to carefully consider, the evidence suggests that neither are problematic in practice. Therefore, I present the main estimates in the next section and interpret those estimates as casual and as being driven by QCD eligibility.

# 5 The Effects of Qualified Charitable Distributions on Donations

In this section, I estimate the effects of QCDs on donations. First, I document average effects across time, distinguishing between post-TCJA estimates in 2019 and pre-TCJA estimates earlier. Next, I assess the robustness of these estimates and carry out a placebo test. Finally, I conduct additional analyses to unpack the main estimates and probe mechanisms.

## 5.1 Main Results

Figure 2 illustrates the effects of QCDs on charitable giving in 2019. Each graph corresponds to a different outcome and provides a visual assessment of the causal effect of interest. Specifically, the graphs plot binned means of the outcomes against the running variable. The vertical lines denote the cutoff, age $70\frac{1}{2}$ in December. The regression lines and confidence intervals to the left and right of the cutoff come from estimating linear relationships between the outcome and the running variable using the underlying, unbinned data on observations within the optimal bandwidth.

Graph (a) depicts the effects of aging into QCD eligibility on the extensive-margin indicator for making any donations to charity. There is little to no graphical evidence that QCDs impacted decisions about whether to donate at all. The graph shows that between about 65% and 70% of people with IRAs on either side of the cutoff donated. In contrast, graph (b) depicts the effects of QCDs on donations, measured in dollars and including zeros, and there is evidence of an effect. This outcome captures both extensive-margin decisions about whether to donate, as well as intensive margin decisions about how much to donate. The binned means to the left of the cutoff indicate that, before becoming eligible for QCDs, people with IRAs approaching 70 donated roughly $2,500 to charity. The binned means to the right of the cutoff indicate that people eligible for QCDs donated more. The mean at the cutoff appears to be roughly $4,000. Taken together, graphs (a) and (b) suggest an increase in giving that occurs on the intensive margin.

Graph (c) shows that, indeed, there was a large, clear, and discontinuous increase in donations for those who gave to charity. The graph plots donations in dollars for only those who donated. Before reaching $70\frac{1}{2}$, average donations for givers amounted to about $4,000. After aging into QCD eligibility, average donations increased to about $6,000 and then decreased as people reached more advanced ages. Overall, this graphical evidence indicates that QCDs induced people who donated to give more money to charity than they otherwise would have.

To quantify and assess the statistical significance of these discontinuities, I turn to the regression analysis. Table 2 reports the results. For each outcome, the table displays the RD estimate from estimating equation (1), the mean of the outcome for observations to the left of the cutoff, the optimal bandwidth (monthly ages) used to estimate the effects on the outcome, and both the number of clusters (households) and observations (individuals) used to estimate the regression. Consistent with the graphical evidence, the estimate in column (1) indicates a lack of a statistically significant effect of QCDs on the likelihood that a person donated to charity, whereas column (2) indicates a large and statistically significant effect on donations (including zeros) that amounts to $1,331.

Column (3) presents the point estimate that corresponds to graph (c) of Figure 2. The estimate indicates that QCD eligibility increased donations for people who donated by $2,229 on average. This estimate is large. Compared to the mean of $4,138, it represents a 53.9% increase. People responded strongly to QCD incentives in 2019.[5]

[5]Recall that averaging the pre-period estimates for years during which QCDs were not in place would

Next, I document the effects in earlier years, before TCJA. During this time period, the standard deduction was lower and itemization rates were higher. More people itemizing means more people that can make tax-deductible gifts to charity, and thus more people that might find it less attractive to use QCDs. Consistent with this idea, I find little to no evidence that aging into QCDs impacted donations before TCJA. Table 3 presents the estimates for all three outcomes in all years, and Appendix Figures A.6, A.7, and A.8 present the RD graphs. Each figure corresponds to a different outcome, and each graph within a figure corresponds to a different year and indicates whether QCD rules were temporary or permanent at the time. None of the point estimates are statistically different from zero at the 5 percent level, and the patterns of the estimates do not consistently point to one sign.

### 5.2 Robustness Checks and a Placebo Test

I conduct several robustness checks. First, I investigate the sensitivity of the estimates to the choice of bandwidth. Figure 3 illustrates the results of this robustness check for the 2019 estimates. Each graph corresponds to a different outcome variable and plots RD estimates and 95% confidence intervals as I vary the bandwidth from 36 months to 180 months. The vertical lines denote the baseline estimates that use the data-driven optimal bandwidth. Graph (a) shows that the point estimate for the likelihood of donating to charity is quite stable and that none of the bandwidths result in an estimate for this outcome that is statistically different from zero. Graphs (b) and (c) show that the estimates for the donation outcomes fluctuate some when I use the smallest bandwidths, but are otherwise stable and consistently statistically significant. These results indicate that the takeaways from the baseline estimates are not sensitive to the choice of bandwidth.[6]

Second, I probe the robustness of my estimates to various regression specification checks. Table 4 presents the results for 2019.[7] The columns of the table correspond to the different outcomes. The rows of the table correspond to the different robustness checks. Row A reproduces the baseline estimates. Row B includes control variables—indicators for being

suggest a \$177 increase in donations (including zeros) and a \$173 increase in conditional donations from turning $70\frac{1}{2}$. Subtracting these averages from the 2019 estimates for these two outcomes would indicate increases of \$1,154 and \$2,056, respectively, which are still large and meaningful.

[6] Appendix Figures A.9, A.10, and A.11 present analogous graphs for the estimates for each of the three main outcomes variables, respectively, in earlier years. The earlier-year estimates are also stable, and they are rarely statistically different from zero at the 5 percent level, which indicates that the lack of evidence for a response in earlier years is also not sensitive to the choice of bandwidth.

[7] Appendix Tables A.6, A.7, A.8, A.9, A.10, and A.11 present analogous tables for each of the earlier tax years. The main estimates in those years, and the resulting takeaway that there is a lack of evidence of a response, are robust to specification checks.

male, for being white, for being married, and for having attended at least some college—in the regressions. Row C drops the triangular weights and thus assigns equal weight to all observations within the optimal bandwidth. Row D uses survey weights instead of triangular weights for population-level representation. Row E clusters standard errors at the level of the running variable instead of at the household level. The results are quite robust to all of these standard specification checks and the takeaways do not change.

The next few rows address measurement of donations. In my baseline analysis, I winsorize donations at the 99.5th percentile to limit the influence of outliers. Row F does not winsorize. The estimates are positive and reasonably similar in magnitude to the baseline estimates, especially considering the standard errors, but they are much less precise. Row G winsorizes slightly more aggressively than the baseline approach, at the 99th percentile. The estimates are similar to the baseline estimates and are more precise. Limiting the influence of outliers appears to be especially important for precision. Finally, row H takes an alternative approach to winsorizing dollar amounts and instead uses log donations as the outcome. The point estimate is positive and statistically significant at the 1% level. It indicates a 38.1% increase in donations for givers, and the corresponding graph in Appendix Figure A.12 shows clear visual evidence of a discontinuous increase in log donations.

Finally, I conduct a placebo test by estimating my RD regression for people who do not own IRAs. These people cannot make a QCD, and therefore there should be no discontinuities in their donation outcomes at the cutoff. Table 5 presents the results for 2019, and Appendix Table A.12 presents the results for the earlier years. Reassuringly, I find little to no evidence of discontinuities in outcomes for this sample. Compared to the main results for 2019, the corresponding placebo estimates are meaningfully smaller in magnitude and are not statistically different from zero. The lack of evidence of discontinuities for this sample provides additional support to the main results being driven by IRA holders making use of QCD rules.

### 5.3 Exploration into Mechanisms

I conclude my analysis by investigating additional outcomes and looking at subsamples that help to unpack the main estimates and shed some light on mechanisms. First, I investigate whether the increase in average donations in 2019 was driven by large gifts. The roughly-$2,200 increase in average donations could be explained by many people donating more or by a smaller number of people making meaningfully large donations. To explore this idea, I estimate the effects of aging into QCDs on a series of indicator variables for making large donations. Specifically, I study the effects on the likelihood of (i) donating more than \$10,000, (ii) donating more than \$15,000, (iii) donating more than \$20,000, and (iv) donating more than \$25,000. For a point of comparison for these chosen values, Appendix Table A.13 presents summary statistics for 2019 and shows that the average amount donated by IRA holders was about \$3,000 and the average amount donated by IRA holders who gave to charity was under \$5,000.

Table 6 displays the regression results and Figure 4 presents the corresponding RD graphs. The estimate in column (1) of the table indicates that there was a large, statistically significant 8.3 percentage point increase in the likelihood of donating more than \$10,000. When compared to the mean of 8.5%, this estimates represents an almost-doubling of the likelihood of donating this relatively large sum. Column (2) shows that there was also a substantial increase in the likelihood of donating more than \$15,000. In contrast, columns (3) and (4) show no statistically significant evidence of increased likelihoods of making very large donations of more than \$20,000 or \$25,000, although I emphasize that donations of this size are rare in the sample. Overall, these results highlight how the average increase in giving in 2019 due to QCDs was influenced by notable increases in the likelihood of making large gifts.[8]

Second, I conduct a subsample analysis to provide some insight into the bundle of incentives tied to QCD eligibility. One key feature of the tax rules is that they allow people who take the standard deduction to make tax-free gifts, and the pattern of the main estimates—large responses after TCJA increased the standard deduction and decreased itemization rates but no evidence of responses earlier—provide some support to the idea that this feature is important in influencing the use of QCDs.

However, another key feature of the rules is that they allow people not relying on IRA withdrawals for financing consumption to reduce any tax-related burdens associated with RMDs. Recall that QCDs (i) count towards required withdrawals and (ii) reduce IRA balances and thus lower future RMDs. While these incentives are inherently bundled with the ability to make tax-free gifts, I can attempt to investigate the extent to which these incentives might also be important for households by looking at subsamples. Specifically, I estimate separate effects for subsamples based on IRA balances. The idea is people with larger IRA balances face greater RMDs and therefore may be more impacted by these additional

[8]For completeness, Appendix Table A.14 presents point estimates for the earlier years. None of the estimates are statistically different from zero, indicating that the null results on average donations during those years are unlikely to be masking an increase in the probability of making large donations for some people.

incentives, whereas people with smaller IRA balances may be less impacted.

Tables 7 and 8 display the estimates for two groups: those with above-median IRA balances and those with below-median balances, respectively. Appendix Figures A.13 and A.14 display the corresponding RD graphs. The point estimates for donations among people with larger IRA balances are statistically significant and greater in magnitude than the main estimates. In contrast, while still positive, the point estimates for donations among people with smaller IRA balances are not statistically different from zero. They are also about four times smaller than the estimates for people with larger IRA balances. While I caution against drawing strong conclusions from these subsample estimates because (i) the sample sizes are small and (ii) IRA balances could of course be correlated with other important characteristics, the results nonetheless suggest that those with large IRA balances donate more when they age into QCDs. They thus provide some supporting evidence to the idea that the RMD-related incentives to use QCDs to make tax-free donations at $70\frac{1}{2}$ enter the decision-making process for some people.

## 6 Conclusion

In this paper, I use data from the Health and Retirement Study and a regression discontinuity design to provide novel causal evidence on charitable giving responses to tax rules pertaining to qualified charitable distributions (QCDs). The rules allow Individual Retirement Account (IRA) holders to make tax-free transfers of funds in the accounts to qualified charities. I find that QCD eligibility led to a \$2,229 increase in average donations for people who gave to charity in 2019, after the Tax Cuts and Jobs Act. I also show that QCDs induced more people to make large donations and that people with larger IRAs responded more than people with smaller IRAs. In contrast, I find no evidence that the tax rules impacted donations before TCJA.

My findings have implications for tax policy. In a direct sense, my results highlight how QCDs can indeed increase total charitable donations, which is presumably the goal of these tax incentives. However, my findings across years highlight how the use of QCDs depends on the broader tax environment and underscore the importance of accounting for interactions between different sets of tax rules. When the standard deduction was low and more people itemized, QCDs were less effective at increasing donations, perhaps because many people could already make tax-advantaged gifts. In the current tax environment though, with greater standard deductions and thus fewer itemizers, the ability to transfer funds tax-free at

$70\frac{1}{2}$ appears to be more valuable, and QCDs thus have more potential to increase donations. Any future changes to the standard deduction or to the amount of itemized deductions that households can take should be expected to influence the use of QCDs.

More generally, my results are informative for policy makers concerned with understanding whether making charitable gifts tax-deductible for more people would increase donations. With the caveat in mind that my estimates are local to IRA holders around age $70\frac{1}{2}$, my results indicate that once people aged into the ability to donate in a tax-advantaged way that did not require itemization, donations increased. This takeaway thus lends some support to the idea that proposed policies to make charitable gifts tax-deductible for everyone and not just those who itemize—like the Universal Charitable Giving Act that was introduced in 2017 (H.R.3988) or the Charitable Act that was introduced in January 2025 (H.R.801)—would increase donations.

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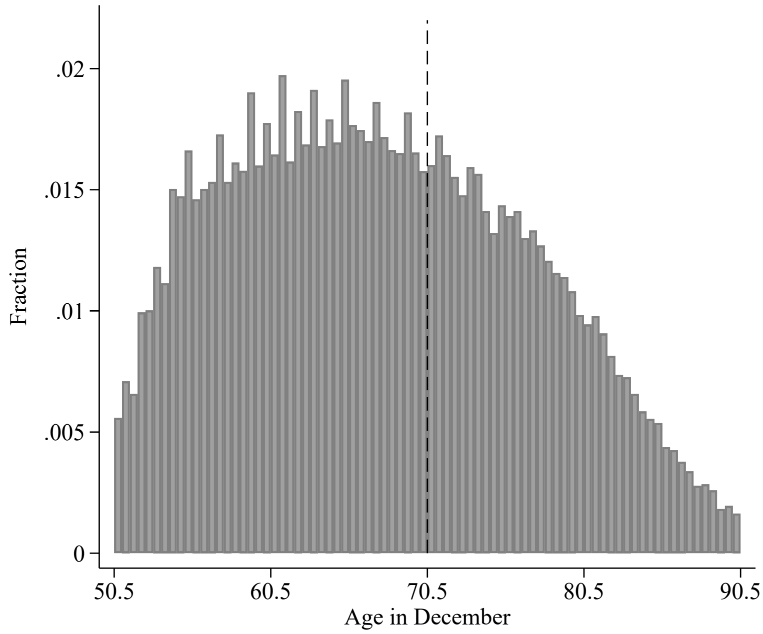
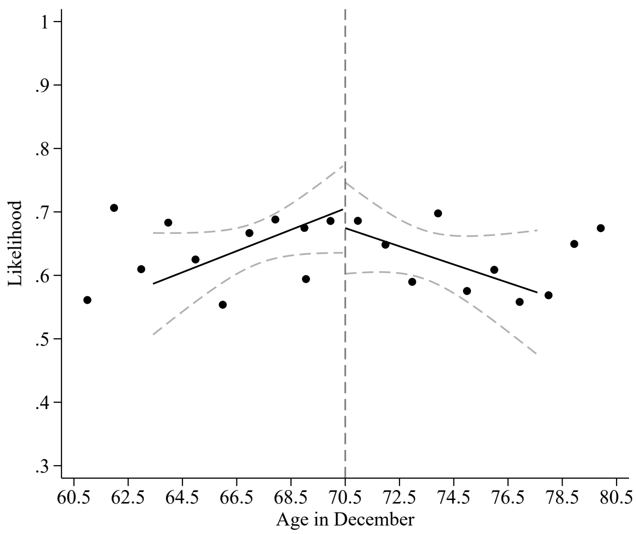
**Figure 1: Histogram of the Running Variable**



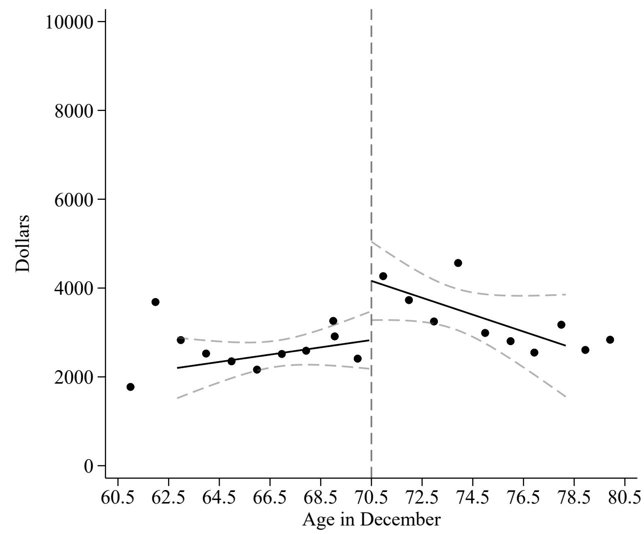

Notes: This figure plots a histogram of the running variable, age in December, for tax year 2019.

