The Impact of Health Insurance on Stockholding: A Regression Discontinuity Approach[#]

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October 10 2019

Abstract

Economic theory predicts that a reduction in background risk should induce financial risk-taking, particularly for individuals with low stock market participation costs. Hence, health insurance coverage could affect financial risk-taking by offsetting health-related background risk. We use a regression discontinuity design to examine whether Medicare eligibility at age 65 increases stockholding in the US and find that it does so for those with college education, but not for their less-educated counterparts who face higher stock market participation costs. Our results are unlikely due to the reduction of medical expenses associated with Medicare coverage because the latter does not affect bondholding.

Keywords: Health Insurance, Medicare, Stockholding, Regression Discontinuity, Household Finance
JEL Codes: D14, I13, G11

[#] We would like to thank Luigi Benfratello, Giorgio Brunello, Mariacristina De Nardi, Asier Mariscal, Luca Nunziata, Lorenzo Rocco, Arthur van Soest, and seminar participants at the Bi-Annual Household and Behavioral Finance Symposium at Cornell University, Queens College – City University of New York, the 8th CSEF/IGIER conference, the 11th CRETE conference, the University of Alicante, Universitat Pompeu Fabra, Universidad Pública de Navarra, the University of Venice Ca' Foscari, the University of Padova, the Netspar International Pension Workshop, the European Central Bank, the University of New South Wales, the 2013 EALE conference, the University of Auckland and CEPS/INSTEAD for helpful comments. Christelis acknowledges financial support from the European Union and the Greek Ministry of Education under program Thales, Grant MIC 380266. Sanz-de-Galdeano is also affiliated with CRES-UPF. She acknowledges financial support from the Spanish Ministry of Economy and Competitiveness Grant ECO2017-87069-P. The opinions expressed in the paper are those of the authors and do not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

1. Introduction

Public policy interventions often have unintended consequences. Health care policies in particular may have broader implications, for example, for household risk-taking and financial investing, that have not been fully explored.[1] This may be the case as health-related background (i.e., not fully insurable) risks are likely to affect financial risk-taking,[2] and especially so among older households, given that health care costs strongly depend on age.[3]

In this paper, we attempt to fill this gap by employing a credible identification strategy to estimate the impact of Medicare on stockholding. Specifically, we exploit the fact that the health insurance status of the US population changes drastically at age 65, when most individuals become eligible for Medicare. This institutional feature lends itself to a regression discontinuity design, such that variations in health coverage near the age 65 threshold are arguably "as good as random". We use data from the US Health and Retirement Study (HRS), a nationally representative survey of older households that provides detailed information on their demographic characteristics and financial decisions. Importantly, the older segment of the population holds the largest share of assets in the United States (78% of gross equities and 75% of net worth held by the total population per the 2007-2010 Survey of Consumer Finances).

As shown by Card, Dobkin and Maestas (2008, henceforth CDM), Medicare eligibility improves health insurance both in terms of coverage (which becomes nearly universal after age 65) and generosity (generally measured as the probability of having two or more health insurance policies). Interestingly, CDM also show that Medicare benefits not only the more disadvantaged but also whites and the better educated, among whom the rise in multiple coverage at age 65 is sharper than among their counterparts from lower socioeconomic backgrounds. Consistent with these patterns, Barcellos and Jacobson (2015,

[1] In contrast, much academic, policy and media attention has been devoted to the relationship between health insurance and labor market outcomes. See Gruber and Madrian (2004) and Madrian (2007) for reviews and the references therein.

[2] For example, per Himmelstein et al. (2009), "62.1% of all bankruptcies in 2007 were medical" in the United States.

[3] Indeed, nearly half of lifetime medical expenditures are incurred after age 65 and, for those who survive to age 85, more than one-third of their lifetime expenditures will accrue in their remaining years (Alemayehu and Warner, 2004). Recent simulations also indicate that, in 2009, a typical married couple age 65 had a 5% probability of lifetime uninsured health care costs over $311,000. If nursing costs are included, this figure reaches $570,000, while by 2007, at the peak of the stock market, less than 15% of households approaching retirement had accumulated that much in total financial assets (Webb and Zhivan, 2010).

henceforth BJ) find that Medicare eligibility reduces out of pocket spending significantly more for the highly educated than for those with less than high school.

Economic theory predicts that a reduction in one type of background risk should induce investment in risky assets, even if the reduced risk is uncorrelated with that of the risky assets (Gollier and Pratt, 1996). Risks related to income, entrepreneurship and health have often been suggested as instances of a background risk that is negatively associated with risky asset ownership.[4] A lower background risk, however, may not suffice to induce investment in risky assets. In fact, despite the equity premium, most US households do not hold stocks, and in several standard life-cycle portfolio models incorporating background risk the optimal level of risky assets is zero after the introduction of participation costs (Haliassos and Bertaut, 1995; Vissing-Jørgensen, 2002).

Transaction costs are a leading explanation for the reluctance of households to hold stocks because, as Haliassos (2002) points out, a risk averse utility maximizing household will always want to invest even a small amount in stocks due to the equity premium. This result was first pointed out by Arrow (1974), and holds in the presence of risky labor income, and also of background risk uncorrelated with stock returns. The intuition is that starting from a position of no stock investment, a marginal addition of a risky asset will not contribute to consumption riskiness, while it will allow the household to take advantage of the equity premium. Therefore, if the household does not invest in stocks, then it is likely that such investment entails some cost.[5]

Hence, the existence of participation costs makes the question of whether the willingness to take financial risks is increased due to the drop in background risk stemming from Medicare's increased insurance coverage generosity ultimately an empirical one.

[4] For instance, Rosen and Wu (2004) find evidence that older households in the US that report having health problems are less likely to invest in stocks. In addition, Coile and Milligan (2009) show that the death of a spouse and the experience of an acute health condition, like a stroke, are associated with a significant portfolio rebalancing. In line with the notion that a reduced exposure to background risk should make individuals more willing to bear other risks, Fairlie, Gates and Kapur (2011) find that business ownership rates increase from just under age 65 to just over age 65. See also Guiso, Jappelli and Terlizzese (1996), Heaton and Lucas (2000), Viceira (2001), Edwards (2008), Yogo (2016), Atella, Brunetti and Maestas (2012).

[5] For example, Vissing-Jorgensen (2002) estimates that participation costs of 50 US dollars (in 2000 prices) are enough to explain the non-participation of about half of US households in 1989 and 1994.

In addition, given that individuals eligible for Medicare face lower out of pocket medical expenditures, they should have more funds at their disposal, which should, in turn, make them more likely to invest in risky assets.

Our paper is, to the best of our knowledge, the first one to analyze the effect of Medicare on stockholding, and contributes to a small and incipient literature that links health insurance and financial decisions.[6] Our primary contribution is to use a highly credible regression discontinuity (RD henceforth) research design that rests on mild identification assumptions to answer a policy relevant question: does the onset of Medicare induce stockholding?

We find that Medicare eligibility induces households with college education to invest in stocks Our preferred estimates suggest an increase in total stockholding (that is, direct, through mutual funds and through IRAs stock ownership), ranging from 7 to about 14 percentage points (pp) for this education group, depending on the method used. On the other hand, we find no effect of Medicare on stockholding for those whose members have not finished college. Our results imply that the reduction in background risk due to Medicare eligibility suffices to overcome the pecuniary and non-pecuniary costs that inhibit participation in the stock market only if these costs are low enough, as is the case for individuals with a higher educational attainment (see Haliassos and Bertaut, 1995). As we discuss below, however, our results likely represent conservative estimates of our effect of interest due to some features of our set-up. Hence, getting health insurance coverage might affect financial risk-taking also for those with less than college education.

An additional factor that might drive our results is the reduction in expected out-of-pocket (henceforth OOP) medical expenditures that Medicare coverage entails. This should lead, however, to

[6] Several influential papers have examined the first-order effects of Medicare on health and health care utilization. Card, Dobkin and Maestas (2009) find that Medicare eligibility significantly reduces the death rate of severely ill patients who are admitted to hospitals through the emergency department for non-deferrable conditions. An earlier study by Decker (2002) also focuses on a subpopulation whose immediate mortality experience is more likely to be affected by Medicare-related changes in health care (breast cancer patients) and provides evidence of better outcomes for those over 65. However, when focusing on the overall population, Finkelstein and McKnight (2005) find that the introduction of Medicare does not reduce the relative mortality of individuals over 65 and Card, Dobkin and Maestas (2004) show that the age profiles of self-reported health status are relatively smooth around age 65. In contrast, conclusions regarding health care utilization are unambiguous: the onset of Medicare age-eligibility significantly increases the use of health services (Card, Dobkin and Maestas, 2008).

increased investment also in less risky financial assets such as bonds. We find no effect of Medicare coverage on bondholding, and thus surmise that our results are primarily driven by the Medicare-induced reduction in background risk.