## Figure 2: Effects of Qualified Charitable Distributions on Charitable Giving After the Tax Cuts and Jobs Act

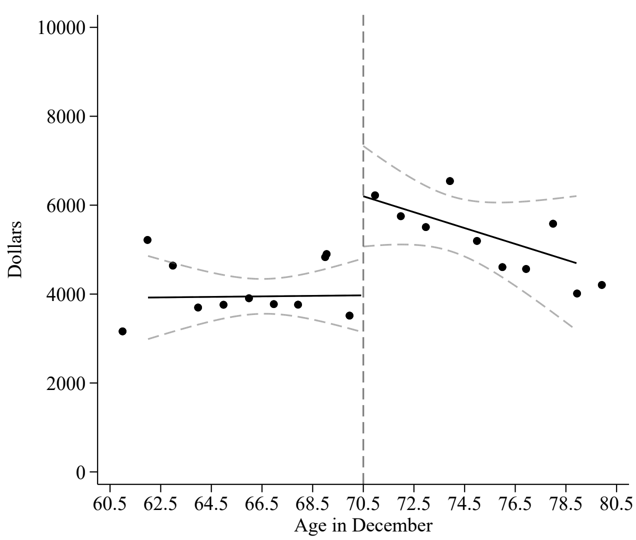
### (a) Indicator for Giving to Charity




### (b) Donations (Including Zeros)



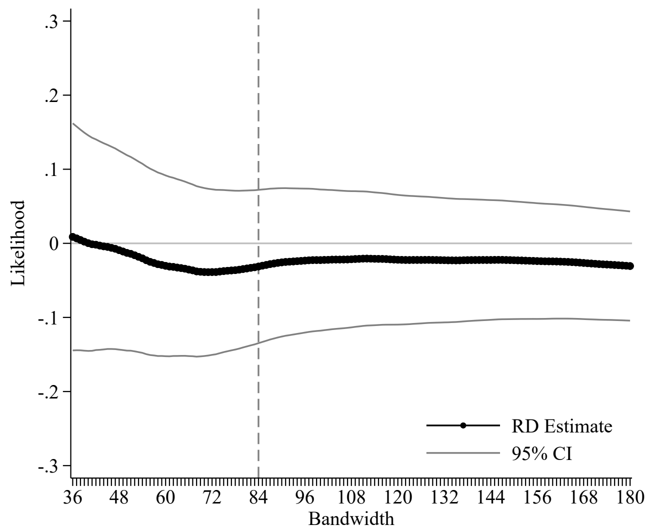

### (c) Donations Conditional on Giving



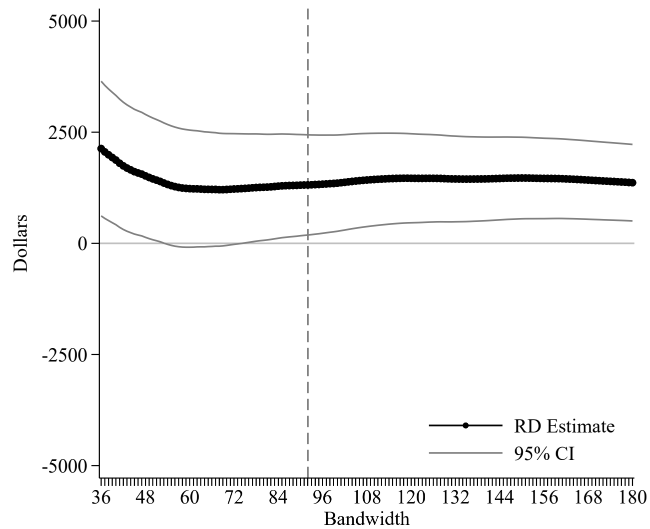

Notes: This figure illustrates the effects of aging into qualified charitable distributions on charitable giving in 2019. Each graph corresponds to a different outcome. Graph (a) is for an indicator variable for giving to charity. Graph (b) is for donations in dollars, including zeros. Graph (c) is for donations in dollars, conditional on giving. Each graph is constructed as follows. The running variable along the horizontal axis is (monthly) age in December of the tax year to which the charitable giving outcomes correspond. The cutoff is $70\frac{1}{2}$ and is denoted by the dashed 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: Robustness of Key Estimates to Bandwidth Selection

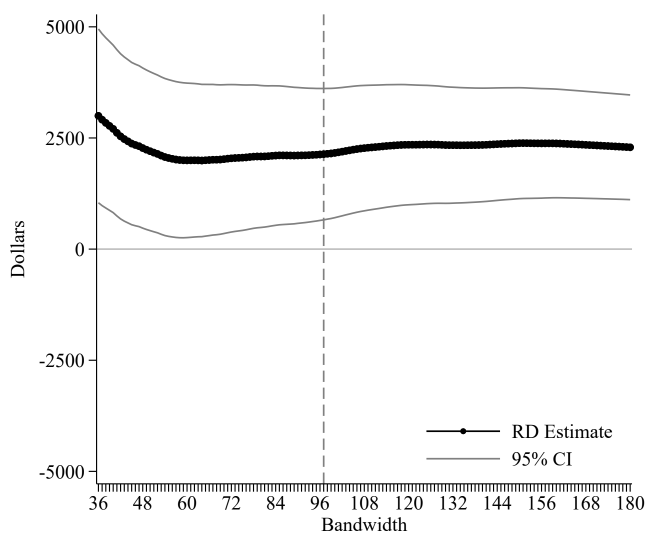
### (a) Indicator for Giving to Charity




### (b) Donations (Including Zeros)

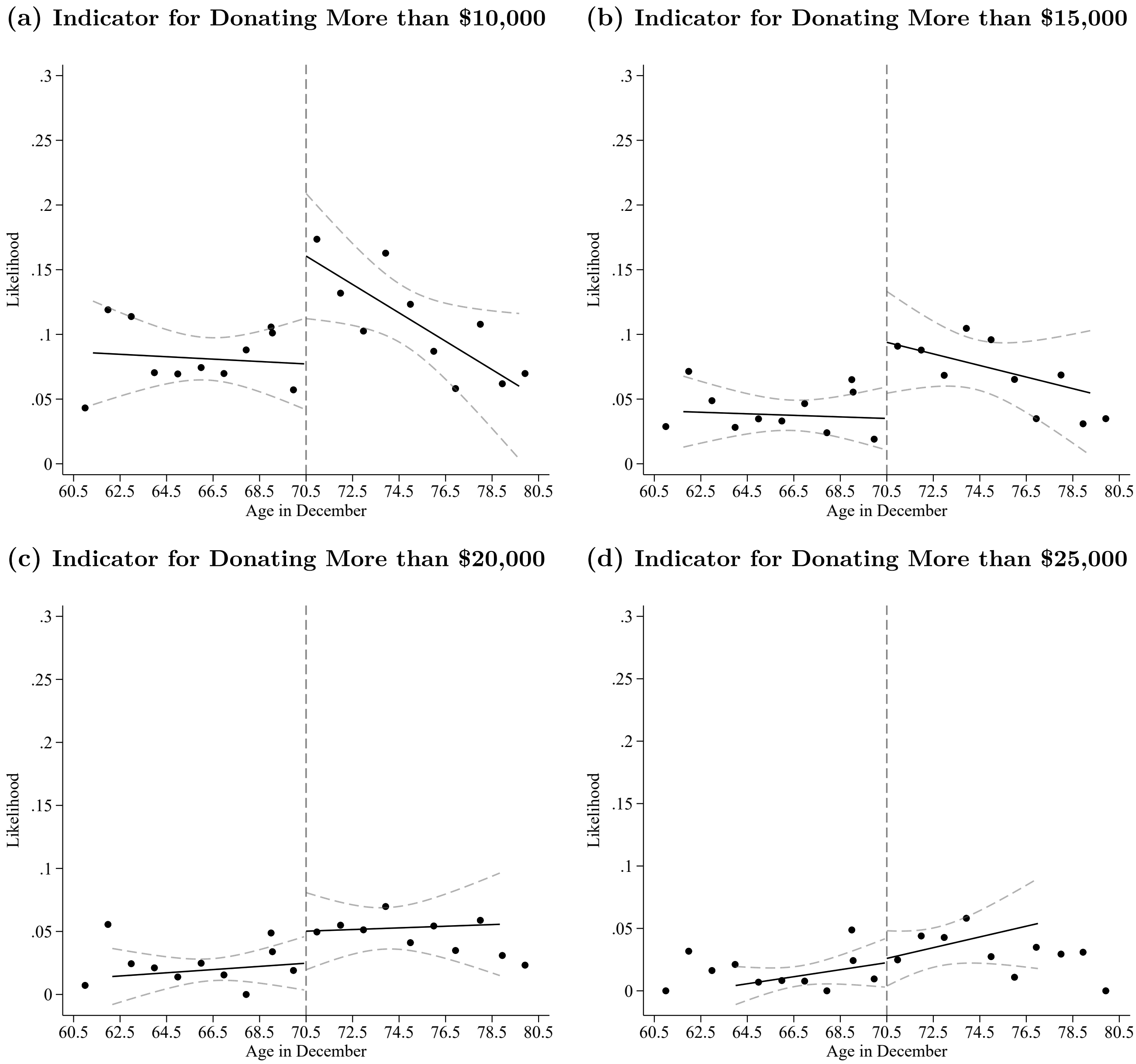



### (c) Donations Conditional on Giving




Notes: This figure illustrates the robustness of the main estimates for 2019 to varying the bandwidth. Each graph plots the RD estimates and 95% confidence intervals that result from using bandwidths ranging from 36 months to 180 months. The vertical dashed lines denote the leading bandwidth.

## Figure 4: Effects of Qualified Charitable Distributions on Giving Large Amounts to Charity After the Tax Cuts and Jobs Act




Notes: This figure illustrates the effects of aging into qualified charitable distributions on indicators for donating large amounts to charity in 2019. Each graph corresponds to a different outcome. Graph (a) is for an indicator variable for donating more than $10,000. Graph (b) is for an indicator variable for donating more than $15,000. Graph (c) if for an indicator variable for donating more than $20,000. Graph (d) is for an indicator variable for donating more than $25,000. See the notes of Figure 2 for more details on how each graph is constructed.

## Table 1: Summary Statistics

| | People With IRAs | | | People Without IRAs | | |
|---|---|---|---|---|---|---|
| | Mean (1) | SD (2) | Obs. (3) | Mean (4) | SD (5) | Obs. (6) |
| Age | 67.28 | 10.04 | 49,963 | 67.34 | 11.91 | 125,026 |
| Tax Year | 2008.72 | 6.08 | 49,963 | 2009.05 | 6.19 | 125,026 |
| Male | 0.47 | 0.50 | 49,963 | 0.39 | 0.49 | 125,026 |
| White | 0.90 | 0.30 | 49,945 | 0.67 | 0.47 | 124,686 |
| Married | 0.71 | 0.46 | 49,941 | 0.54 | 0.50 | 124,877 |
| College | 0.64 | 0.48 | 49,961 | 0.35 | 0.48 | 124,999 |
| Retired | 0.54 | 0.50 | 49,963 | 0.59 | 0.49 | 125,026 |
| Receives Social Security Benefits | 0.58 | 0.49 | 49,963 | 0.56 | 0.50 | 125,026 |
| Gives to Charity | 0.65 | 0.48 | 49,963 | 0.30 | 0.46 | 125,026 |
| Donations (Including Zeros) | 2,921 | 5,168 | 49,963 | 898 | 2,678 | 125,026 |
| Donations Conditional on Giving | 4,523 | 5,841 | 32,263 | 2,971 | 4,190 | 37,805 |
| IRA Balances | 230,541 | 573,522 | 49,963 | – | – | – |
| Individuals | | | 13,180 | | | 29,408 |

Notes: This table reports summary statistics for two groups. The underlying samples contain data from survey waves 5 through 15. The first three columns report means, standard deviations, and observations for people who own an IRA and make up my analysis sample. The next three columns report the same statistics for people in households where no member owns an IRA. The bottom row displays the number of unique individuals in each group.

**Table 2: Effects of Qualified Charitable Distributions on Charitable Giving After the Tax Cuts and Jobs Act**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| RD Estimate for 2019 | -0.031 | 1,331** | 2,229*** |
| | (0.052) | (570) | (731) |
| Mean | 0.653 | 2,571 | 4,138 |
| Bandwidth (Months) | 86 | 93 | 103 |
| Clusters (Households) | 1,314 | 1,410 | 972 |
| Observations (Individuals) | 1,579 | 1,710 | 1,220 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into qualified charitable distributions on charitable giving after the Tax Cuts and Jobs Act, in 2019. 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: Effects of Qualified Charitable Distributions on Charitable Giving Before the Tax Cuts and Jobs Act**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| RD Estimate for 2007 | 0.085* | -13 | -580 |
| | (0.050) | (580) | (748) |
| Mean | 0.661 | 3,224 | 4,764 |
| Bandwidth (Months) | 55 | 66 | 70 |
| Clusters (Households) | 1,310 | 1,501 | 1,028 |
| Observations (Individuals) | 1,529 | 1,805 | 1,273 |
| RD Estimate for 2009 | 0.065 | 789 | 741 |
| | (0.043) | (500) | (719) |
| Mean | 0.648 | 2,819 | 4,331 |
| Bandwidth (Months) | 80 | 89 | 80 |
| Clusters (Households) | 1,671 | 1,818 | 1,073 |
| Observations (Individuals) | 2,039 | 2,240 | 1,337 |
| RD Estimate for 2011 | 0.014 | 52 | -33 |
| | (0.044) | (547) | (812) |
| Mean | 0.646 | 3,036 | 4,652 |
| Bandwidth (Months) | 91 | 83 | 76 |
| Clusters (Households) | 1,689 | 1,557 | 937 |
| Observations (Individuals) | 2,050 | 1,875 | 1,137 |
| RD Estimate for 2013 | 0.009 | 154 | 134 |
| | (0.049) | (566) | (783) |
| Mean | 0.653 | 3,447 | 5,291 |
| Bandwidth (Months) | 84 | 66 | 64 |
| Clusters (Households) | 1,555 | 1,228 | 787 |
| Observations (Individuals) | 1,897 | 1,459 | 948 |
| RD Estimate for 2015 | -0.015 | -757 | -1,122 |
| | (0.049) | (715) | (949) |
| Mean | 0.671 | 3,433 | 5,019 |
| Bandwidth (Months) | 110 | 79 | 79 |
| Clusters (Households) | 1,803 | 1,292 | 867 |
| Observations (Individuals) | 2,237 | 1,562 | 1,067 |
| RD Estimate for 2017 | -0.089* | 104 | 785 |
| | (0.050) | (700) | (907) |
| Mean | 0.674 | 3,009 | 4,483 |
| Bandwidth (Months) | 94 | 95 | 95 |
| Clusters (Households) | 1,447 | 1,456 | 956 |
| Observations (Individuals) | 1,744 | 1,759 | 1,170 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into qualified charitable distributions on charitable giving before the Tax Cuts and Jobs Act, in odd-numbered years from 2007 to 2017. 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 4: Robustness of Key Estimates to Specification Checks**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| A. Baseline | -0.031 | 1,331** | 2,229*** |
| | (0.052) | (570) | (731) |
| B. Include Controls | -0.048 | 1,157** | 2,117*** |
| | (0.050) | (551) | (711) |
| C. Drop Triangular Weights | -0.001 | 1,425*** | 2,718*** |
| | (0.049) | (529) | (701) |
| D. Use Survey Weights | 0.005 | 1,080 | 2,381*** |
| | (0.056) | (673) | (883) |
| E. Cluster on Running Variable | -0.031 | 1,331*** | 2,229*** |
| | (0.046) | (501) | (606) |
| F. No Winsorizing | – | 970 | 1,676 |
| | | (987) | (1,357) |
| G. Winsorize More | – | 1,236** | 2,120*** |
| | | (503) | (594) |
| H. Log Donations | – | – | 0.381** |
| | | | (0.149) |

Notes: This table reports results from assessing the sensitivity of the 2019 estimates to various specification checks. Each column corresponds to a main outcome variable. Each row indicates the robustness check. Row A reproduces the baseline estimates for comparison. Row B adds control variables for gender, race, marital status, and college education to the regressions. Row C drops the triangular weights. Row D uses household survey weights instead of triangular weights. Row E clusters standard errors at the level of the running variable instead of at the household level. Row F does not winsorize donations. Row G winsorizes donations at the 99th percentile instead of the 99.5th percentile. Row H uses log donations as the outcome variable instead of donations conditional on giving measured in dollars. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

## Table 5: Placebo Estimates for People Without Individual Retirement Accounts

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| Placebo RD Estimate for 2019 | -0.001 | 79 | 352 |
| | (0.031) | (171) | (483) |
| Mean | 0.272 | 681 | 2,482 |
| Bandwidth (months) | 105 | 90 | 91 |
| Clusters | 3,515 | 2,983 | 835 |
| Observations | 4,349 | 3,621 | 1,060 |

Notes: This table reports placebo regression discontinuity (RD) estimates for people in households with no IRAs after the Tax Cuts and Jobs Act, in 2019. Standard errors clustered at the household level are in parentheses. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$

**Table 6: Effects of Qualified Charitable Distributions on Giving Large Amounts to Charity After the Tax Cuts and Jobs Act**

| | Indicator for Giving More than \$10,000 (1) | Indicator for Giving More than \$15,000 (2) | Indicator for Giving More than \$20,000 (3) | Indicator for Giving More than \$25,000 (4) |
|---|---|---|---|---|
| RD Estimate for 2019 | 0.083*** | 0.059** | 0.025 | 0.003 |
| | (0.031) | (0.024) | (0.019) | (0.017) |
| Mean | 0.085 | 0.040 | 0.022 | 0.013 |
| Bandwidth (Months) | 111 | 106 | 101 | 79 |
| Clusters (Clusters) | 1,663 | 1,591 | 1,527 | 1,220 |
| Observations (Households) | 2,048 | 1,956 | 1,871 | 1,458 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into qualified charitable distributions on indicator variables for making large donations to charity after the Tax Cuts and Jobs Act, in 2019. 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 7: Effects of Qualified Charitable Distributions on Charitable Giving After the Tax Cuts and Jobs Act for People with Above-Median Individual Retirement Account Balances**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| RD Estimate for 2019 | -0.031 | 2,036** | 3,025*** |
| | (0.067) | (865) | (1,092) |
| Mean | 0.707 | 3,086 | 4,390 |
| Bandwidth (Months) | 87 | 92 | 92 |
| Clusters (Households) | 723 | 752 | 513 |
| Observations (Individuals) | 911 | 957 | 665 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into qualified charitable distributions on charitable giving after the Tax Cuts and Jobs Act, in 2019, for the subsample of people with above-median household IRA balances in 2019. 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 8: Effects of Qualified Charitable Distributions on Charitable Giving After the Tax Cuts and Jobs Act for People with Below-Median Individual Retirement Account Balances**

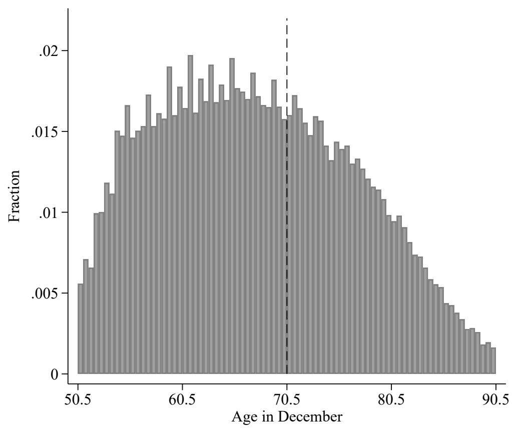
| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| RD Estimate for 2019 | -0.030 | 507 | 744 |
| | (0.079) | (622) | (970) |
| Mean | 0.578 | 1,971 | 3,179 |
| Bandwidth (Months) | 94 | 104 | 84 |
| Clusters (Households) | 671 | 749 | 334 |
| Observations (Individuals) | 754 | 844 | 380 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into qualified charitable distributions on charitable giving after the Tax Cuts and Jobs Act, in 2019, for the subsample of people with below-median household IRA balances in 2019. The RD estimates come from estimating equation (1). Standard errors clustered at the household level are in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

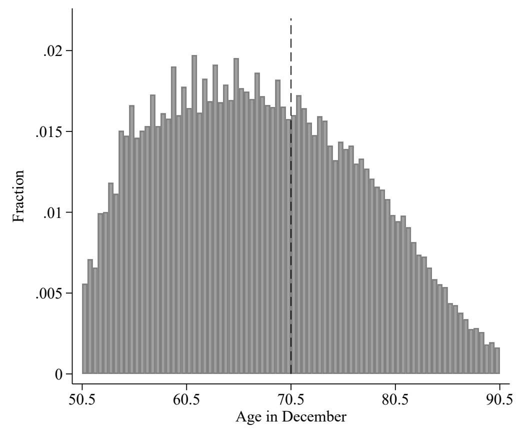
# Appendix A Additional Figures and Tables

**Figure A.1: Histograms of the Running Variable Before the Tax Cuts and Jobs Act**

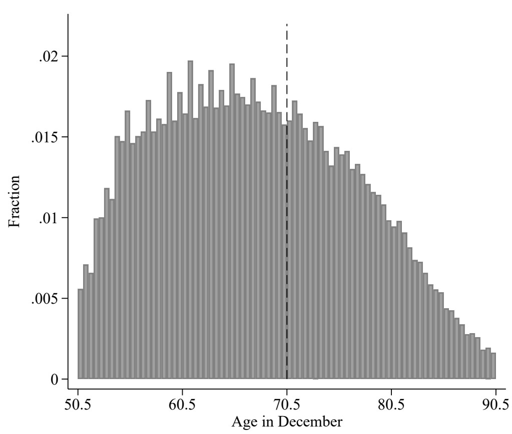
**(a) Temporary Policy: 2007**



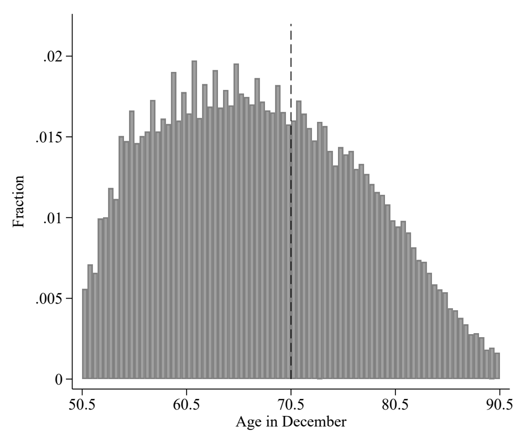

**(b) Temporary Policy: 2009**



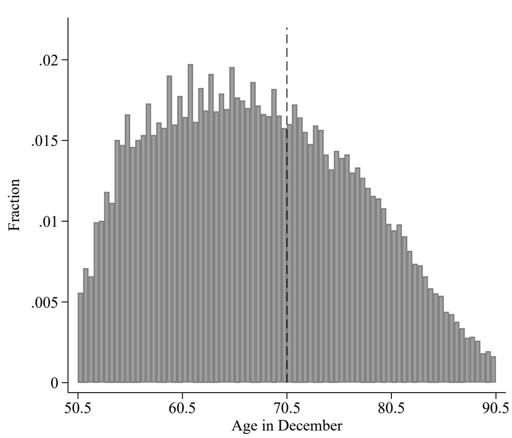

**(c) Temporary Policy: 2011**



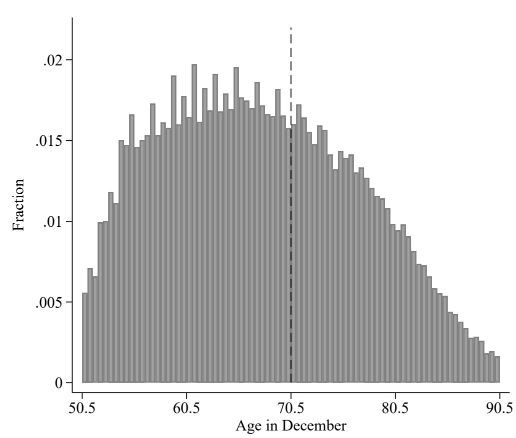

**(d) Temporary Policy: 2013**




**(e) Permanent Policy: 2015**



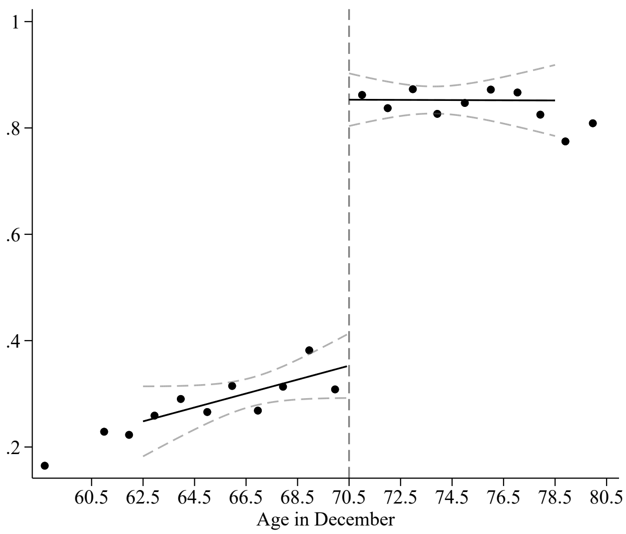

**(f) Permanent Policy: 2017**



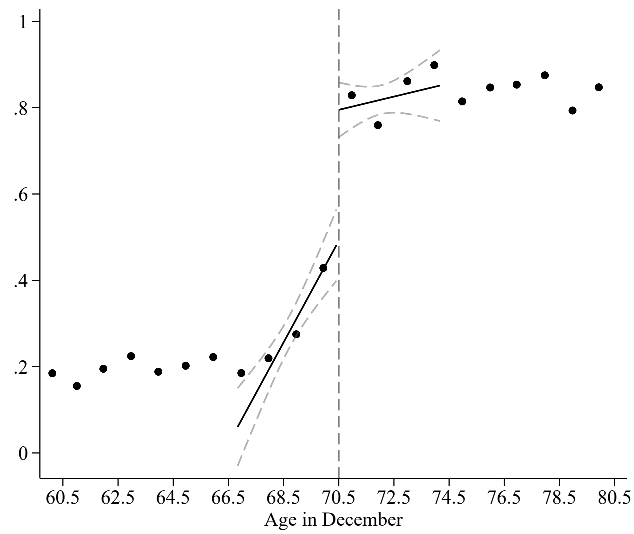

Notes: This figure plots histograms of the running variable, age in December, for tax years 2007 to 2017.

## Figure A.2: Investigating Confounding Policies: Effects of Reaching $70\frac{1}{2}$ on Withdrawals from Individual Retirement Accounts in the Pre-Period, Before Qualified Charitable Distributions Existed

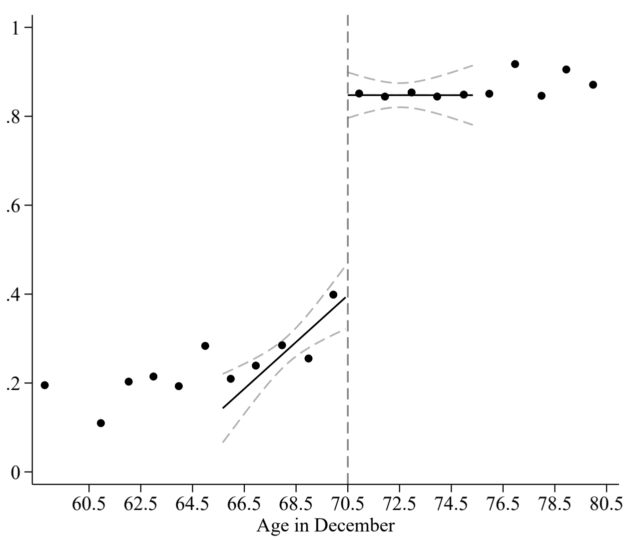
**(a) Indicator for IRA Withdrawal: 1999**