A paper that is similar in spirit to ours is Goldman and Maestas (2013, henceforth GM), who also explore the relationship between health insurance coverage and financial risk-taking. While GM provide insightful evidence, our work differs from theirs in several important ways.

First, our work is the first to investigate whether Medicare, the second largest social insurance program in the United States, may have unintended consequences on the financial decisions of the elderly. Instead, GM focus on the implications of obtaining additional supplemental insurance[7] among Medicare beneficiaries. They find that this supplemental insurance has an economically sizeable and statistically significant effect on risky asset ownership. Interestingly, given that the heterogeneity in terms of coverage and its characteristics is much wider between Medicare beneficiaries and non-beneficiaries than among Medicare beneficiaries, one would expect the onset of Medicare eligibility to have even larger effects on portfolio decisions than those estimated for supplemental insurance (among 65+ Medicare beneficiaries). In any case, the potential consequences of Medicare on financial markets is an important aspect that policy makers may need to be aware of and give consideration when contemplating future health care reforms.

Second, we importantly differ from GM in terms of identification. Estimating the causal effect of health insurance coverage on financial risk-taking behavior is complicated by the fact that insurance coverage is an endogenous variable, and there are concerns over the potential confounding role of unobservables, such as individual health status and risk aversion. GM use an IV approach to address the endogeneity of supplemental insurance choice among Medicare beneficiaries. Specifically, they use as instruments the variation in county-level non-Medicare HMO market penetration and in state laws that limit the structure of risk pooling by insurers. Therefore, their identification strategy crucially relies on the assumption that neither of these instruments correlate with risky asset ownership other than through their effect on supplemental insurance choices. By contrast, we rely on a RD design that

[7] Through Medigap, an employer, or a Medicare HMO.

exploits the Medicare-induced discontinuity in health coverage at age 65 to identify the causal effect of interest under seemingly mild assumptions compared to those needed for other non-experimental approaches (Hahn et al., 2001).[8]

In work subsequent to ours, Ayyagari and He (2017, henceforth AH) study the effect on portfolio choice of Medicare Part D, which provides a prescription drug benefit and was introduced in 2006. Using HRS data and a difference-in-differences (DiD) identification strategy they find that Medicare Part D increases the propensity to invest in risky assets. Our identification strategy on the other hand does not rely on the parallel trends assumption required in DiD estimation, while our treatment is coverage by the main Medicare program, and not just Part D.

In another related paper subsequent to ours Angrisani et al. (2016), using HRS data and fixed-effects estimation techniques, investigate whether Medicare coverage mitigates the negative effect of bad health on financial risk-taking, and whether this interaction effect is stronger for those who had no health insurance coverage prior to the time they became covered by Medicare. Hence, they do not estimate the direct effect of Medicare coverage on financial risk-taking, but they still find that Medicare coverage makes those in poor health more likely to assume financial risk.

Finally, we examine different subgroups that, in line with economic theory, should exhibit a different propensity to hold stocks in response to Medicare eligibility. Specifically, stock market participation costs which can be both pecuniary (e.g., brokerage fees) and non-pecuniary (e.g., time spent to find the most suitable assets to invest in, to consult with financial advisors, to monitor market developments) typically vary by education. A higher level of human capital is associated with higher financial resources and more efficient information processing, making both these costs easier to bear. Hence, we examine different education groups, as it is natural to expect the impact of a reduction in background risk on stockholding to differ by education due to the education-induced variation in stock market participation costs. In line with this idea, we find that getting Medicare coverage induces

[8] Some earlier studies have also used a regression discontinuity design that exploits the onset of Medicare at age 65, but with a different aim (see for instance, Card, Dobkin and Maestas, 2008 and 2009; Fairlie, Kapur and Gates, 2011; BJ).

stockholding for those with college education, for whom informational and pecuniary stock market participation costs are relatively low, but not for their less-educated counterparts.

The remainder of the paper is organized as follows. Section 2 gives some details on the institutional features of Medicare. We discuss our data and empirical methodology in Section 3 and our main results in Section 4. In Section 5 we describe various specification and robustness checks that we have performed, while Section 6 concludes.

2. Medicare eligibility, health insurance and health expenditures of the elderly

Medicare, which represents by far the largest government insurance program in the US, was implemented in 1965 to provide health insurance coverage at older ages.[9] Thanks mainly to Medicare, only about one percent of older households (65+) are uninsured (Madrian, 2007).

Individuals become eligible for Medicare when they turn 65 if they or their spouses have worked for at least 10 years in Medicare-covered employment. Individuals under 65 years of age are also eligible for Medicare if they are getting Social Security Disability Insurance or if they have end-stage renal disease and either they or their spouses have met the Medicare work requirement. Eligible individuals who enroll in Medicare obtain hospital insurance (Part A) for free, while Part B, which covers doctor services, outpatient care, and some preventive services that are not covered under Part A, is available for a modest monthly premium.[10]

It is well documented that health insurance coverage status changes remarkably at age 65 as most people become eligible for Medicare. For example, Card, Goldman and Maestas (2004, 2008 and 2009) show that this is indeed the case using data from the National Health Interview Survey. Figure 1 confirms this pattern for our representative sample of elderly households from the HRS. Medicare coverage rises by 73.4 percentage points at age 65, from 15.4% to 88.8% among 64- and 66-year olds,

[9] Medicare accounts for a substantial and growing share of total health care spending in the US. Specifically, Medicare spending, which represented 20 percent of national health spending in 2012, grew 4.8 percent to $572.5 billion in the same year (Centers for Medicare & Medicaid Services, 2013). Moreover, according to the Congressional Budget Office (2013), federal spending on the government's major health care programs is projected to rise substantially relative to GDP.

[10] Additionally, U.S. citizens and legal aliens with at least five years of residency who do not qualify can also enroll in Medicare by paying monthly premiums for both Parts A and B coverage.

respectively. Since Medicare enrollment prior to 65 is lower among college-educated households, the coverage gap between 64 and 65 is even more pronounced for them (80 pp) than for non-college educated households (72 pp), which is consistent with Disability Insurance enrollment patterns for minorities and less educated individuals (Autor and Duggan, 2003).

Note also that, although Medicare unquestionably increases access to coverage (see, e.g., CDM), individuals very often choose to supplement it by purchasing Medigap plans, enrolling in Medicare Advantage, a Medicare HMO or obtaining retiree health insurance through employers (Baicker and Levy, 2012).

In addition, CDM show that the onset of Medicare improves coverage generosity especially for better-off population groups like college graduates and whites, who are more likely to obtain supplemental coverage (i.e., to report two or more policies) after age 65.[11] As a consequence of obtaining more generous coverage, these groups are also found to have a much higher increase in relatively high-cost procedures —including hospitalization for bypass surgery and hip and knee replacement— relative to their less educated and non-white counterparts.

Importantly, there is also evidence that Medicare offers older people significant protection against medical expenditure risk and financial strain. Specifically, BJ find that, at age 65, OOP expenditures drop by about 33% at the mean ($326) and 53% ($1,730) among the top 5% of spenders. Moreover, they also find large reductions in several measures of financial strain at age 65. In sum, while it is well established that Medicare eligibility significantly affects health insurance (in terms of both coverage and generosity) and medical expenditure risk, it remains to be analyzed if and the extent to which it impacts financial risk-taking behavior.

3. Data and Methodology

3.1 Data

[11] Such multiple coverage schemes are often considered very generous and even "too much insurance", as they not only provide additional benefits but often cover the cost-sharing and deductibles in the basic Medicare package, which lacks a cap on out of pocket spending (Baicker and Levy, 2012).

We utilize data from the Health and Retirement Study (HRS), a nationally representative, longitudinal survey offering detailed information on household socioeconomic characteristics, income, and wealth. The survey was launched in 1992 and interviews every two years about 20,000 Americans aged 50 and older. The HRS is the dataset that best serves our purposes because it collects high quality data on both household portfolio and health insurance for a representative sample of older households and it records the month and year of birth of all household members, which is crucial for the implementation of the RD method in our context.[12]

HRS respondents are asked in every survey year whether they are covered by Medicare. In addition, households are asked whether they own stocks in different forms: i) directly or through mutual funds (i.e., it is not possible to distinguish between stocks held directly and stocks held through mutual funds); ii) since the 1998 wave, through Individual Retirement Accounts (IRAs), which represent the most common form of stockholding in the U.S.[13] More specifically, IRA owners are asked whether their funds have been allocated mostly in stocks, bonds or split between the two.

One important advantage of using the broader definition of stockholding is that it is not affected by any misclassification by the respondents of one form of stock ownership into another. For example, if they invest in mutual funds through their IRAs they could conceivably report this investment when asked whether they own stock mutual funds.

When comparing data before 1998 from the HRS and the Survey of Consumer Finances, which is the most comprehensive micro-data survey on assets in the US, we find that the prevalence of the first form of stockholding (direct or through mutual funds) is significantly overestimated in the HRS. On the other hand, the two datasets match very closely from the 1998 wave onwards for both forms of stockholding. This pattern implies that in pre-1998 waves numerous HRS respondents who held stocks through IRAs reported them as being held directly or through mutual funds, most probably because the

[12] Data from the HRS have been extensively used in empirical household finance literature. For an early analysis of asset transitions among older households see Hurd (2002). See also, Hong, et al. (2004), Rosen and Wu (2004), and Bogan (2008) who examine, respectively, the effects of sociability, reported health, and internet use on stockholding decisions.

[13] See for example Christelis, Georgarakos and Haliassos (2011), who study household stock investing through different saving vehicles and show that the expansion in the pool of stockholders over the 1990s is mainly linked to the increasing number of households investing in stocks through IRAs.

question on stockholding through IRAs was not asked before 1998. Consequently, ownership of stocks held directly or through mutual funds is likely to be significantly overestimated in HRS waves prior to the 1998 one. In view of all the above, we opted to use data starting from the 1998 wave and up to the 2012 wave in the RAND HRS files (i.e., we use eight waves in total).[14]

The HRS collects information on health insurance and demographic characteristics of each member of a couple. As it is typical in surveys measuring household finances, information regarding wealth and its various components (including stocks) is jointly reported for couples. Hence, in the case of households formed by a married or cohabiting couple, one needs to decide how to link age, which triggers our treatment variable, to stock ownership.

One possibility would be to treat each partner in a couple as a separate observation and assume that a couple's stockownership status applies to both partners. However, even if stocks are jointly held, one cannot tell from the data whether both partners agreed on this decision, or whether they disagreed but one partner prevailed on the other, or whether one of the partners did not really have an opinion on the matter. Hence attributing a positive attitude to stockholding to both partners in the case of observed stock ownership in the couple is not warranted. Correspondingly, one cannot attribute a negative attitude to both partners when no stockholding is observed.

In addition, as Lee and Lemieux (2010, LL henceforth) point out, one can think about a regression discontinuity design within a potential outcomes framework (Rubin, 1974). One key assumption needed in such a framework is that of the Stable Unit Treatment Value Assumption (SUTVA), which states that the potential outcome of one unit is not affected by the treatment assigned to another one. This assumption is unlikely to hold in our set-up, given that one partner's portfolio choices following treatment typically affect the choices of the untreated partner.[15]

[14] The RAND HRS Data file is an easy to use longitudinal data set based on the HRS data. It was developed at RAND with funding from the National Institute on Aging and the Social Security Administration. For further information see http://www.rand.org/labor/aging/dataprod/hrs-data.html.
[15] De Nardi et al. (2014) provide evidence of substantial such spillovers in couples.

In light of the above, we conduct our analysis at the household level (i.e., by treating the two partners in a couple as one decision-unit.[16] Specifically, we take the maximum age of the two partners, as crossing the age 65 threshold for the older partner surely represents a potential reduction in background risk and/or a potential reduction in medical outlays, while such reductions might not be as large for the couple when the younger partner crosses the same age threshold.

Correspondingly to the household-level definition of the outcome, we define our treatment variable at the household level. Specifically, we use a binary variable denoting Medicare coverage in the household if any of the two partners in couple is covered. This definition covers the cases in which a younger partner is covered while the older is not, possibly due to an early onset of Medicare coverage due to disability. Another possibility would be to define Medicare coverage at the household level using only the information on the coverage of the older partner. In practice the two definitions are essentially equivalent, as in only 1.36% of married or co-habiting households aged 60-69 is the younger partner the only one covered by Medicare. Hence, the two alternative definitions lead to essentially identically estimates of the effects of interest.

Therefore, the sample used in our baseline analyses consists of both singles and couples. Our conclusions remain basically unaffected when our sample is constrained only to singles and couples in which both partners are of the same age.[17]

For completeness, we examine separately as outcomes the two possible stock ownership modes; direct or through mutual funds, and direct or through mutual funds or through IRAs. In what follows, we refer to the latter stockholding mode as stockownership in any form or total stockholding.

Table 1 shows the prevalence of stock ownership for all households in which the oldest member is aged from 60 to 69 by type of stockholding mode and level of education, defined in the case of couples as the maximum education level over the two partners. We note that only about 45% of all

[16] Choosing the financial respondent to represent a couple would not be a solution given that this designation applies to different partners across waves and is often assigned based on convenience, i.e., on who has more time available to be interviewed.

[17] In a previous version of the paper we showed results only for singles, for whom the choice of age is unambiguous, and, as a robustness check, we analyzed singles together with couples in which both partners have the same age (thus crossing the age 65 threshold together). Reassuringly, we reached similar conclusions to those in this paper. See Christelis, Georgarakos and Sanz-de-Galdeano (2014).

households in the sample invest in stocks in any form. The likelihood of holding stocks increases considerably with education, a finding that is well documented by the household finance literature.[18] Specifically, total stockholding rates are remarkably higher among college-educated households (71.4%) than among households with less than high school education (8.8%). This data pattern is consistent, as discussed in the Introduction, with the fact that stock market participation costs go down with educational attainment.

3.2 Methodology

Our goal is to estimate the causal impact of having insurance through Medicare on stock ownership. To this purpose, we use a RD design.[19] In our context, the basic idea behind the RD method is that eligibility for medical services through Medicare is determined at least partly by the value of a forcing or treatment-determining variable, which is age, being on either side of a fixed threshold (65). As we have shown in Figure 1, the probability of having Medicare does not change from zero to one at age 65; instead, there are individuals below 65 who already have Medicare coverage (about 8.5% in our sample), even if there is indeed a very large jump in the probability of being covered by Medicare at age 65. Given that there is no one-to-one correspondence between our treatment and the indicator for being at or above the RD threshold (i.e., being at age 65 or above), we use a fuzzy RD (FRD henceforth) design to estimate the impact of having Medicare insurance.

Our general framework is the same as that in BJ, so we adapt their equations (1)-(3) (pp. 47-48 in BJ) to our question of interest. In particular, we postulate an equation for stockholding as follows:

$$s_i = \alpha + f(age_i, \boldsymbol{\lambda}) + \beta Med_i + \delta \boldsymbol{X}_i + \varepsilon_i, \tag{1}$$

where s_i is a binary indicator denoting stockholding by household i, Med is a binary indicator denoting Medicare insurance, $\boldsymbol{X}$ is a vector of covariates and $f(age, \boldsymbol{\gamma})$ a polynomial in age (in our baseline specification we use a linear term). As we are interested in estimating the effect of Medicare

[18] See for example the empirical contributions in Guiso, Haliassos, Jappelli (2002).
[19] See for example Hahn et al. (2001), Imbens and Lemieux (2008), and LL, who provide a review of the issues in the implementation of RD designs and a guide to empirical practice.

on stockholding, our coefficient of interest is β. We estimate β using fuzzy RD estimation, as implemented in Imbens and Lemieux (2008, p. 627). In the FRD design, we estimate the average causal effect of Medicare coverage as the ratio in the estimate of the jump at age 65 of risky asset ownership over the jump at age 65 in Medicare coverage. Computing this ratio is numerically equivalent to using a two-stage least square (2SLS) estimator, with an indicator variable taking the value 1 if age is not below the age 65 threshold as the excluded instrument (Imbens and Lemieux, 2008, henceforth IL; Hahn et al., 2001). Hence, our estimated effect is a local average treatment effect, that is, it is the effect that having Medicare insurance has on stockholding for those who get this insurance when reaching 65. This subsample is a very large one, as shown in Figure 1, and is also the relevant one, given that RD estimates an effect around the age 65 threshold.