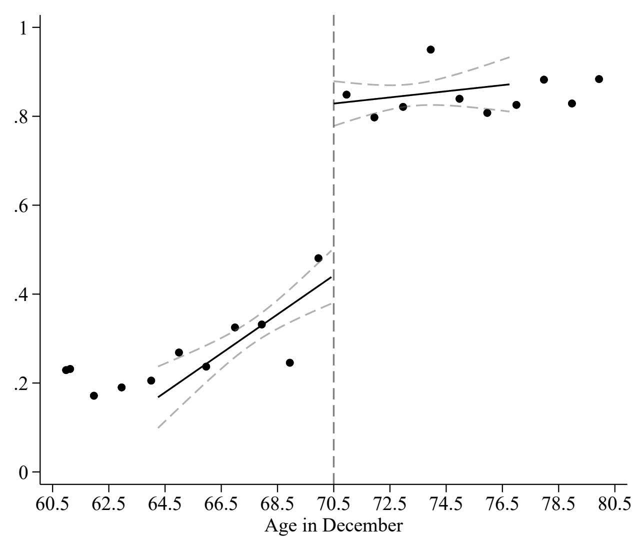

**(b) Indicator for IRA Withdrawal: 2001**




**(c) Indicator for IRA Withdrawal: 2003**

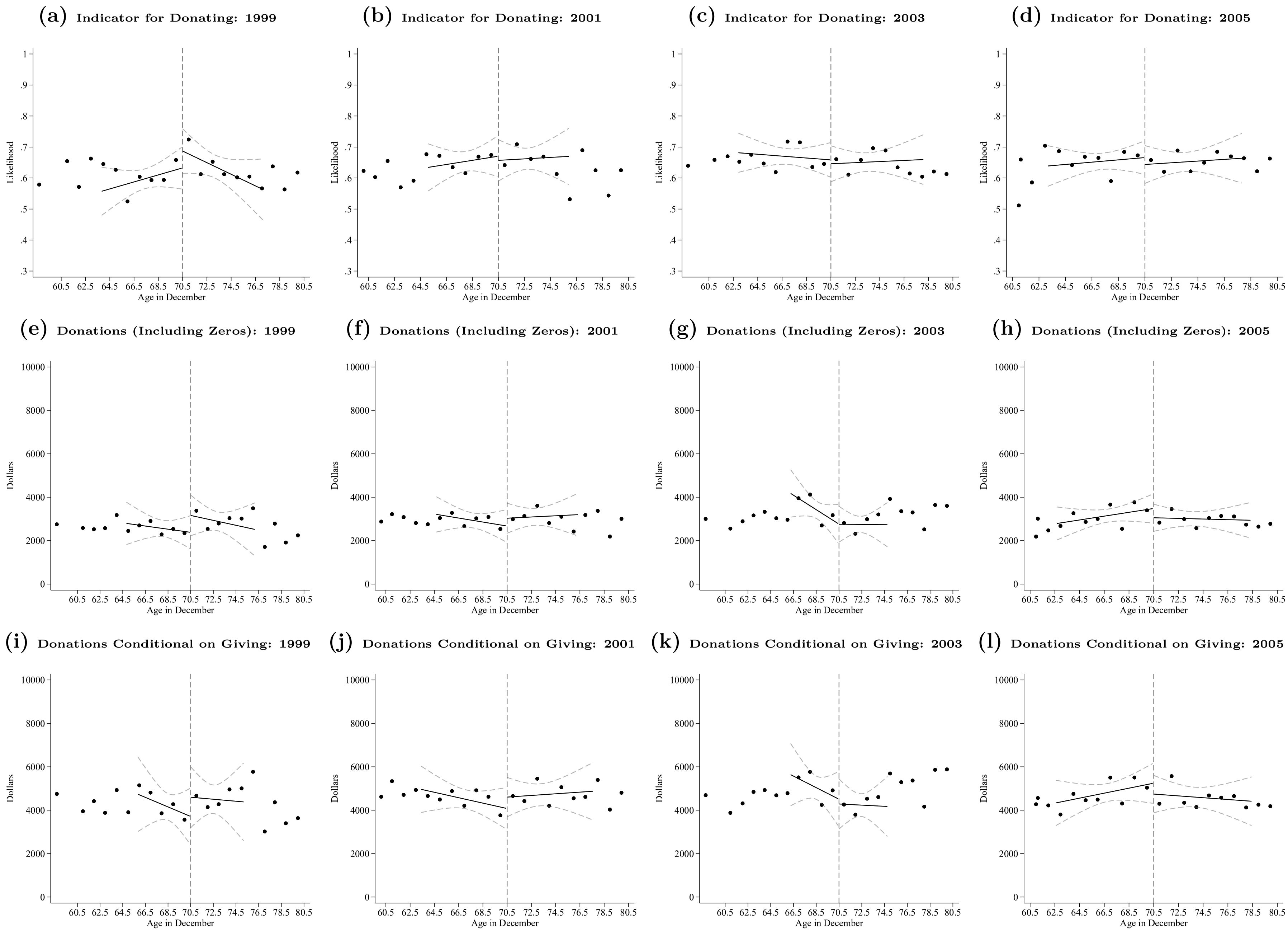



**(d) Indicator for IRA Withdrawal: 2005**



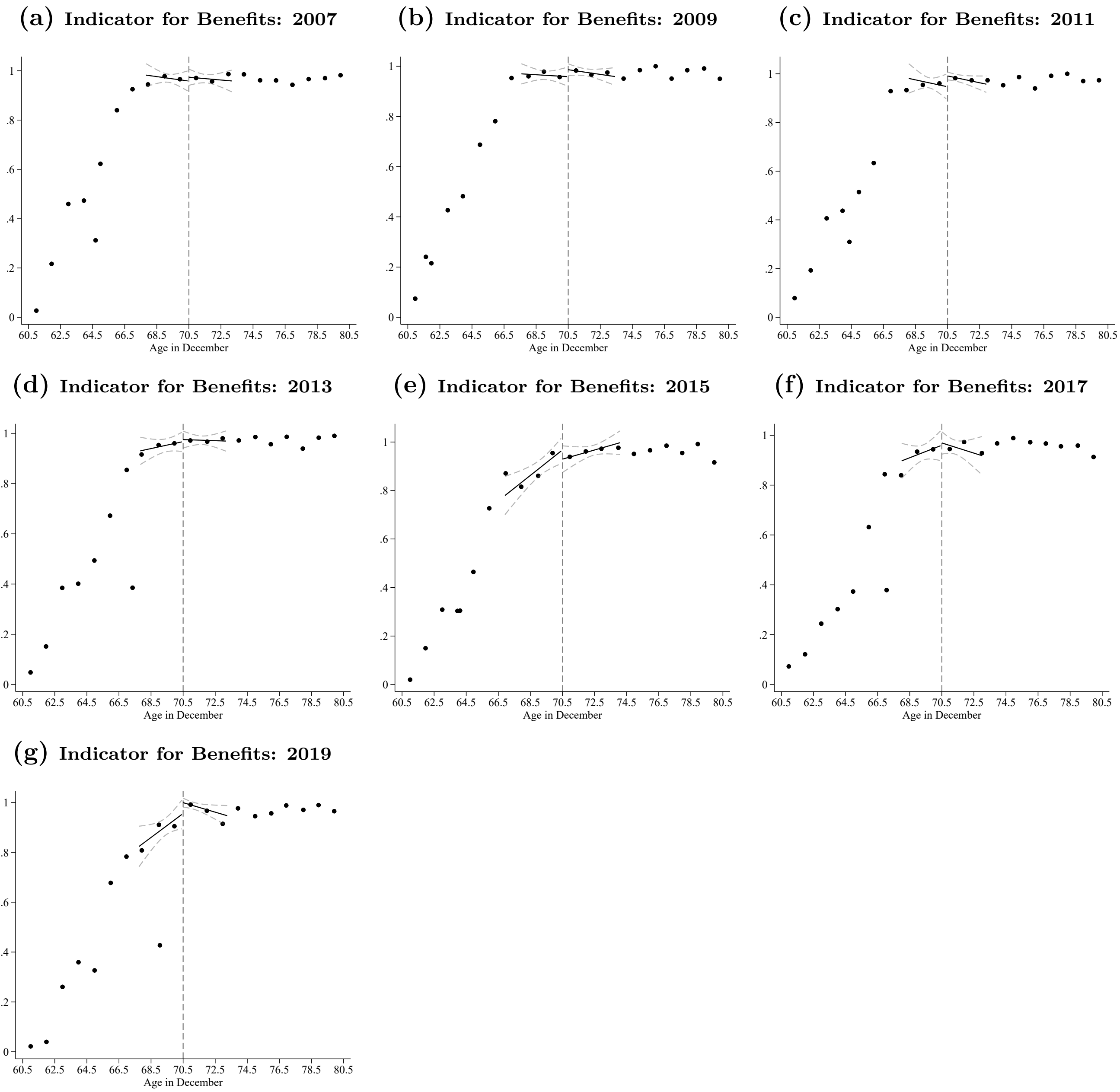

Notes: This figure illustrates the effects of reaching $70\frac{1}{2}$ on an indicator for withdrawing funds from an Individual Retirement Account in the pre-period, when required minimum distributions were in effect but before qualified charitable distributions existed. Each graph corresponds to a different outcome-tax-year combination. See the notes of Figure 2 for more details on how each graph is constructed.

## Figure A.3: Investigating Confounding Policies: Effects of Reaching $70\frac{1}{2}$ on Charitable Giving in the Pre-Period, Before Qualified Charitable Distributions Existed




Notes: This figure illustrates the effects of reaching $70\frac{1}{2}$ on charitable giving outcomes during the pre-period, before qualified charitable distributions existed. Each graph corresponds to a different outcome-tax-year combination. See the notes of Figure 2 for more details on how each graph is constructed.

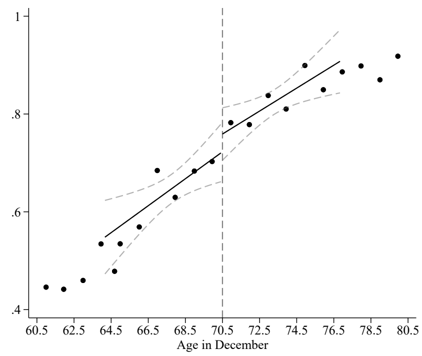
## Figure A.4: Investigating Confounding Policies: Effects of Reaching $70\frac{1}{2}$ on Receiving Social Security Benefits



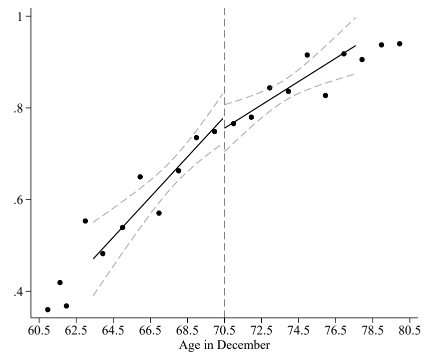

Notes: This figure illustrates the effects of reaching $70\frac{1}{2}$ on an indicator for receiving Social Security benefits. Each graph corresponds to a different outcome-tax-year combination. See the notes of Figure 2 for more details on how each graph is constructed.

## Figure A.5: Investigating Confounding Policies: Effects of Reaching $70\frac{1}{2}$ on Retirement

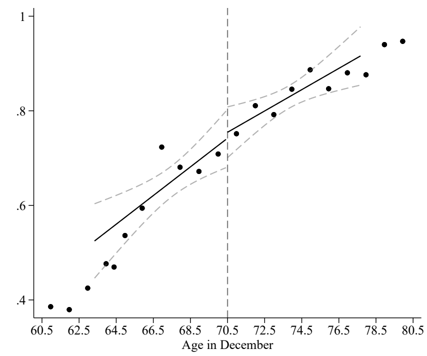
**(a) Indicator for Retired: 2007**



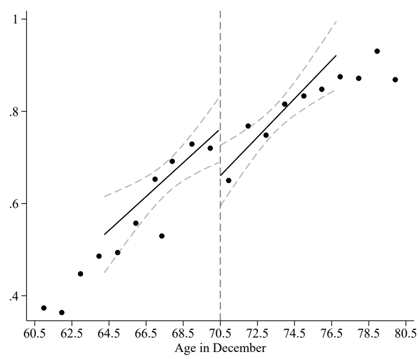

**(b) Indicator for Retired: 2009**



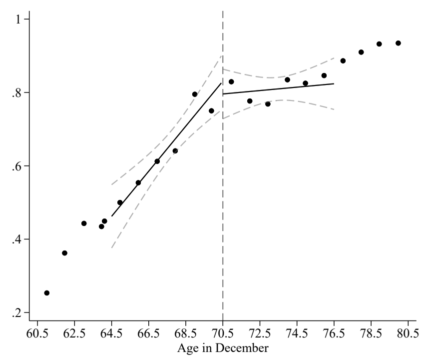

**(c) Indicator for Retired: 2011**



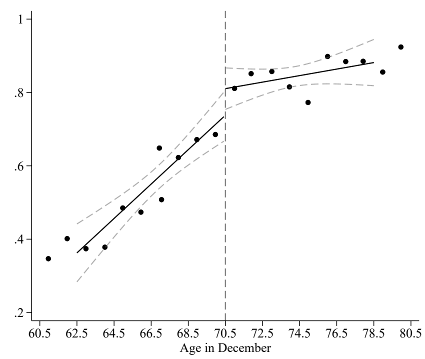

**(d) Indicator for Retired: 2013**



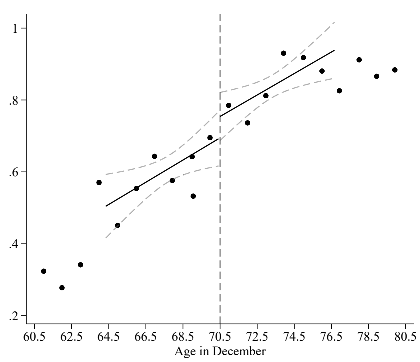

**(e) Indicator for Retired: 2015**




**(f) Indicator for Retired: 2017**

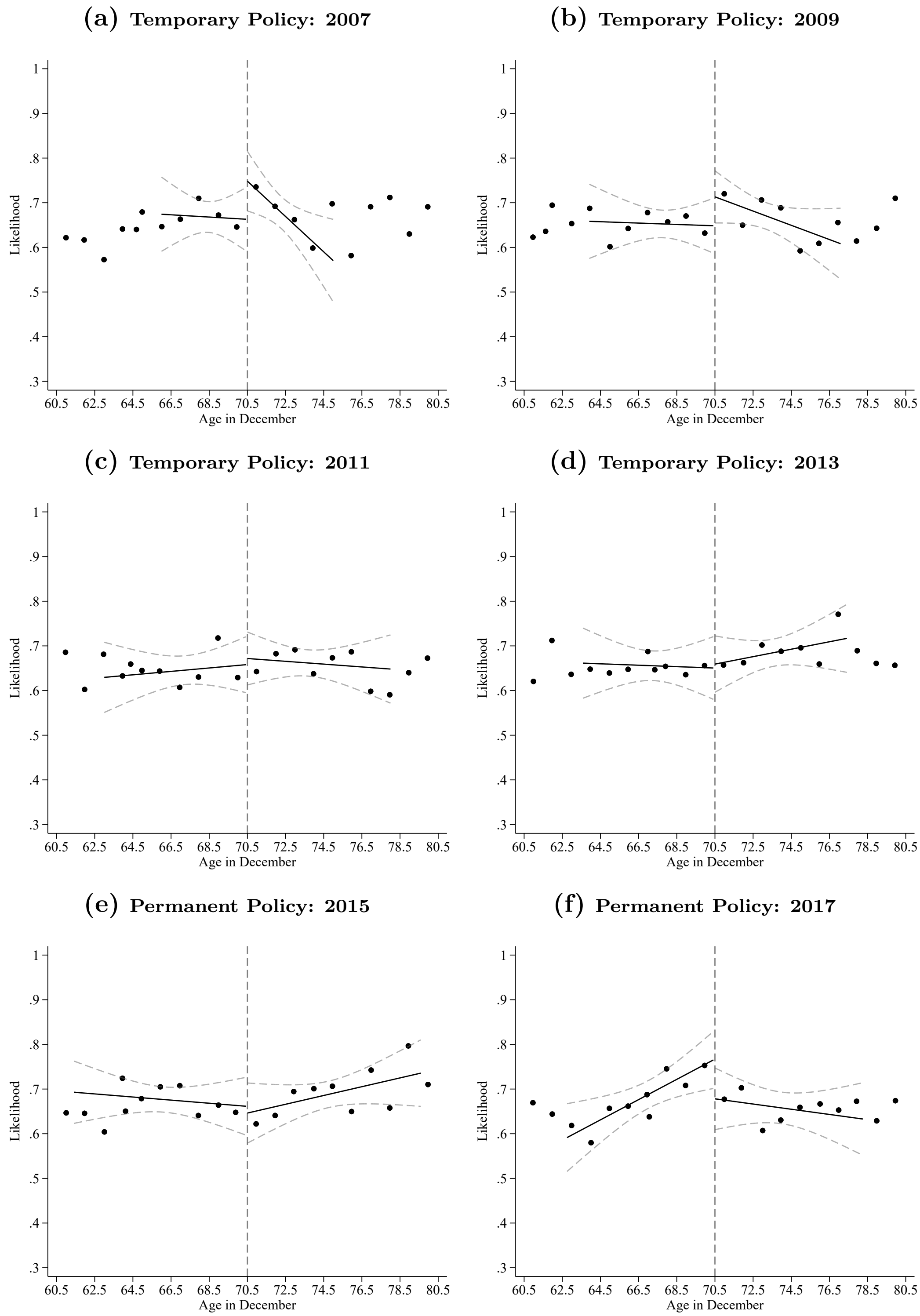



**(g) Indicator for Retired: 2019**




Notes: This figure illustrates the effects of reaching $70\frac{1}{2}$ on an indicator for being retired. Each graph corresponds to a different outcome-year combination. See the notes of Figure 2 for more details on how each graph is constructed.

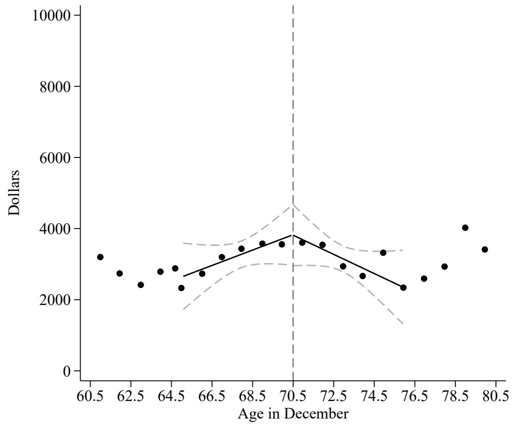
**Figure A.6: Effects of Qualified Charitable Distributions on an Indicator for Giving to Charity Before the Tax Cuts and Jobs Act**



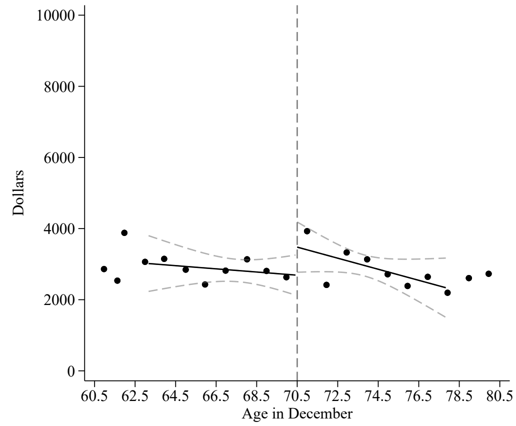

Notes: This figure illustrates the effects of aging into qualified charitable distributions an indicator for giving to charity before the Tax Cuts and Jobs Act. Each graph corresponds to a different tax year. See the notes of Figure 2 for more details on how each graph is constructed.

## Figure A.7: Effects of Qualified Charitable Distributions on Donations (Including Zeros) Before the Tax Cuts and Jobs Act

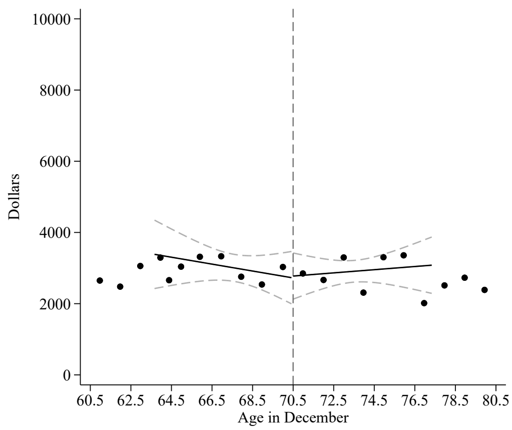
**(a) Temporary Policy: 2007**



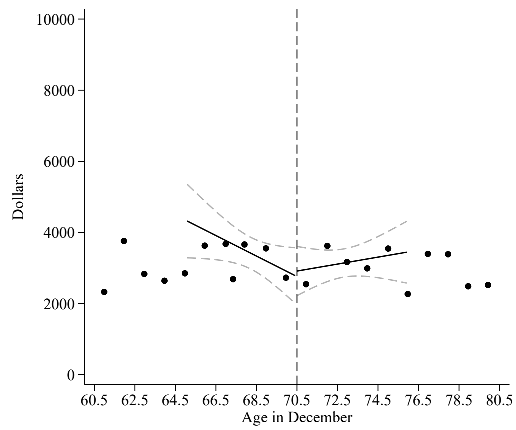

**(b) Temporary Policy: 2009**



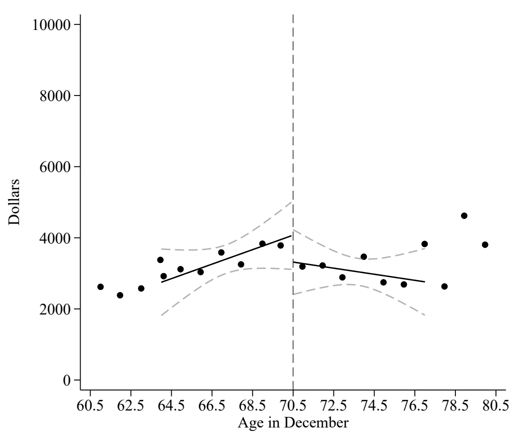

**(c) Temporary Policy: 2011**



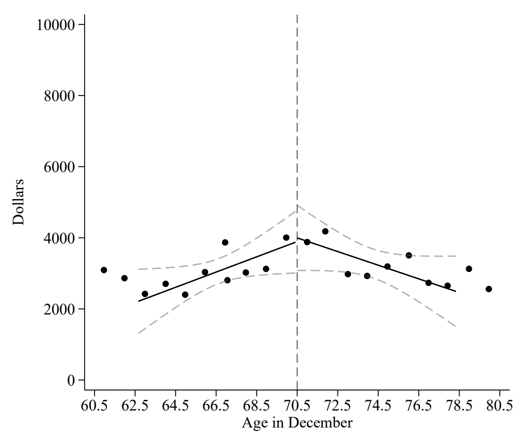

**(d) Temporary Policy: 2013**




**(e) Permanent Policy: 2015**

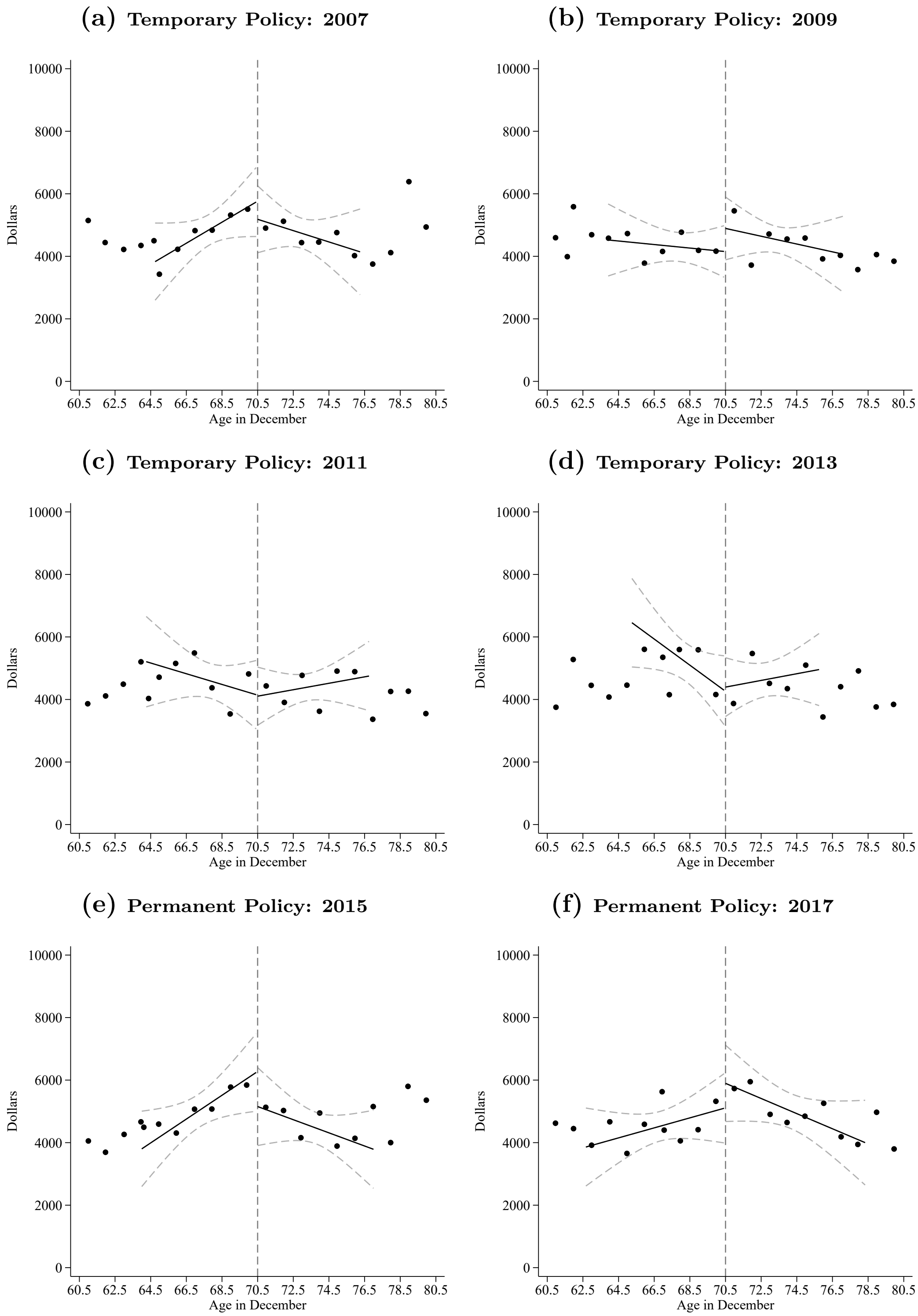



**(f) Permanent Policy: 2017**




Notes: This figure illustrates the effects of aging into qualified charitable distributions on donations (including zeros) before the Tax Cuts and Jobs Act. Each graph corresponds to a different tax year. See the notes of Figure 2 for more details on how each graph is constructed.

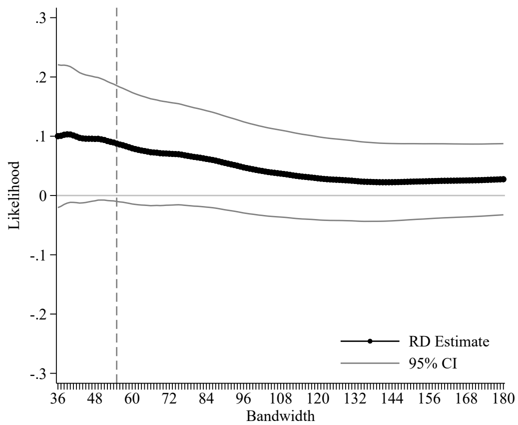
**Figure A.8: Effects of Qualified Charitable Distributions on Donations Conditional on Giving Before the Tax Cuts and Jobs Act**



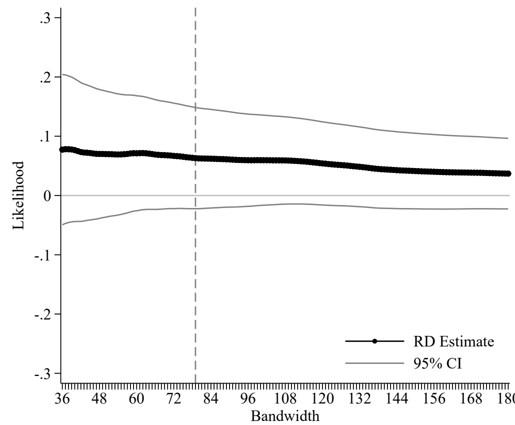

Notes: This figure illustrates the effects of aging into qualified charitable distributions on donations conditional on giving before the Tax Cuts and Jobs Act. Each graph corresponds to a different tax year. See the notes of Figure 2 for more details on how each graph is constructed.