As pointed out in BJ (p. 48), the effect of the treatment, that is, having Medicare, captures a weighted average of the effect of coverage and of the effect of the increased generosity of Medicare. This is the case with the coefficient of any binary treatment when underlying this variable there's another continuous one affecting the outcome (generosity in our case).

As in BJ, one can also postulate a second equation that relates having Medicare insurance to being at age 65 or above, which is as follows:

$$Med_i = \gamma + g(age_i, \boldsymbol{\mu}) + \pi T_i + \varphi \boldsymbol{X}_i + u_i, \tag{2}$$

where T is an indicator denoting being age 65 or above, and $g(age, \boldsymbol{\mu})$ an age polynomial. Combining (1) and (2) gives us the reduced form equation, which is also the one used for the sharp RD estimation, namely

$$s_i = \omega + h(age_i, \boldsymbol{\rho}) + \tau T_i + \theta \boldsymbol{X}_i + v_i, \tag{3}$$

where $\omega = \alpha + \beta\gamma, h(age_i, \boldsymbol{\rho}) = f(.) + \beta g(.), \tau = \beta\pi, \theta = \alpha + \beta\delta, v_i = \varepsilon_i + \beta u_i$. Hence, sharp RD estimates in equation (3) the product of our coefficient of interest β with the coefficient of the binary threshold in the equation for the treatment (the coefficient of being at or above 65 in our case). That is, sharp RD estimates $\tau = \beta\pi$. In other words, the sharp RD coefficient is the product of the coefficient of interest with another coefficient that denotes treatment uptake. Clearly, the sharp RD

coefficient is not any more informative than the fuzzy RD one in terms of the breakdown between coverage and generosity, and we are still interested in estimating β.

One could be inclined to interpret the sharp RD estimate τ as an estimate of the effect of Medicare eligibility, that is, as an estimate of the intent to treat. This interpretation, however, would be erroneous because Medicare eligibility is not determined solely by being 65 and above. There are additional conditions that allow respondents to become eligible at ages younger than 65, such as getting Social Security Disability Insurance or having end-stage renal disease and having met the Medicare work requirement either on their own or through their spouse. These additional conditions make a non-trivial number of individuals (as already stated, about 8.5% in our sample) covered by Medicare at ages below 65. Hence, being at or above 65 is not a necessary condition for Medicare eligibility, and thus the sharp RD (reduced form) equation (3) does not allow the estimation of the effect of Medicare eligibility, but only of the effect of being aged 65 or above.

We are, on the other hand, interested in estimating the effect of having insurance through Medicare, and this is the reason why we choose fuzzy RD as our mainline estimation methodology. We show, however, in Section 4 the sharp RD results as well. The associated estimates are smaller than the fuzzy RD ones because they are the product of the latter with the change in treatment uptake (i.e., having Medicare) at the threshold, which is very large, as shown in Fig. 1, but smaller than one.

An important feature of our set-up is the fact that the discontinuity threshold is determined by age. As LL point out, since the assignment variable is age, which cannot be manipulated, individuals cannot choose to be situated to the right or to the left of the discontinuity threshold. This is crucial for identification because the existence of a treatment being a discontinuous function of an assignment variable is *not* sufficient to justify the validity of an RD design. Moreover, as Lee (2008) shows, the fact that the variation in treatment (insurance coverage) near the threshold (age 65) is random as though it were a result of a randomized experiment is a consequence of individuals' inability to precisely manipulate the assignment variable (age).

It is also worth noting that, while individuals cannot manipulate age, they can anticipate the onset of the age-triggered treatment (i.e., Medicare in our case), and hence anticipate choices that are

influenced by it. In our context, this implies that respondents could assume additional financial risk before becoming 65 years old, as they anticipate that they will be eligible for Medicare when they reach that age, and thus their background risk will diminish accordingly. If present, this anticipation effect will reduce the change in the prevalence of stockholding at age 65, and hence our estimates should be lower bounds for the effect of Medicare on financial risk-taking.

Furthermore, as LL point out, to the extent that the influence of the treatment induced by the discontinuity is not immediate but rather takes place over time, the jump in the outcome at the discontinuity point will again be reduced.[20] In our context, this implies that if individuals decide to assume more financial risk with some delay after getting Medicare, then this delay will reduce the increase in the prevalence of stockholding at age 65. Hence, our estimated effect of Medicare on financial risk-taking through RD will likely be an underestimate of the overall effect over time.

In addition, LL point out that one needs to check if there are any events other than Medicare that are also triggered at age 65 and that could also affect stockholding, thus acting as confounders for the effect of Medicare on it. In Section 5 we will discuss robustness checks that address this issue.

One important concern in the application of RD designs, given that they focus on the average effect of the treatment for units with values of the forcing variable close to the threshold, is the issue of the sensitivity to the bandwidth choice. We present results based on the optimal bandwidth choice methodology proposed by Calonico, Cattaneo and Titiunik (2014, henceforth CCT), and we also show results from local linear regression for various age ranges.

Another important decision that we need to make is how to measure age, i.e., our running variable. Our dataset provides information on age measured in months, and thus we can also measure it bimonthly, in quarters, in six-month intervals or in years. As LL point out, if the running variable is measured in units that are too narrow, estimates can become very noisy. On the other hand, if the measurement units are too wide, then each age interval will contain observations that are further off

[20] LL give as an example the effect of being eligible for Social Security on labor supply. As they point out, if this effect is not immediate but rather takes place over time, an RD estimation strategy will likely not find a decrease in working hours at the age of eligibility.

from the discontinuity threshold. To formally choose the age measurement unit, we follow the suggestion of LL and run regressions of our outcomes of interest on monthly dummies (our narrowest age measurement unit). Subsequently, we use joint F-tests to check whether all the coefficients of the dummies are equal to each other within a broader age-measurement unit (but differing across the broader units). For example, when we examine quarters, we test whether all the monthly dummy coefficients in each quarter are equal to each other, and do the same test for all quarters. If the p-value of the F-test indicates that the null of the equality of the monthly dummy coefficients in broader age measurement units cannot be rejected, then it would be advisable to measure age using this broader unit to reduce noise in our estimates.

The p-values of these F-tests are shown in Appendix Table A.1, with Panel A depicting results for stocks directly held and Panel B results for stocks held in any form. Results clearly indicate that when age is measured in years or in six-month intervals the F-tests very often reject the equality of the monthly dummy coefficients within each year or six-month interval, and thus neither years nor six-month intervals are appropriate age measurement units. When age is measured in quarters, the pattern is more varied, but low p-values are still relatively frequent, especially when analyzing stocks held in any form. In contrast, p-values of the F-tests are generally high when age is measured in bimonthly intervals. In light of these results, we use bimonthly intervals as an age measurement unit in our baseline analysis. In Section 5, however, we also perform robustness checks in which age is measured instead in monthly and quarterly intervals.

As LL point out, covariates are not needed in the specification used in RD estimation. Hence, we estimate our baseline specification without any covariates, but we do include them in alternative specification to check the robustness of our results. Furthermore, following the suggestion in Lee and Card (2008), we cluster standard errors at the level of the age measurement unit, that is, bimonthly intervals in our baseline specification.

As it is customary in the RD literature, we first show some graphical evidence. Specifically, we visually check for discontinuities in the distribution of the outcome variable at the threshold point. Figures 2A and 2B provide the relevant plots for the ownership of stocks and mutual funds and for

stockholding in any form, respectively. We also plot simple local linear and local squared polynomial regression lines, estimated using a quarterly bandwidth, as discussed above. We note that there is indeed an upward jump in the ownership of stocks held directly and through mutual funds (Fig. 2A) for the college educated subsample, but no such jump for the whole sample, or for any of the other education subsamples. The same pattern is observed for total stockholding (Fig. 2B).

As we discuss in Section 4 below, our estimation results indeed reflect these observed data patterns. In addition, in Section 5 we estimate "placebo" RD models in which the threshold for Medicare eligibility is set at ages different than 65, and we show that the jump in stock ownership observed at age 65 among the college educated is not due to random data noise.

4. Results

We first examine the fuzzy RD results, shown in Table 2, for the whole sample as well as by education. As discussed in the Introduction, there are good reasons for studying financial risk-taking separately for groups having different levels of education. Specifically, the reduction in background risk (due to Medicare coverage) can have different implications for stockholding across investors bearing different pecuniary and non-pecuniary stock market participation costs that vary with education. We therefore show results for the whole sample as well as by education level.