## Figure A.9: Robustness of Estimates for the Indicator for Giving to Charity in Earlier Years to Bandwidth Selection

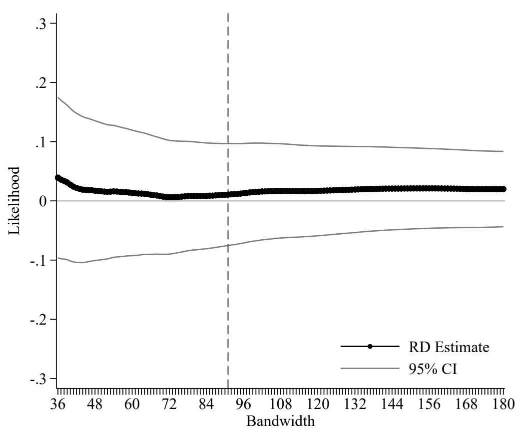
**(a) Temporary Policy: 2007**



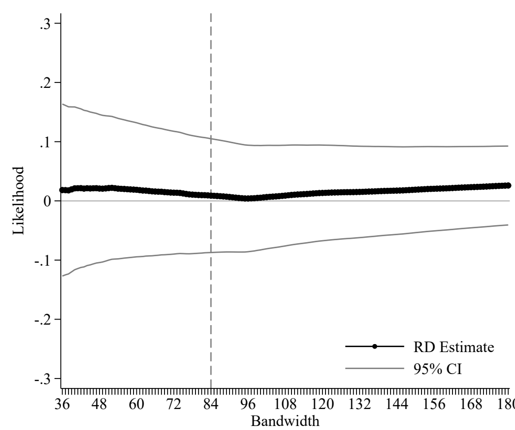

**(b) Temporary Policy: 2009**



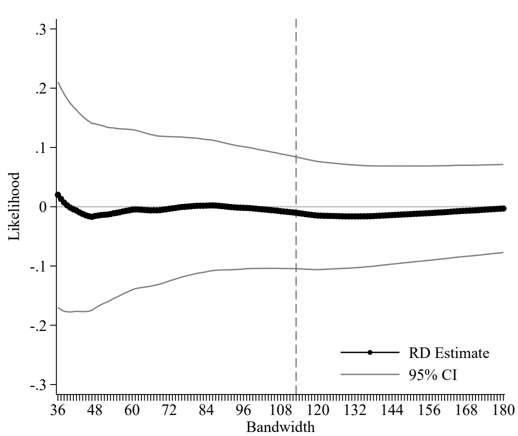

**(c) Temporary Policy: 2011**



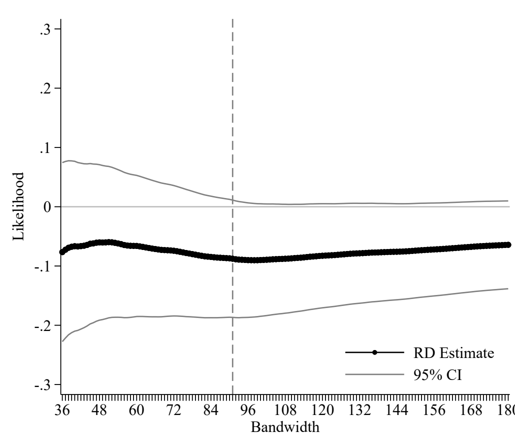

**(d) Temporary Policy: 2013**




**(e) Permanent Policy: 2015**

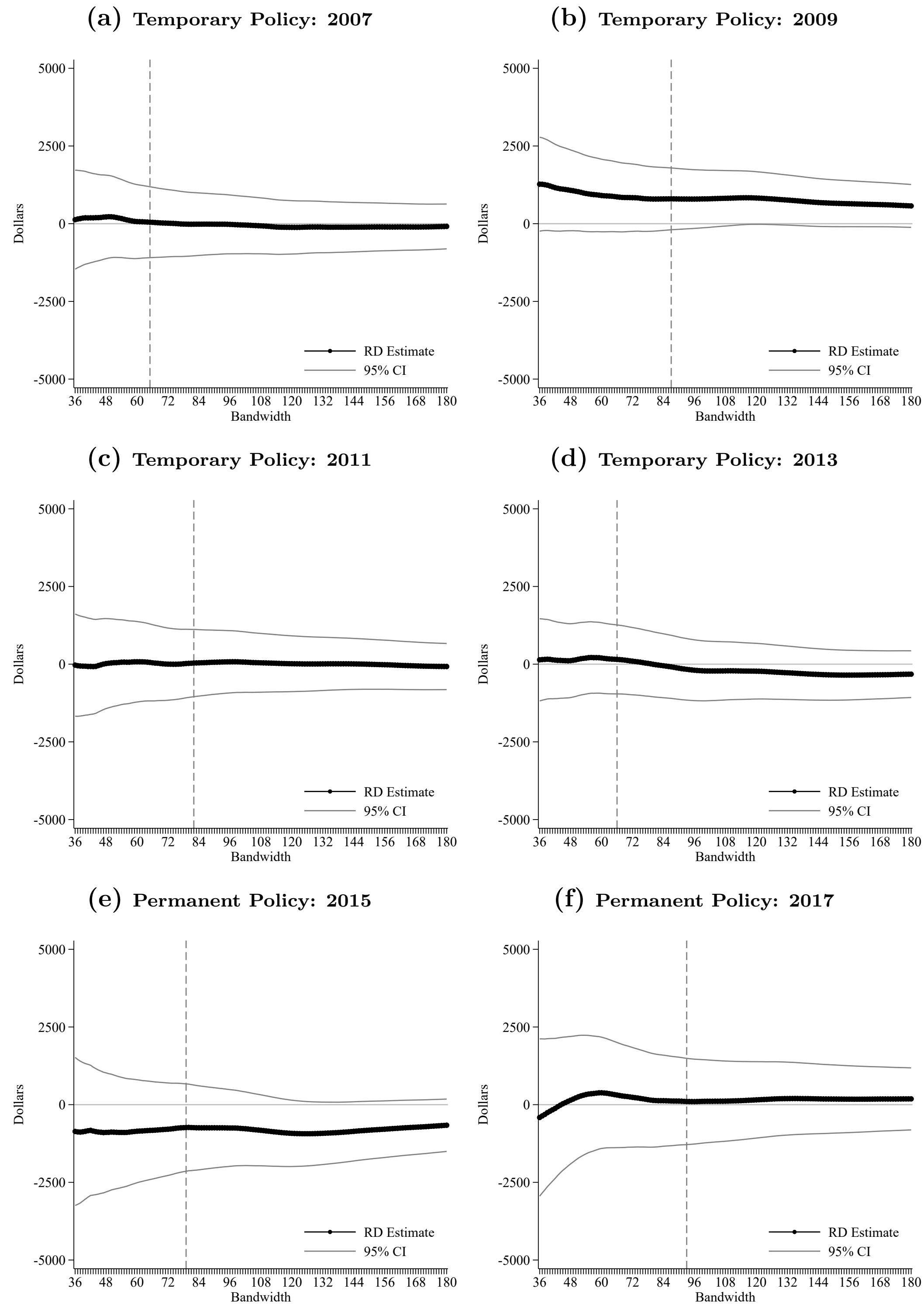



**(f) Permanent Policy: 2017**




Notes: This figure illustrates the robustness of the estimates for the indicator for giving to charity in earlier years to varying the bandwidth. Each graph plots the RD estimates and 95% confidence intervals that result from using bandwidths ranging from 36 months to 180 months. The vertical dashed lines denote the leading bandwidth.

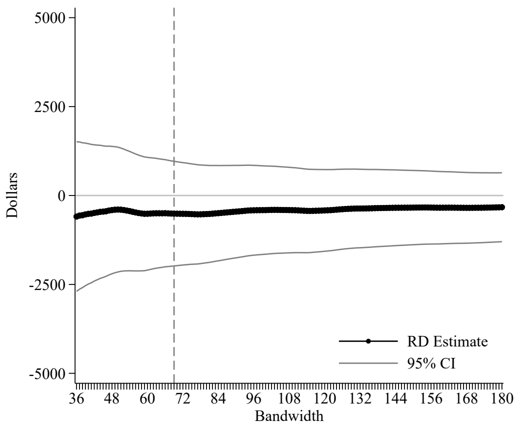
**Figure A.10: Robustness of Estimates for Donations (Including Zeros) in Earlier Years to Bandwidth Selection**



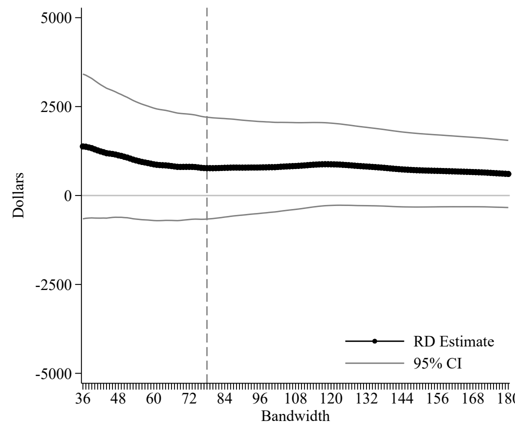

Notes: This figure illustrates the robustness of the estimates for donations (including zeros) in earlier years to varying the bandwidth. Each graph plots the RD estimates and 95% confidence intervals that result from using bandwidths ranging from 36 months to 180 months. The vertical dashed lines denote the leading bandwidth.

## Figure A.11: Robustness of Estimates for Donations Conditional on Giving in Earlier Years to Bandwidth Selection

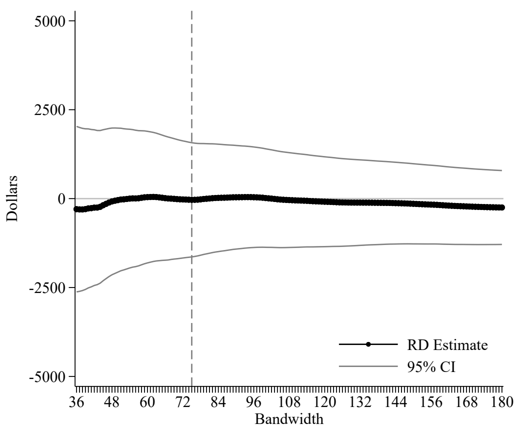
**(a) Temporary Policy: 2007**



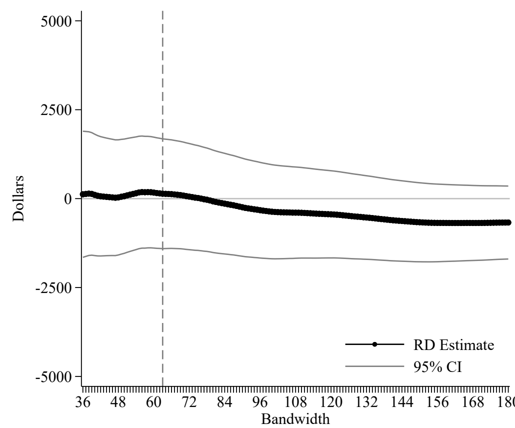

**(b) Temporary Policy: 2009**



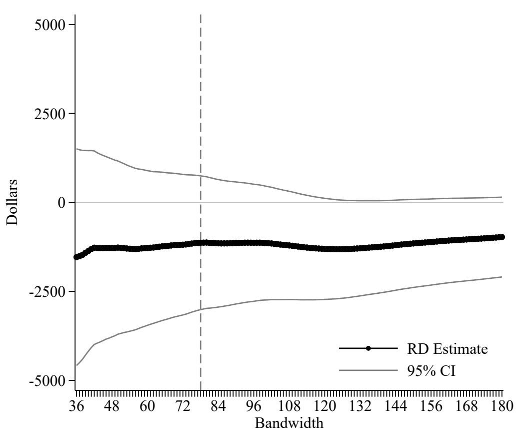

**(c) Temporary Policy: 2011**



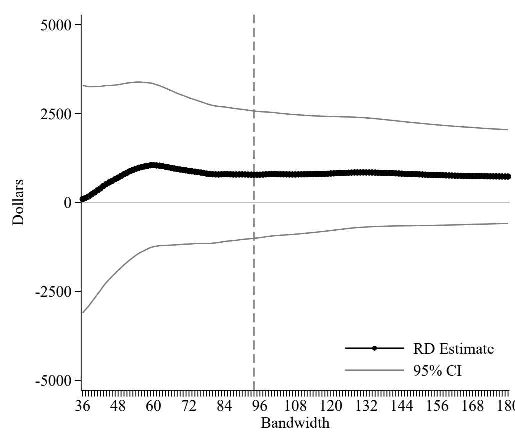

**(d) Temporary Policy: 2013**




**(e) Permanent Policy: 2015**



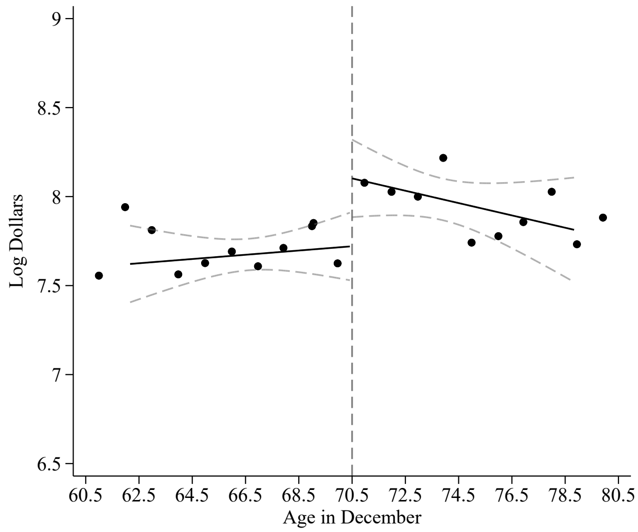

**(f) Permanent Policy: 2017**




Notes: This figure illustrates the robustness of the estimates for the indicator for donations conditional on giving in earlier years to varying the bandwidth. Each graph plots the RD estimates and 95% confidence intervals that result from using bandwidths ranging from 36 months to 180 months. The vertical dashed lines denote the leading bandwidth.

**Figure A.12: Effects of Qualified Charitable Distributions on Log Donations After the Tax Cuts and Jobs Act**

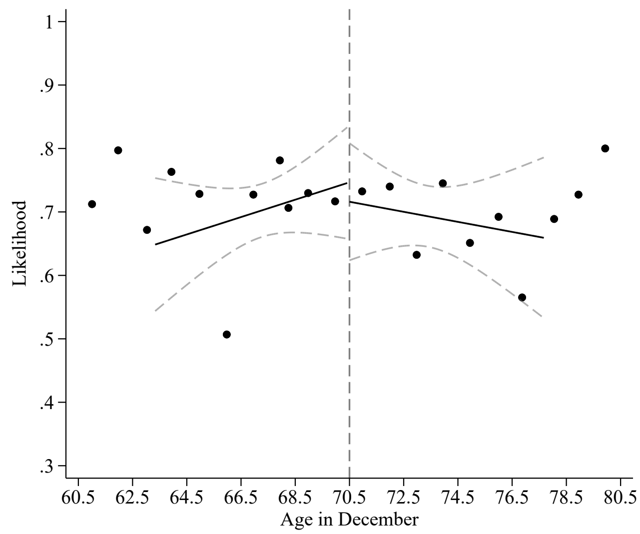
**(a) Log Donations**



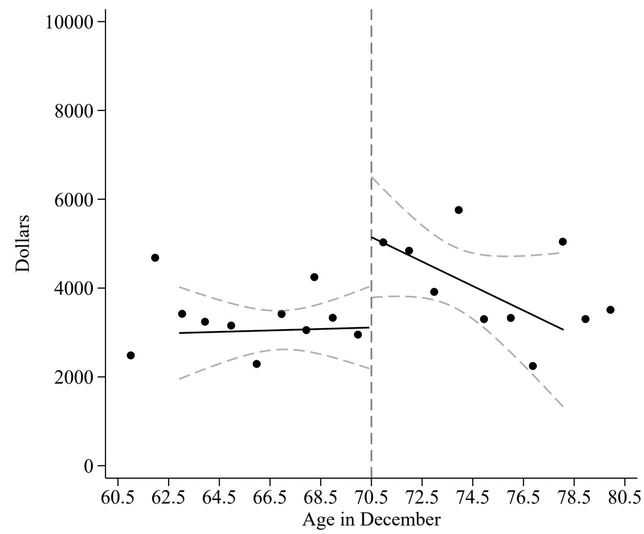

Notes: This figure illustrates the effects of aging into qualified charitable distributions on log donations in 2019. See the notes of Figure 2 for more details on how each graph is constructed.

**Figure A.13: Effects of Qualified Charitable Distributions on Charitable Giving After the Tax Cuts and Jobs Act for People with Above-Median Individual Retirement Account Balances**

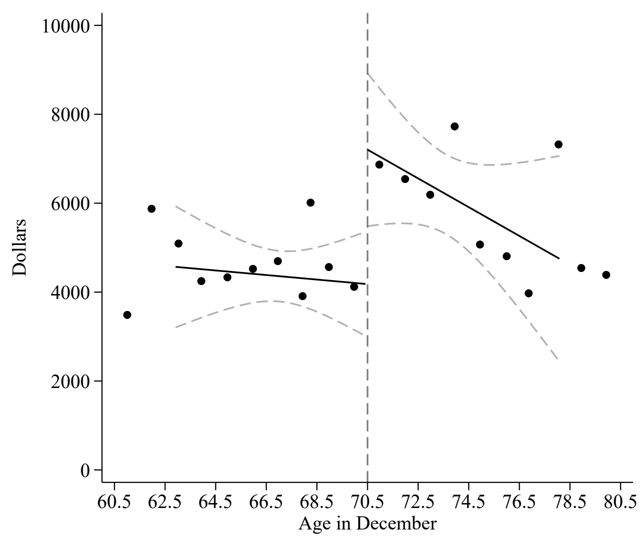
**(a) Indicator for Giving to Charity**




**(b) Donations (Including Zeros)**




**(c) Donations Conditional on Giving**



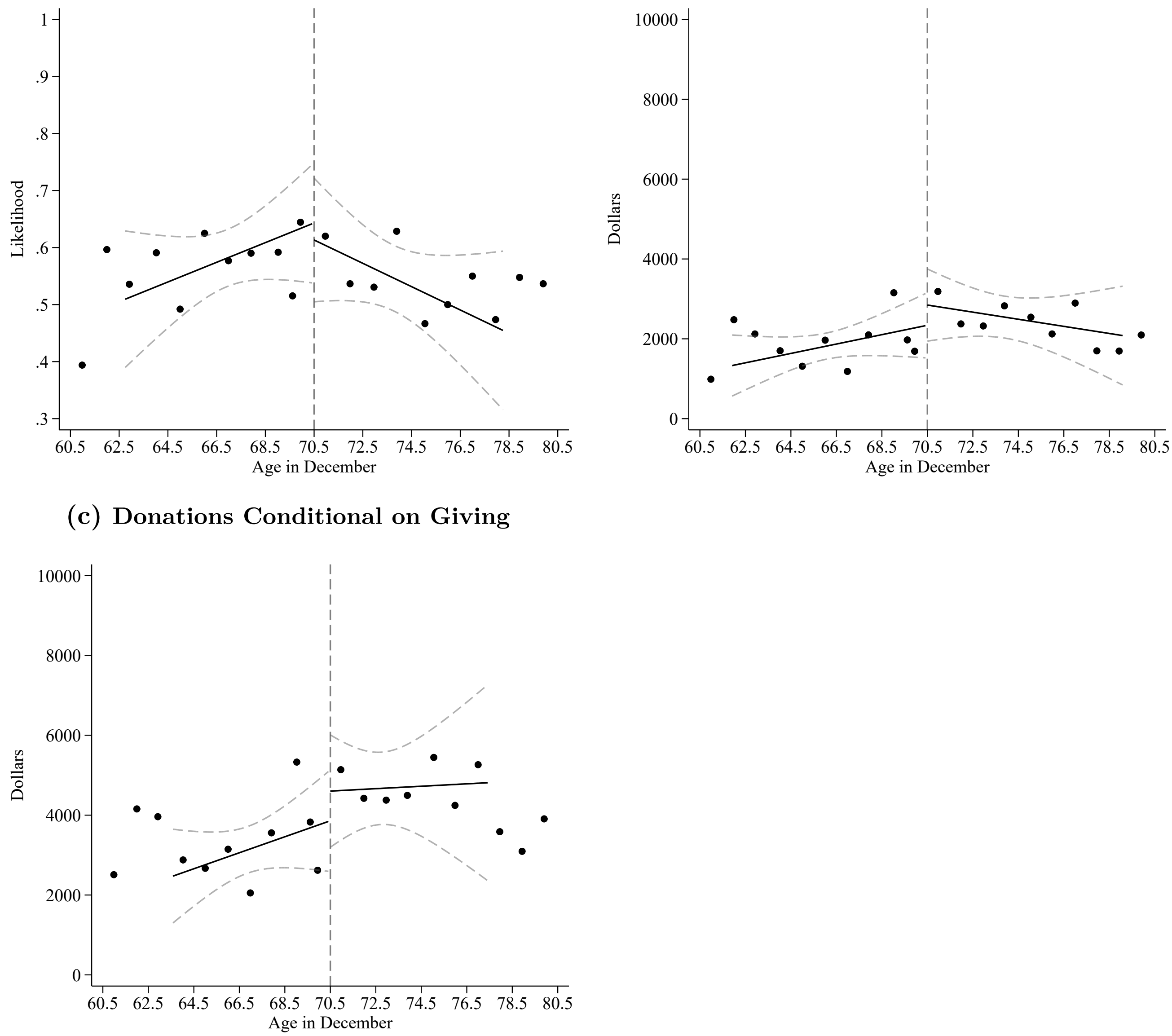

Notes: This figure illustrates the effects of aging into qualified charitable distributions on charitable giving in 2019 for the subsample of people who have above-median household IRA balances. Each graph corresponds to a different outcome. Graph (a) is for an indicator variable for giving to charity. Graph (b) is for donations in dollars, including zeros. Graph (c) is for donations in dollars, conditional on giving. See the figure notes of Figure 2 for more details on the construction of each graph.

**Figure A.14: Effects of Qualified Charitable Distributions on Charitable Giving After the Tax Cuts and Jobs Act for People with Below-Median Individual Retirement Account Balances**

**(a) Indicator for Giving to Charity**

**(b) Donations (Including Zeros)**

**(c) Donations Conditional on Giving**




Notes: This figure illustrates the effects of aging into qualified charitable distributions on charitable giving in 2019 for the subsample of people who have below-median household IRA balances. Each graph corresponds to a different outcome. Graph (a) is for an indicator variable for giving to charity. Graph (b) is for donations in dollars, including zeros. Graph (c) is for donations in dollars, conditional on giving. See the figure notes of Figure 2 for more details on the construction of each graph.

**Table A.1: Sample Restrictions and Resulting Sample Sizes**

| | Number of Individuals<br>(1) | Number of Observations<br>(2) |
|---|---|---|
| Keep waves 5 through 15 | 36,529 | 208,674 |
| Keep people with IRAs | 13,574 | 53,830 |
| Drop observations with missing donation outcomes | 13,180 | 49,963 |

Notes: This table reports the resulting numbers of unique individuals and observations after implementing each of the three analysis sample restrictions. The final analysis sample consists of 49,963 observations on 13,180 individuals.

## Table A.2: Density Test Results for Each Year

| | t-statistic (2) | p-value (2) |
|---|---|---|
| 2007 | 1.192 | 0.233 |
| 2009 | 1.220 | 0.222 |
| 2011 | -0.123 | 0.902 |
| 2013 | 0.368 | 0.713 |
| 2015 | -1.339 | 0.181 |
| 2017 | 1.683 | 0.092 |
| 2019 | -0.391 | 0.696 |

Notes: This table reports the resulting t-statistics and p-values from the formal density tests as proposed by Cattaneo, Jansson and Ma (2020) for each year.

**Table A.3: Regression Discontinuity Estimates Using Covariates as Outcome Variables**

| | Male<br>(1) | White<br>(2) | Married<br>(3) | College<br>(4) |
|---|---|---|---|---|
| RD Estimate for 2007 | -0.009 | 0.019 | -0.014 | -0.011 |
| | (0.054) | (0.023) | (0.044) | (0.044) |
| Mean | 0.518 | 0.919 | 0.747 | 0.598 |
| Bandwidth (Months) | 58 | 87 | 63 | 89 |
| Clusters (Households) | 1,355 | 1,833 | 1,444 | 1,861 |
| Observations (Individuals) | 1,600 | 2,276 | 1,726 | 2,316 |
| RD Estimate for 2009 | 0.007 | 0.020 | 0.061 | -0.036 |
| | (0.045) | (0.025) | (0.041) | (0.043) |
| Mean | 0.444 | 0.917 | 0.743 | 0.631 |
| Bandwidth (Months) | 87 | 74 | 78 | 90 |
| Clusters (Households) | 1,784 | 1,587 | 1,641 | 1,837 |
| Observations (Individuals) | 2,194 | 1,935 | 1,997 | 2,267 |
| RD Estimate for 2011 | 0.060 | 0.008 | -0.044 | 0.022 |
| | (0.048) | (0.030) | (0.044) | (0.047) |
| Mean | 0.433 | 0.914 | 0.757 | 0.684 |
| Bandwidth (Months) | 85 | 72 | 84 | 88 |
| Clusters (Households) | 1,589 | 1,384 | 1,575 | 1,643 |
| Observations (Individuals) | 1,917 | 1,656 | 1,900 | 1,987 |
| RD Estimate for 2013 | 0.056 | -0.001 | 0.040 | 0.092* |
| | (0.052) | (0.027) | (0.046) | (0.052) |
| Mean | 0.431 | 0.886 | 0.748 | 0.709 |
| Bandwidth (Months) | 76 | 84 | 79 | 74 |
| Clusters (Households) | 1,420 | 1,554 | 1,469 | 1,375 |
| Observations (Individuals) | 1,712 | 1,896 | 1,781 | 1,656 |
| RD Estimate for 2015 | -0.013 | -0.004 | 0.010 | -0.049 |
| | (0.053) | (0.030) | (0.046) | (0.045) |
| Mean | 0.459 | 0.868 | 0.738 | 0.766 |
| Bandwidth (Months) | 96 | 103 | 107 | 111 |
| Clusters (Households) | 1,594 | 1,694 | 1,755 | 1,821 |
| Observations (Individuals) | 1,947 | 2,091 | 2,169 | 2,264 |
| RD Estimate for 2017 | -0.069 | 0.005 | 0.036 | -0.033 |
| | (0.058) | (0.035) | (0.047) | (0.041) |
| Mean | 0.454 | 0.867 | 0.711 | 0.790 |
| Bandwidth (Months) | 75 | 89 | 95 | 115 |
| Clusters (Households) | 1,133 | 1,361 | 1,455 | 1,723 |
| Observations (Individuals) | 1,346 | 1,642 | 1,758 | 2,122 |
| RD Estimate for 2019 | -0.017 | 0.011 | 0.040 | 0.044 |
| | (0.059) | (0.036) | (0.051) | (0.045) |
| Mean | 0.465 | 0.845 | 0.711 | 0.789 |
| Bandwidth (Months) | 71 | 84 | 87 | 87 |
| Clusters (Households) | 1,096 | 1,286 | 1,333 | 1,334 |
| Observations (Individuals) | 1,296 | 1,543 | 1,600 | 1,601 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of reaching $70\frac{1}{2}$ on control variables in odd-numbered years from 2007 to 2017. Standard errors clustered at the household level are in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

**Table A.4: Investigating Confounding Policies: Effects of Reaching $70\frac{1}{2}$ on Charitable Giving in the Pre-Period, Before Qualified Charitable Distributions Existed**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| RD Estimate for 1999 | 0.054 | 778 | 886 |
| | (0.051) | (618) | (978) |
| Mean | 0.603 | 2,576 | 4,323 |
| Bandwidth (Month) | 81 | 69 | 57 |
| Clusters (Households) | 1,731 | 1,478 | 758 |
| Observations (Individuals) | 1,731 | 1,478 | 758 |
| RD Estimate for 2001 | -0.013 | 362 | 527 |
| | (0.048) | (564) | (726) |
| Mean | 0.662 | 2,947 | 4,510 |
| Bandwidth (Month) | 66 | 71 | 86 |
| Clusters (Households) | 1,433 | 1,526 | 1,123 |
| Observations (Individuals) | 1,763 | 1,901 | 1,470 |
| RD Estimate for 2003 | -0.013 | -5 | -219 |
| | (0.041) | (644) | (903) |
| Mean | 0.668 | 3,516 | 5,147 |
| Bandwidth (Month) | 92 | 52 | 52 |
| Clusters (Households) | 2,033 | 1,235 | 811 |
| Observations (Individuals) | 2,553 | 1,473 | 986 |
| RD Estimate for 2005 | -0.022 | -427 | -502 |
| | (0.041) | (455) | (623) |
| Mean | 0.658 | 3,139 | 4,742 |
| Bandwidth (Month) | 89 | 95 | 96 |
| Clusters (Households) | 1,946 | 2,035 | 1,329 |
| Observations (Individuals) | 2,430 | 2,567 | 1,707 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of reaching $70\frac{1}{2}$ on charitable giving in the pre-period, when required minimum distributions were in effect but before qualified charitable distributions existed. Each panel corresponds to a different pre-period year. Standard errors clustered at the household level are in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

**Table A.5: Investigating Confounding Policies: Effects of Reaching $70\frac{1}{2}$ on Social Security Benefits and Retirement**

| | Indicator for Social Security Benefits (1) | Indicator for Being Retired (2) |
|---|---|---|
| RD Estimate for 2007 | 0.016 | 0.036 |
| | (0.027) | (0.041) |
| Mean | 0.968 | 0.635 |
| Bandwidth (months) | 33 | 77 |
| Clusters | 840 | 1,684 |
| Observations | 932 | 2,063 |
| RD Estimate for 2009 | 0.028 | -0.025 |
| | (0.023) | (0.039) |
| Mean | 0.965 | 0.640 |
| Bandwidth (months) | 36 | 86 |
| Clusters | 905 | 1,764 |
| Observations | 1,028 | 2,167 |
| RD Estimate for 2011 | 0.044 | 0.013 |
| | (0.029) | (0.042) |
| Mean | 0.958 | 0.627 |
| Bandwidth (months) | 30 | 87 |
| Clusters | 635 | 1,624 |
| Observations | 709 | 1,966 |
| RD Estimate for 2013 | 0.008 | -0.102** |
| | (0.027) | (0.049) |
| Mean | 0.945 | 0.625 |
| Bandwidth (months) | 33 | 76 |
| Clusters | 621 | 1,420 |
| Observations | 691 | 1,712 |
| RD Estimate for 2015 | -0.038 | -0.035 |
| | (0.041) | (0.052) |
| Mean | 0.875 | 0.631 |
| Bandwidth (months) | 44 | 73 |
| Clusters | 678 | 1,189 |
| Observations | 762 | 1,427 |
| RD Estimate for 2017 | 0.009 | 0.072 |
| | (0.039) | (0.045) |
| Mean | 0.916 | 0.536 |
| Bandwidth (months) | 31 | 97 |
| Clusters | 468 | 1,479 |
| Observations | 525 | 1,789 |
| RD Estimate for 2019 | 0.043 | 0.059 |
| | (0.032) | (0.052) |
| Mean | 0.879 | 0.588 |
| Bandwidth (months) | 34 | 75 |
| Clusters | 561 | 1,163 |
| Observations | 627 | 1,381 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of reaching $70\frac{1}{2}$ on indicators for receiving Social Security benefits and for being retired. Each panel corresponds to a different year. Standard errors clustered at the household level are in parentheses. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$

**Table A.6: Robustness of Estimates for 2007 to Specification Checks**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| A. Baseline | 0.085* | -13 | -580 |
| | (0.050) | (580) | (748) |
| B. Include Controls | 0.086* | -16 | -584 |
| | (0.048) | (564) | (742) |
| C. Drop Triangular Weights | 0.054 | -102 | -640 |
| | (0.047) | (518) | (673) |
| D. Use Survey Weights | 0.051 | -201 | -741 |
| | (0.050) | (549) | (715) |
| E. Cluster on Running Variable | 0.085* | -13 | -580 |
| | (0.045) | (499) | (672) |
| F. No Winsorizing | – | -2,889 | -4,804 |
| | | (2,089) | (3,122) |
| G. Winsorize More | – | -75 | -602 |
| | | (490) | (613) |
| H. Log Donations | – | – | -0.089 |
| | | | (0.125) |

Notes: This table reports results from assessing the sensitivity of the 2007 estimates to various specification checks. Each column corresponds to a main outcome variable. Each row indicates the robustness check. Row A reproduces the baseline estimates for comparison. Row B adds control variables for gender, race, marital status, and college education to the regressions. Row C drops the triangular weights. Row D uses household survey weights instead of triangular weights. Row E clusters standard errors at the level of the running variable instead of at the household level. Row F does not winsorize donations. Row G winsorizes donations at the 99th percentile instead of the 99.5th percentile. Row H uses log donations as the outcome variable instead of donations conditional on giving measured in dollars. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$