In Panels A.1 and B.1 of Table 2 we show results obtained through the CCT method, while in Panels A.2 and B.2 those obtained through local linear regressions. We let the CCT method choose the optimal age bandwidth, while we use five different age bands for the local linear regression, the narrowest being one year away from the discontinuity threshold in each direction (ages 64-65), while the widest is five years away (ages 60-69). The choice of age band creates a bias-variance trade off: the narrower the band, the more unbiased estimates will be, albeit noisier, while wider age bands will yield more precise estimates, but more likely to be biased.[21]

[21] The optimal bandwidths produced by the CCT method are not displayed but they are available upon request from the authors. Sample sizes shown in all our tables denote the number of observations in the optimal bandwidth selected (CCT method) or in each of the age intervals (local linear regression).

Results using the CCT method suggest that there is no impact of Medicare coverage on the portfolio decisions of households who have not finished college, with the exception of total stockholding for those with less than high school education. However, the local linear results for this subsample are not statistically significant. Moreover, we show below that they are not robust to the addition of other covariates. In general, estimates are quite small in magnitude and almost always very far from achieving standard levels of statistical significance. Results for the whole sample are statistically significant in the CCT case for total stockholding and in various age ranges in the local linear regressions for both types of stockholding. Once more, however, these results are not robust to the addition of covariates, as shown below.

The picture changes completely for college-educated households, where our estimates are sizeable and statistically significant. First, the CCT estimates are 11.1 and 14.8 percentage points for direct and total stockholding, respectively, both strongly statistically significant. Second, when using local linear regression (Panels A.2 and B.2 of Table 2), as the sample size increases as we sequentially depart from narrower age intervals, the estimated effect of Medicare on stockholding is reduced but is still sizeable. The median local linear estimate is about 7 percentage points for both types of stockholding, and again strongly statistically significant.

These estimates are both statistically significant and economically important, especially when considering that the overall prevalence of direct and total stockholding for the college-educated is about 48.7% and 71.4%, as can be seen from Table 1. Importantly, our results are also plausible given the sizable (especially for the highly educated) effects of Medicare on medical expenditure risk and financial strain previously uncovered by BJ (2015).

We next show the sharp RD results, which, as already discussed, show the effect of being age 65 and above on stockholding. As is well known, the sharp RD estimate should be smaller than the corresponding FRD one because it is not divided by the change in the probability of getting Medicare at age 65. This pattern is clearly present in the results shown in Table 3, as RD estimates are smaller by about 1.5 to 5 pp, and show a very similar pattern of statistical significance to the one found in the fuzzy RD results.

Importantly, our results are in line with other ones in the literature (even if they are neither easily nor directly comparable), and we argue they can even be viewed as relatively conservative in light of previous evidence.

First, BJ (2015, Table 6, Panel B, column 6, p. 62) estimate that Medicare induces a sizeable reduction in out of pocket spending of 34% for those with more than 12 years of education. Hence, our sharp RD/reduced form effects (8-10%) for the highly educated subgroup appear plausible given this reduction in OOP expenditures.[22]

Additionally, we compare our results with those of GM, who consider the subpopulation of Medicare beneficiaries and study how their willingness to hold risky assets is affected by their supplemental insurance arrangements.[23] They find that HMO participation increases total stockholding by 13 percentage points in the general population. The prevalence of total stockholding in their sample is 50%, so this estimate implies a 26% increase in risky asset ownership.

GM do not study how their results vary by education, so comparing their results with ours is not straightforward. Importantly, given that there is less heterogeneity in coverage and in generosity among Medicare beneficiaries than between beneficiaries and non-beneficiaries (the comparison we make), one would expect the onset of Medicare eligibility to have even larger effects on portfolio decisions than those estimated by GM for supplemental insurance (among 65+ Medicare beneficiaries). Interestingly, GM indicate that the decrease in OOP spending for those enrolled in an HMO (versus having just Medicare Part A+B) is 20% in their sample (while their estimated increase in stock ownership is 13 percentage points or 26% of total stockholding prevalence). The equivalent OOP decrease for the sample of highly educated individuals (the sample for whom we obtain significant results) computed by BJ amounts to 34%, i.e., much larger than the one in GM for the whole population.

[22] There are two features worth noting: i) BJ (2015) use a sharp RD design, so it seems more suitable to us to compare their results with our sharp RD results; ii) GM mainly rely on data from the Medical Expenditure Panel Survey in their analyses because of its high quality data on health care spending, but they indicate that their results hold with the HRS (the same data that we use) and they show it in the Appendix.

[23] That is: being enrolled in a Medicare health maintenance organization or HMO, which offers the most generous coverage such that risk exposure is lowest; having supplemental insurance by a former employer or through a Medigap plan, such that risk exposure is moderate; or having no supplemental coverage on top of Medicare A and B package, such that risk exposure is highest.

Hence, one would expect that the increase in stock ownership for that group would be much larger than the 13 percentage points increase estimated by GM for the whole population. On the other hand, our estimated increase in stock ownership ranges from 7 (using the median fuzzy RD estimate from local linear regression) to 15 percentage points (using the CCT methodology) or 10%-21% of total stockholding prevalence for this subgroup.

Hence, we conclude that, all in all, our 2SLS/fuzzy RD estimated effects are not too large compared to GM's 13 percentage points (rather the opposite). We note that we compare their estimated effects with our fuzzy RD/2SLS results because they use an IV approach to address the endogeneity of supplemental insurance choice among Medicare beneficiaries. However, the comparison with our sharp RD results would only strengthen our point as they are smaller.

AH study how Medicare Part D (which was introduced in 2006 with the aim of helping the elderly pay for self-administered prescription drugs) affected stock ownership among Medicare beneficiaries. Their main finding is that Part D increased stockholding by 2.25 percentage points, which amounts to a 4.5% increase with respect to the pre-2006 ownership rate of those 65 and older. Note, however, that the reduction in OOP spending induced by Part D for those 65+ is also smaller than the 34% reduction in OOP spending caused by Medicare for the highly educated estimated by BJ. Additionally, in the Appendix AH show that they find no significant effect for those with less than a high school degree. They do not show the estimated effect for those with at least some college education, but it is expected to be larger than the 2.25 percentage points estimate they obtain for the whole sample. Hence, given the larger drop in OOP in the college-educated subsample in our case, as well as the fact that we examine the impact of the whole Medicare program as opposed to only Part D, we consider our estimated (through sharp RD) 10 percentage points increase in stockholding to be a result compatible with the findings of AH. Note that, since they use a diff in diff estimator, we have compared their results with our sharp RD (reduced form) estimates.

When interpreting our results, one should keep in mind that, as discussed in Section 4, they may underestimate the true effect of Medicare on financial risk-taking due to the possibility of anticipation of the stockholding decision before age 65, and the possibility that Medicare affects financial risk-taking

not immediately after eligibility but over a longer period. Hence, it could be the case that Medicare induces financial risk-taking even for those who have not finished college, but we are not able to uncover this effect because age is the assignment variable in our RD setup. The fact, however, that we find an effect for the group for which we expect it the most, i.e., the college-educated that bear lower informational costs, is congruent with the notion that such costs have an important and sizeable influence on financial risk-taking.

5. Specification and Robustness Checks

To check our results, we perform various robustness tests. Due to space constraints, we show the results of only some of them, but all are available from the authors upon request.

We first check whether the jump in the prevalence of stockholding at age 65 observed in the college-educated subsample (as evidenced in Fig. 2A and 2B) is due to noise in the data. To that effect, we perform "placebo" RD estimations in the subsample of the college-educated and for age thresholds different than 65, starting from age 59 and until age 71, i.e., six years to the left and to the right of the age for Medicare eligibility. Each age interval is defined to the left or the right of age 65, as suggested by IL (Section 7.3), so as to avoid including in the estimation a point where the regression function has a discontinuity. We set the placebo thresholds equal to the median age of each age interval, again following IL. If the effect observed at age 65 is a genuine one, i.e., due to having Medicare, then there should be no effect observed at other age thresholds. Our results are shown in Table 4, for both kinds of stockholding (direct and through mutual funds, and total), and for both estimation methods (CCT and local linear regression). We find that in only one of the 40 possible combinations of age intervals, stockholding mode and estimation method at age thresholds other than 65 do we obtain a result significant at the 5% level. In contrast, and in line with the impact of Medicare on stockholding being genuine for the college-educated subsample, the results at age 65 shown in Table 2 are consistently strong and statistically significant. Hence, we conclude that there is little evidence that our results are due to noisy jumps in the data.

One additional specification test suggested by LL is to perform the estimation using additional covariates. Such covariates should not affect the consistency of the estimates. However, they could make them more efficient. To that effect, we add to our specification: time dummies, an indicator for being white, an indicator for whether the household contains a person with health problems as indicated by having at least one limitation in activities of daily living (ADLs), an indicator for whether the household is formed by a couple, and income quartiles. Our results are shown in Table 5. We find that our point estimates for the college-educated subsample are barely affected by the inclusion of these additional covariates. On the other hand, results for the whole sample and for the least educated subsample are now uniformly not statistically significant.

We next examine whether Medicare induces investment in less risky assets like bonds. As discussed in the Introduction, one may expect the onset of Medicare to affect portfolio investment through two mechanisms. First, the onset of Medicare may also increase individuals' willingness to hold risky assets because of its associated reduction in background risk. Second, since Medicare eligibility significantly reduces out of pocket expenditures (even more so for the better educated, as documented by BJ), eligible individuals will be less cash constrained and hence more likely to invest not only in stocks but also in bonds and/or other financial products. If we found a relevant impact of Medicare on the probability of holding bonds, which represent a less risky investment than stocks, this would suggest that increased risk tasking due to reduced background risk might not be the only factor driving our results for stocks. Results for bond ownership are shown in Table 6, columns 1-4, and they clearly indicate that we cannot reject the null of no effect of Medicare on bondholding. This suggests that the significant estimated effect of Medicare on stockholding is consistent with the notion of additional risk-tasking in view of a reduction in another source of background risk. Importantly, this evidence also suggests against the possibility that having more funds at one's disposal may be the only reason behind our results for stockholding.

A potentially interesting outcome is also the intensive margin of stockholding, that is, whether households increase their investment in stocks, conditional on owning them. Here, however, we run into a rather serious data problem: capital gains and losses were remarkably high during our sample

period, that includes the runup of stock prices in the late 90s, the crash of 2000, the recovery and subsequent runup till 2008, the large stock market crash of 2008-2009 due to the Great Recession, and the brisk recovery of the market from the second part of 2009 till 2012. Hence, stock amounts in the HRS are unlikely to solely reflect deliberate financial decisions made by households. Instead, variations in the extensive margin reflect both active investing and price changes. Unfortunately, the HRS does not gather separate data on capital gains and losses because respondents are asked about the value of investments at the time of the interview, and thus this value includes capital gains and losses. In any case, our results for amounts (in logarithms) of stocks directly held are shown in columns 5-8 and those for total stocks in columns 9-12 in Table 6. We observe that none of the estimates are statistically significant. However, given that the data do not allow us to attribute changes in amounts to deliberate actions by households, we cannot give our results a behavioral interpretation.

As discussed in Section 3, we need to consider other possible factors that might change at age 65 and influence the decision to own stocks. The most salient such factor is household income. If such a change occurred, it could be negative, due to retirement or reduced working hours, but it could also be positive, due to the receipt of private pension and Social Security income. Given the well-documented positive association between income and stockholding, a reduced (increased) level of income at age 65 would tend to reduce (increase) our estimates of the effect of Medicare on financial risk-taking. When we perform a sharp RD estimation for income, however, we find no evidence of any change at age 65 (results are shown in columns 13-16 of Table 6 for income transformed used the inverse hyperbolic sine transformation). BJ report the same result with data from the Medical Expenditure Panel Survey and the Health Tracking Household Survey. We thus conclude that our estimates of the effect of Medicare on stockholding are unlikely to be affected by any income developments at that age.

Another factor that might change at age 65 and might affect stockholding would be the decision to retire. It is not theoretically obvious why retirement should induce someone to acquire stocks. In fact, retirement could well reduce stockholding if individuals liquidate their retirement accounts, through which they could have invested in stocks. In addition, empirical findings typically suggest either no association between stock ownership retirement (e.g., see the contributions in Guiso, Haliassos and

Jappelli, 2001), or a negative one (see, e.g., Addoum, 2017, who, like us, uses the HRS). On the other hand, some individuals who retire might roll over their retirement accounts in mutual funds that invest in stocks. At any rate, when we graph the data in Figure 3 (local linear regression lines are also included), we observe no spike in the prevalence of retirement at age 65.[24] Moreover, and to check whether there is a significant increase in the proportion of retiree at 65, we perform a sharp RD estimation for the decision to retire. Results are shown in columns 17-20 of Table 6, and clearly indicate that one cannot reject the null of no spike in retirement at 65. Reassuringly, this conclusion has also been reached by other authors using alternative datasets. Specifically, similar smooth employment-related outcomes have been uncovered by CDM using both the National Health Interview Survey and the March CPS, and by BJ using both the Medical Expenditure Panel Survey and the Health Tracking Household Survey. Hence, our finding that Medicare increases stockholding for the college-educated household should not be affected by their retirement decisions around 65.

As discussed in Section 3.2 we choose to measure age bimonthly for our baseline specifications. We also performed our FRD estimation, however, with age measured in quarterly and in months. The results for the former case are displayed in Appendix Table A.2, while those for the latter in Appendix Table A.3 The conclusions are essentially the same as those reached in Section 4: Medicare eligibility significantly rises stockholding for college-educated households and its median estimated effect is economically relevant, as it ranges approximately from 7 to 15 percentage points for both directly held stocks and stocks held in any form.

To see whether our results differ by the insurance one had before age 65, we repeated our analyses for households with at least one member uninsured before getting Medicare and before age 65 and compared results to those obtained using households with no such uninsured members. In line with intuition and with the fact that risk reduction is likely larger for households with members who had no insurance prior to 65, the estimated effects are much larger for such households in the college-educated subsample. However, these estimates for the uninsured subsample, while statistically significant, have

[24] Given that both our outcomes and our treatment are defined at the household level, we define retirement at the household level as well by using a binary variable denoting retirement if any of the two partners in a couple is retired.

wide confidence intervals due to the small sample size (there are few uninsured among the college-educated). These confidence intervals include by a wide margin the point estimate of the subsample of households in which all members had insurance before Medicare and before age 65, and thus we cannot reject the null hypothesis that the effect of the onset of Medicare does not differ between the two groups of households.

On the other hand, for households with no college graduate we still find no significant effect of Medicare on stockholding either for the previously insured or for the previously uninsured subsamples. This suggests that the higher participation costs of stockholding for these households dominates the effect of the reduction in background risk.

We also did a sample split by cognition, as the latter has been strongly positively associated with stockholding (see, e.g. Christelis et al, 2010). In particular, we used the delayed recall test in the HRS, during which households are asked to repeat 10 words that have been read to them earlier in the interview. We split the sample in approximately two equal subsamples using a score of 5 words as the threshold.

For households with higher scores the estimates are strongly statistically significant, while for households with lower scores they are not. However, the magnitudes of the CCT estimates are similar in the two household groups. The difference in the statistical significance is again suggestive evidence that higher cognition households are more likely to appreciate the reduction in background risk that having Medicare entails, which is what one would a priori expect. On the other hand, the fact that the CCT estimates for the low cognition households are similar to the estimates for the higher cognition ones suggests that the differences are not statistically significant, which in turn could be due to the small sample of lower cognition households with college education.

In addition, we experimented with adding higher order age polynomial terms to our local regression specification, as recommended by LL. We tried polynomials of order two and our results did not change.[25]

[25] Results for polynomials of higher order than two are likely untrustworthy, as shown by Gelman and Imbens (2014).

Finally, given that our outcome is a binary variable, we estimate non-linear binary choice models. As Medicare eligibility is also a binary variable that needs to be instrumented for a FRD estimation, we used a bivariate probit model in which the second equation had Medicare eligibility as an outcome and a dummy variable for being over 65 as the excluded instrument. We find that the marginal effects of Medicare on stockholding obtained through this model are very close to those obtained from the local linear regression.

6. Discussion and Conclusions

Economic theory predicts that a reduction in health-related background risk should induce financial risk-taking, particularly so for households who are subject to relatively low stock market participation costs. We investigate this largely understudied but quite topical issue in a set-up that allows for credible identification of the relevant effect. Specifically, we utilize data on older individuals who control a significant fraction of society's economic resources, at the time they get covered by a comprehensive public health insurance program. To identify the causal effect of interest, we employ a regression discontinuity design that exploits the discontinuity in health insurance coverage and generosity due to the onset of Medicare.

We find that Medicare eligibility has a quantitatively and statistically significant impact on stockholding for the college-educated households. In contrast, our results indicate that the onset of Medicare does not significantly alter the financial risk-taking behavior of households whose members have not finished college. Taken together, our results suggest that the reduction in background risk due to Medicare suffices for overcoming all stock market participation costs (both informational and pecuniary) when such costs are relatively low, as is the case for the higher educated.