## Table A.7: Robustness of Estimates for 2009 to Specification Checks

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| A. Baseline | 0.065 | 789 | 741 |
| | (0.043) | (500) | (719) |
| B. Include Controls | 0.058 | 769 | 812 |
| | (0.042) | (490) | (714) |
| C. Drop Triangular Weights | 0.054 | 751$^{*}$ | 703 |
| | (0.040) | (442) | (658) |
| D. Use Survey Weights | 0.028 | 685 | 715 |
| | (0.045) | (494) | (754) |
| E. Cluster on Running Variable | 0.065 | 789 | 741 |
| | (0.040) | (503) | (707) |
| F. No Winsorizing | – | 2,190 | 2,810 |
| | | (1,947) | (2,863) |
| G. Winsorize More | – | 673 | 590 |
| | | (417) | (596) |
| H. Log Donations | – | – | 0.077 |
| | | | (0.140) |

Notes: This table reports results from assessing the sensitivity of the 2009 estimates to various specification checks. Each column corresponds to a main outcome variable. Each row indicates the robustness check. Row A reproduces the baseline estimates for comparison. Row B adds control variables for gender, race, marital status, and college education to the regressions. Row C drops the triangular weights. Row D uses household survey weights instead of triangular weights. Row E clusters standard errors at the level of the running variable instead of at the household level. Row F does not winsorize donations. Row G winsorizes donations at the 99th percentile instead of the 99.5th percentile. Row H uses log donations as the outcome variable instead of donations conditional on giving measured in dollars. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

## Table A.8: Robustness of Estimates for 2011 to Specification Checks

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| A. Baseline | 0.014 | 52 | -33 |
| | (0.044) | (547) | (812) |
| B. Include Controls | 0.018 | 75 | -85 |
| | (0.043) | (538) | (806) |
| C. Drop Triangular Weights | 0.022 | 174 | -18 |
| | (0.041) | (488) | (711) |
| D. Use Survey Weights | 0.051 | 798 | 601 |
| | (0.047) | (541) | (771) |
| E. Cluster on Running Variable | 0.014 | 52 | -33 |
| | (0.040) | (567) | (873) |
| F. No Winsorizing | – | 438 | 501 |
| | | (1,421) | (2,135) |
| G. Winsorize More | – | 57 | 27 |
| | | (455) | (660) |
| H. Log Donations | – | – | 0.076 |
| | | | (0.143) |

Notes: This table reports results from assessing the sensitivity of the 2011 estimates to various specification checks. Each column corresponds to a main outcome variable. Each row indicates the robustness check. Row A reproduces the baseline estimates for comparison. Row B adds control variables for gender, race, marital status, and college education to the regressions. Row C drops the triangular weights. Row D uses household survey weights instead of triangular weights. Row E clusters standard errors at the level of the running variable instead of at the household level. Row F does not winsorize donations. Row G winsorizes donations at the 99th percentile instead of the 99.5th percentile. Row H uses log donations as the outcome variable instead of donations conditional on giving measured in dollars. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

## Table A.9: Robustness of Estimates for 2013 to Specification Checks

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| A. Baseline | 0.009 | 154 | 134 |
| | (0.049) | (566) | (783) |
| B. Include Controls | -0.003 | -63 | -193 |
| | (0.049) | (557) | (767) |
| C. Drop Triangular Weights | -0.003 | 69 | 74 |
| | (0.045) | (562) | (793) |
| D. Use Survey Weights | 0.055 | 317 | -14 |
| | (0.052) | (620) | (887) |
| E. Cluster on Running Variable | 0.009 | 154 | 134 |
| | (0.041) | (502) | (701) |
| F. No Winsorizing | – | 409 | 550 |
| | | (807) | (1,032) |
| G. Winsorize More | – | 65 | 1 |
| | | (522) | (717) |
| H. Log Donations | – | – | -0.031 |
| | | | (0.158) |

Notes: This table reports results from assessing the sensitivity of the 2013 estimates to various specification checks. Each column corresponds to a main outcome variable. Each row indicates the robustness check. Row A reproduces the baseline estimates for comparison. Row B adds control variables for gender, race, marital status, and college education to the regressions. Row C drops the triangular weights. Row D uses household survey weights instead of triangular weights. Row E clusters standard errors at the level of the running variable instead of at the household level. Row F does not winsorize donations. Row G winsorizes donations at the 99th percentile instead of the 99.5th percentile. Row H uses log donations as the outcome variable instead of donations conditional on giving measured in dollars. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.1$

**Table A.10: Robustness of Estimates for 2015 to Specification Checks**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| A. Baseline | -0.015 | -757 | -1,122 |
| | (0.049) | (715) | (949) |
| B. Include Controls | -0.008 | -673 | -1,195 |
| | (0.047) | (698) | (937) |
| C. Drop Triangular Weights | -0.031 | -675 | -1,045 |
| | (0.044) | (624) | (831) |
| D. Use Survey Weights | -0.060 | -812 | -1,009 |
| | (0.051) | (767) | (1,029) |
| E. Cluster on Running Variable | -0.015 | -757 | -1,122 |
| | (0.042) | (704) | (983) |
| F. No Winsorizing | – | -893 | -1,327 |
| | | (848) | (1,174) |
| G. Winsorize More | – | -725 | -1,070 |
| | | (651) | (845) |
| H. Log Donations | – | – | -0.245 |
| | | | (0.175) |

Notes: This table reports results from assessing the sensitivity of the 2015 estimates to various specification checks. Each column corresponds to a main outcome variable. Each row indicates the robustness check. Row A reproduces the baseline estimates for comparison. Row B adds control variables for gender, race, marital status, and college education to the regressions. Row C drops the triangular weights. Row D uses household survey weights instead of triangular weights. Row E clusters standard errors at the level of the running variable instead of at the household level. Row F does not winsorize donations. Row G winsorizes donations at the 99th percentile instead of the 99.5th percentile. Row H uses log donations as the outcome variable instead of donations conditional on giving measured in dollars. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

## Table A.11: Robustness of Estimates for 2017 to Specification Checks

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| A. Baseline | -0.089* | 104 | 785 |
| | (0.050) | (700) | (907) |
| B. Include Controls | -0.094* | 116 | 837 |
| | (0.049) | (679) | (881) |
| C. Drop Triangular Weights | -0.097** | 65 | 793 |
| | (0.046) | (613) | (804) |
| D. Use Survey Weights | -0.102** | -188 | 514 |
| | (0.051) | (749) | (960) |
| E. Cluster on Running Variable | -0.089* | 104 | 785 |
| | (0.045) | (719) | (896) |
| F. No Winsorizing | – | 709 | 1,797 |
| | | (1,290) | (1,981) |
| G. Winsorize More | – | 166 | 828 |
| | | (604) | (766) |
| H. Log Donations | – | – | 0.235 |
| | | | (0.161) |

Notes: This table reports results from assessing the sensitivity of the 2017 estimates to various specification checks. Each column corresponds to a main outcome variable. Each row indicates the robustness check. Row A reproduces the baseline estimates for comparison. Row B adds control variables for gender, race, marital status, and college education to the regressions. Row C drops the triangular weights. Row D uses household survey weights instead of triangular weights. Row E clusters standard errors at the level of the running variable instead of at the household level. Row F does not winsorize donations. Row G winsorizes donations at the 99th percentile instead of the 99.5th percentile. Row H uses log donations as the outcome variable instead of donations conditional on giving measured in dollars. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.12: **Placebo Estimates for People Without Individual Retirement Accounts in Earlier Years**

| | Indicator for Giving to Charity (1) | Donations (Including Zeros) (2) | Donations Conditional on Giving (3) |
|---|---|---|---|
| Tax Year: 2007 | | | |
| Placebo RD Estimate for 2007 | -0.025 | -79 | 30 |
| | (0.028) | (142) | (398) |
| Mean | 0.330 | 1,110 | 3,414 |
| Bandwidth (Months) | 90 | 109 | 96 |
| Clusters (Households) | 3,608 | 4,021 | 1,090 |
| Observations (Individuals) | 4,570 | 5,198 | 1,501 |
| Tax Year: 2009 | | | |
| Placebo RD Estimate for 2009 | -0.025 | -207 | -467 |
| | (0.028) | (153) | (385) |
| Mean | 0.350 | 1,034 | 2,896 |
| Bandwidth (Months) | 95 | 103 | 114 |
| Clusters (Households) | 3,563 | 3,786 | 1,309 |
| Observations (Individuals) | 4,538 | 4,869 | 1,803 |
| Tax Year: 2011 | | | |
| Placebo RD Estimate for 2011 | -0.023 | -250 | -628 |
| | (0.028) | (205) | (551) |
| Mean | 0.342 | 945 | 2,731 |
| Bandwidth (Months) | 111 | 103 | 87 |
| Clusters (Households) | 4,330 | 3,981 | 1,054 |
| Observations (Individuals) | 5,591 | 5,128 | 1,437 |
| Tax Year: 2013 | | | |
| Placebo RD Estimate for 2013 | 0.027 | 413** | 989* |
| | (0.033) | (210) | (556) |
| Mean | 0.323 | 921 | 2,733 |
| Bandwidth (Months) | 107 | 76 | 72 |
| Clusters (Households) | 4,040 | 2,793 | 840 |
| Observations (Individuals) | 5,088 | 3,438 | 1,089 |
| Tax Year: 2015 | | | |
| Placebo RD Estimate for 2015 | -0.007 | 219 | 709 |
| | (0.036) | (194) | (481) |
| Mean | 0.312 | 821 | 2,685 |
| Bandwidth (Months) | 99 | 108 | 83 |
| Clusters (Households) | 3,667 | 4,012 | 930 |
| Observations (Individuals) | 4,546 | 5,016 | 1,201 |
| Tax Year: 2017 | | | |
| Placebo RD Estimate for 2017 | -0.013 | 150 | 457 |
| | (0.037) | (211) | (555) |
| Mean | 0.291 | 763 | 2,623 |
| Bandwidth (Months) | 94 | 107 | 97 |
| Clusters (Households) | 3,064 | 3,536 | 940 |
| Observations (Individuals) | 3,759 | 4,394 | 1,228 |

Notes: This table reports placebo regression discontinuity (RD) estimates for people in households with no IRAs before the Tax Cuts and Jobs Act, in odd-numbered years from 2007 to 2017. Standard errors clustered at the household level are in parentheses. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$

## Table A.13: Summary Statistics for 2019

| | People With IRAs | | | People Without IRAs | | |
|---|---|---|---|---|---|---|
| | Mean (1) | SD (2) | Obs. (3) | Mean (4) | SD (5) | Obs. (6) |
| Age | 69.56 | 10.20 | 3,672 | 67.37 | 11.01 | 9,622 |
| Tax Year | 2019.00 | 0.00 | 3,672 | 2019.00 | 0.00 | 9,622 |
| Male | 0.45 | 0.50 | 3,672 | 0.39 | 0.49 | 9,622 |
| White | 0.85 | 0.36 | 3,671 | 0.57 | 0.50 | 9,567 |
| Married | 0.66 | 0.47 | 3,666 | 0.52 | 0.50 | 9,593 |
| College | 0.74 | 0.44 | 3,672 | 0.43 | 0.50 | 9,619 |
| Retired | 0.59 | 0.49 | 3,672 | 0.59 | 0.49 | 9,622 |
| Receives Social Security Benefits | 0.59 | 0.49 | 3,672 | 0.54 | 0.50 | 9,622 |
| Gives to Charity | 0.62 | 0.49 | 3,672 | 0.29 | 0.45 | 9,622 |
| Donations (Including Zeros) | 2,905 | 5,146 | 3,672 | 825 | 2,578 | 9,622 |
| Donations Conditional on Giving | 4,685 | 5,863 | 2,277 | 2,845 | 4,144 | 2,792 |
| IRA Balances | 338,865 | 535,959 | 3,672 | – | – | – |
| Individuals | | | 3,672 | | | 9,622 |

Notes: This table reports summary statistics for two groups. The underlying samples contain data from survey 15, which contains information on charitable giving for tax year 2019. The first three columns report means, standard deviations, and observations for people who own an IRA and make up my analysis sample. The next three columns report the same statistics for people in households where no member owns an IRA. The bottom row displays the number of unique individuals in each group.

## Table A.14: Effects of Qualified Charitable Distributions on Giving Large Amounts to Charity Before the Tax Cuts and Jobs Act

| | Indicator for Giving More than \$10,000 (1) | Indicator for Giving More than \$15,000 (2) | Indicator for Giving More than \$20,000 (3) | Indicator for Giving More than \$25,000 (4) |
|---|---|---|---|---|
| RD Estimate for 2007 | -0.018 | -0.014 | -0.010 | 0.019 |
| | (0.024) | (0.021) | (0.018) | (0.015) |
| Mean | 0.066 | 0.040 | 0.026 | 0.013 |
| Bandwidth (Months) | 71 | 69 | 63 | 52 |
| Clusters (Households) | 1,593 | 1,559 | 1,444 | 1,244 |
| Observations (Individuals) | 1,932 | 1,883 | 1,726 | 1,443 |
| RD Estimate for 2009 | 0.023 | 0.019 | 0.016 | 0.006 |
| | (0.021) | (0.017) | (0.015) | (0.012) |
| Mean | 0.061 | 0.027 | 0.020 | 0.015 |
| Bandwidth (Months) | 87 | 91 | 96 | 104 |
| Clusters (Households) | 1,784 | 1,853 | 1,924 | 2,049 |
| Observations (Individuals) | 2,194 | 2,289 | 2,400 | 2,565 |
| RD Estimate for 2011 | -0.014 | 0.001 | -0.001 | 0.003 |
| | (0.026) | (0.020) | (0.016) | (0.014) |
| Mean | 0.083 | 0.044 | 0.027 | 0.015 |
| Bandwidth (Months) | 76 | 77 | 99 | 93 |
| Clusters (Households) | 1,443 | 1,463 | 1,816 | 1,715 |
| Observations (Individuals) | 1,734 | 1,755 | 2,225 | 2,087 |
| RD Estimate for 2013 | 0.018 | -0.006 | 0.007 | 0.015 |
| | (0.031) | (0.023) | (0.016) | (0.010) |
| Mean | 0.105 | 0.051 | 0.024 | 0.018 |
| Bandwidth (Months) | 67 | 84 | 73 | 69 |
| Clusters (Households) | 1,248 | 1,555 | 1,362 | 1,289 |
| Observations (Individuals) | 1,481 | 1,897 | 1,631 | 1,527 |
| RD Estimate for 2015 | -0.050 | 0.010 | -0.018 | 0.001 |
| | (0.039) | (0.027) | (0.017) | (0.013) |
| Mean | 0.099 | 0.043 | 0.027 | 0.016 |
| Bandwidth (Months) | 87 | 80 | 105 | 115 |
| Clusters (Households) | 1,443 | 1,306 | 1,724 | 1,885 |
| Observations (Individuals) | 1,756 | 1,580 | 2,129 | 2,347 |
| RD Estimate for 2017 | -0.002 | 0.010 | 0.009 | -0.004 |
| | (0.038) | (0.030) | (0.026) | (0.016) |
| Mean | 0.097 | 0.040 | 0.028 | 0.020 |
| Bandwidth (Months) | 94 | 96 | 97 | 127 |
| Clusters (Households) | 1,447 | 1,469 | 1,479 | 1,887 |
| Observations (Individuals) | 1,744 | 1,778 | 1,789 | 2,340 |

Notes: This table reports regression discontinuity (RD) estimates for the effects of aging into qualified charitable distributions on indicator variables for making large donations to charity before the Tax Cuts and Jobs Act, in odd-numbered years from 2007 to 2017. The RD estimates come from estimating equation (1). Standard errors clustered at the household level are in parentheses. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$