As discussed, our estimates may be conservative estimates of the true effect of Medicare on financial risk-taking. This is so both because households might anticipate the stockholding decision before age 65 and because the influence of Medicare on financial risk-taking might not occur immediately at age 65, but rather over a longer period.

Our findings suggest that future reforms to Medicare (e.g., with respect to the extent of coverage and/or the age of eligibility) are, inter alia, likely to influence households' financial risk-taking behavior and, more broadly, the size and composition of the population of stockholders. Hence, policy-makers may want to consider this implication when contemplating any such reforms. Likewise, if they are concerned about the low prevalence of stock holding, then they need to examine the extent to which it is due to poor health insurance coverage.

Large public policy interventions have often implications for wealth inequality. In our context, if better educated households, following the onset of Medicare, become increasingly more likely to invest in an asset with large risk-adjusted returns (as the equity premium suggests), then the discrepancy in wealth between them and their less educated counterparts is likely to become larger.

Finally, to the extent that our results can be generalized to include others kinds of background risk (e.g., due to unemployment), they imply that facilitating broader insurance coverage for such risks may enhance financial risk-taking.

References

Addoum, J. (2017), "Household portfolio choice and retirement," Review of Economics and Statistics, 99(5):870-883.

Alemayehu, B. and K. E. Warner (2004), "The lifetime distribution of health care costs," *Health Services Research*, 39(3): 627-642.

Angrisani, M., Atella, V., and M. Brunetti (2016), "Public health insurance and household portfolio choices: Unraveling financial "side effects" of Medicare," *Journal of Banking and Finance*, 93:198-212.

Arrow, K. (1974), *Essays in the theory of risk bearing*, Amsterdam: North Holland.

Atella, V., M. Brunetti and N. Maestas (2012), "Household portfolio choices, health status and health care systems: A cross-country analysis based on SHARE," *Journal of Banking and Finance*, 36(5): 1320-1355.

Autor, D. H. and M. Duggan (2003), "The rise in the disability rolls and the decline in unemployment," *Quarterly Journal of Economics*, 118(1): 157-205.

Ayyagari, P., and He, D. (2017), "The role of medical expenditure risk in portfolio allocation decisions," *Health Economics*, 26(11):1447-1558.

Baicker, K. and H. Levy **(**2012), "The insurance value of Medicare," *New England Journal of Medicine,* 367 (19): 1773–75.

Barcellos, S. H. and M. Jacobson (2015), "The effects of Medicare on medical expenditure risk and financial strain," *American Economic Journal: Economic Policy*, 7(4): 41-70.

Bogan, V. (2008), "Stock market participation and the Internet," *Journal of Financial and Quantitative Analysis*, 43: 191–212.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014), "Robust nonparametric confidence intervals for regression-discontinuity designs," *Econometrica*, 82(6): 2295-2326.

Card, D., C. Dobkin and N. Maestas (2004), "The impact of nearly universal coverage on health care utilization: evidence from Medicare," NBER Working Paper. No. 10365.

Card, D., C. Dobkin and N. Maestas (2008), "The impact of nearly universal coverage on health care utilization: evidence from Medicare," *American Economic Review*, 98(5), 2242-2258.

Card, D., C. Dobkin and N. Maestas (2009), "Does Medicare save lives?," *Quarterly Journal of Economics*, 124(2): 597-636.

Centers for Medicare & Medicaid Services (2013), *National health expenditures 2012: Highlights*. Available at: http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/downloads/highlights.pdf

Christelis, D., D. Georgarakos and M. Haliassos (2011), "Stockholding: Participation, location, and participation spillovers," *Journal of Banking and Finance*, 35(8): 1918-1930.

Christelis, D., D. Georgarakos and A. Sanz-de-Galdeano (2014), "The impact of health insurance on stockholding: A regression discontinuity approach," IZA Discussion Paper No. 8635.

Christelis, D., Jappelli, T., and M. Padula (2010), "Cognitive abilities and portfolio choice," *European Economic Review*, 54(1): 18-36.

Congressional Budget Office, 2013, *The 2013 long-term budget outlook*. Available at: http://www.cbo.gov/sites/default/files/cbofiles/attachments/44521-LTBO2013_0.pdf

Coile, C. and K. Milligan (2009), "How household portfolios evolve after retirement: The effect of aging and health shocks," Review of Income and Wealth, 55(2): 226-248.

Decker, S.L. and C. Rapaport (2002), "Medicare and inequalities in health outcomes: the case of breast cancer," *Contemporary Economic Policy*, 20(1): 1-11.

De Nardi, M., French, E. and J. B. Jones (2014), "Couples and singles' savings after retirement," Institute of Fiscal Studies Working Paper, available at http://www.ifs.org.uk/uploads/cemmap/forms/CouplesandSingles14.pdf

Edwards, R. D. (2008), "Health risk and portfolio choice," *Journal of Business & Economic Statistic*s, 26: 472-485.

Fairlie, R. W., K. Kapur, and S. M. Gates (2011), "Is employer-based health insurance a barrier to entrepreneurship?," *Journal of Health Economics*, 30: 146-162.

Finkelstein, A. and R. McKnight (2008), "What did Medicare do (and was it worth it)?," Journal of Public Economics, 92:1644-1668.

Gelman, A., and G. Imbens (2014), "Why higher order polynomials should not be used in regression discontinuity designs," NBER Working Paper 20405.

Goldman, D.P. and N. Maestas (2013), "Medical expenditure risk and household portfolio choice," *Journal of Applied Econometrics*, 28(4): 527-550.

Gollier, C., and J. W. Pratt (1996), "Risk vulnerability and the tempering effect of background risk," *Econometrica*, 64(5): 1109-23.

Gruber, J., and B. C. Madrian (2004), "Health insurance, labor force participation, and job choice: A critical review of the literature," in Catherine McLaughlin, editor, *Health Policy and the Uninsured*, Washington, DC: Urban Institute Press.

Guiso, L., Jappelli, T., and D. Terlizzese (1996), "Income risk, borrowing constraints and portfolio choice," *American Economic Review*, 86(1):158-172.

Guiso, L., M. Haliassos, and T. Jappelli (Eds.) (2002), *Household portfolios*, Cambridge, MA: MIT Press.

Hahn, J., P. Todd, and W. van der Klaauw (2001), "Identification and estimation of treatment effects with a regression discontinuity design", *Econometrica*, 69(1): 201-09.

Haliassos, M. (2002), "Stockholding: lessons from theory and computations", in L. Guiso, M. Haliassos, and T. Jappelli (eds), *Stockholding in Europe*, London: Palgrave Macmillan Press, 30-51.

Haliassos, M., and C. C. Bertaut (1995), "Why do so few hold stocks?," *The Economic Journal*, 105: 1110-1129.

Heaton, J., and D. Lucas (2000), "Portfolio choice in the presence of background risk," *The Economic Journal*, 110:460: 1-26.

Himmelstein, D. U., Thorne, D., Warren, E., and S. Woolhandler (2009), "Medical bankruptcy in the United States, 2007: Results of a national study", *The American Journal of Medicine*, 2(8): 741-746.

Hong, H., J. Kubik, and J. Stein, J. (2004), “Social interaction and stock market participation,” *Journal of Finance*, 59: 137–163.

Hurd, M. (2002), “Portfolio holdings by the elderly,” in L. Guiso, Haliassos, M. and T. Jappelli (eds.), *Household Portfolios*, Cambridge, Mass.: MIT Press.

Imbens, G., and T. Lemieux, 2008, “Regression discontinuity designs: A guide to practice,” *Journal of Econometrics*, 162(2): 615-35.

Lee, D. (2008), “Randomized experiments from non-random selection in U.S. House elections,” *Journal of Econometrics*, 142 (2): 675–697.

Lee, D., and T. Lemieux (2010), “Regression discontinuity designs in economics,” *Journal of Economic Literature*, 48(2): 281-355.

Lee, D. S., and D. Card, (2008), “Regression discontinuity inference with specification error,” Journal of Econometrics, 142(2): 655-674.

Madrian, B. C. (2007), “The U.S. health care system and labor markets,” in Jane Sneddon Little, (editor), *Wanting It All: The Challenge of Reforming the U.S. Health Care System*, Boston: Federal Reserve Bank of Boston, 137-163.

Rosen, H., and S. Wu (2004), “Portfolio Choice and Health Status,” *Journal of Financial Economics*, 72: 457-484.

Rubin, D. (1974), “Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies,” *Journal of Educational Psychology*, 66(5): 688–701.

Viceira, L. M. (2001), "Optimal portfolio choice for long-horizon investors with nontradable labor income," *Journal of Finance*, 56(2): 433-470.

Vissing-Jørgensen, A. (2002), “Limited asset market participation and the elasticity of intertemporal substitution,” *Journal of Political Economy*, 110(4): 825-853.

Webb, A., and N. Zhivan (2010), “What is the distribution of lifetime health care costs from age 65?,” Center for Retirement Research Working Paper No. 10-4.

Yogo, M. (2016), "Portfolio choice in retirement: health risk and the demand for annuities, housing, and risky assets," Journal of Monetary Economics, 80: 17-34.

Figure 1. Medicare Coverage Rates

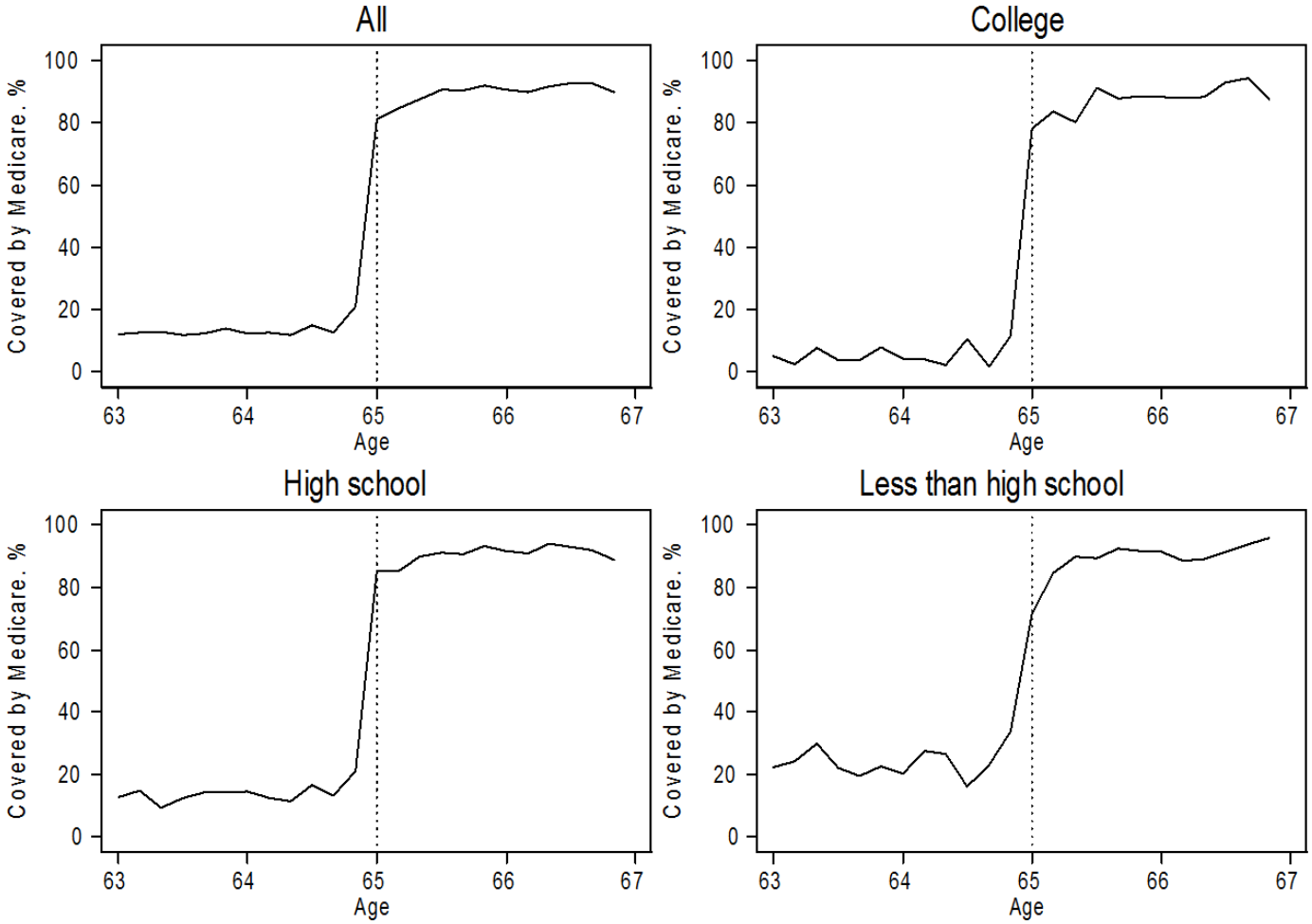

Figure 2A. Rate of ownership of stocks held directly or through mutual funds

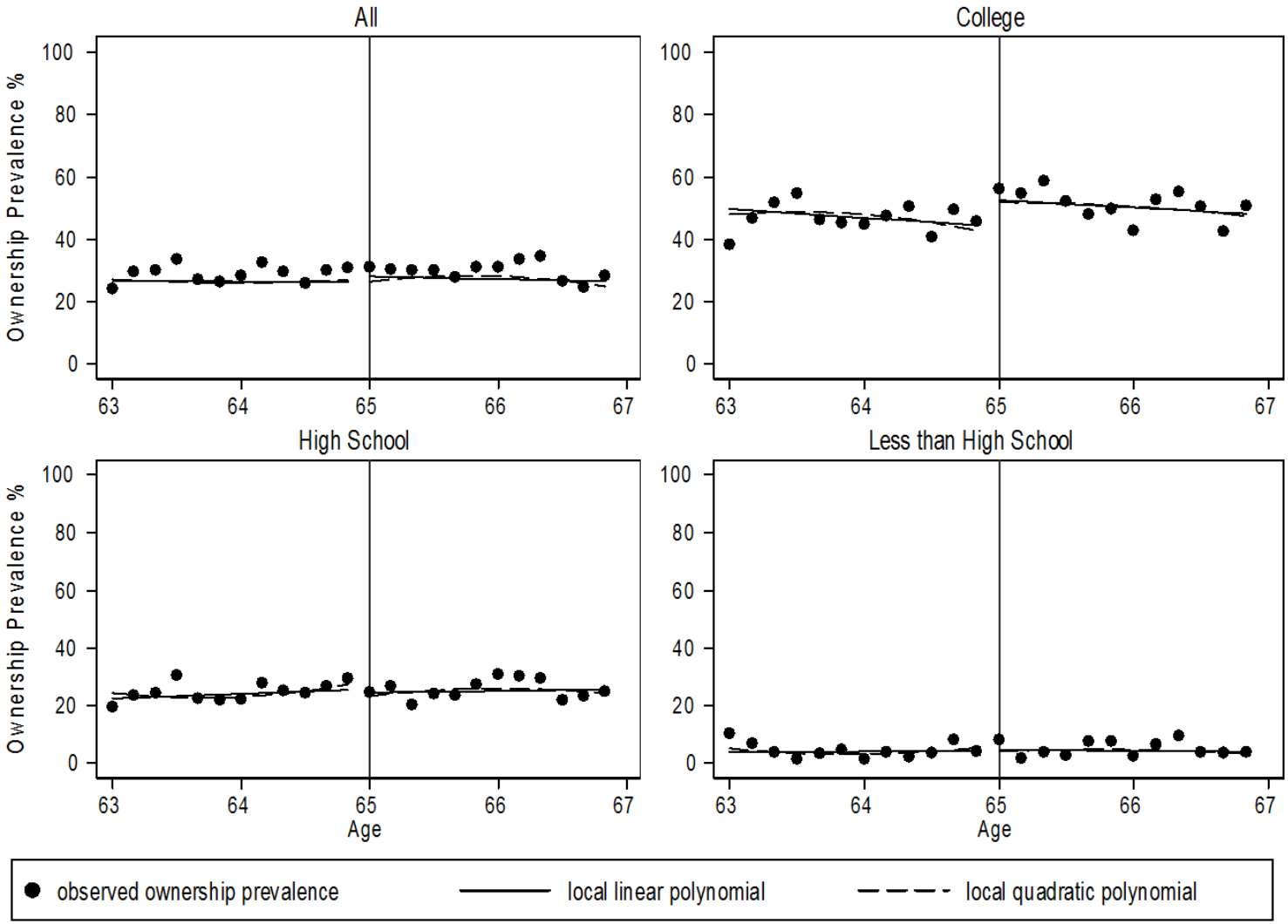

Figure 2B. Rate of ownership of stocks held in any form

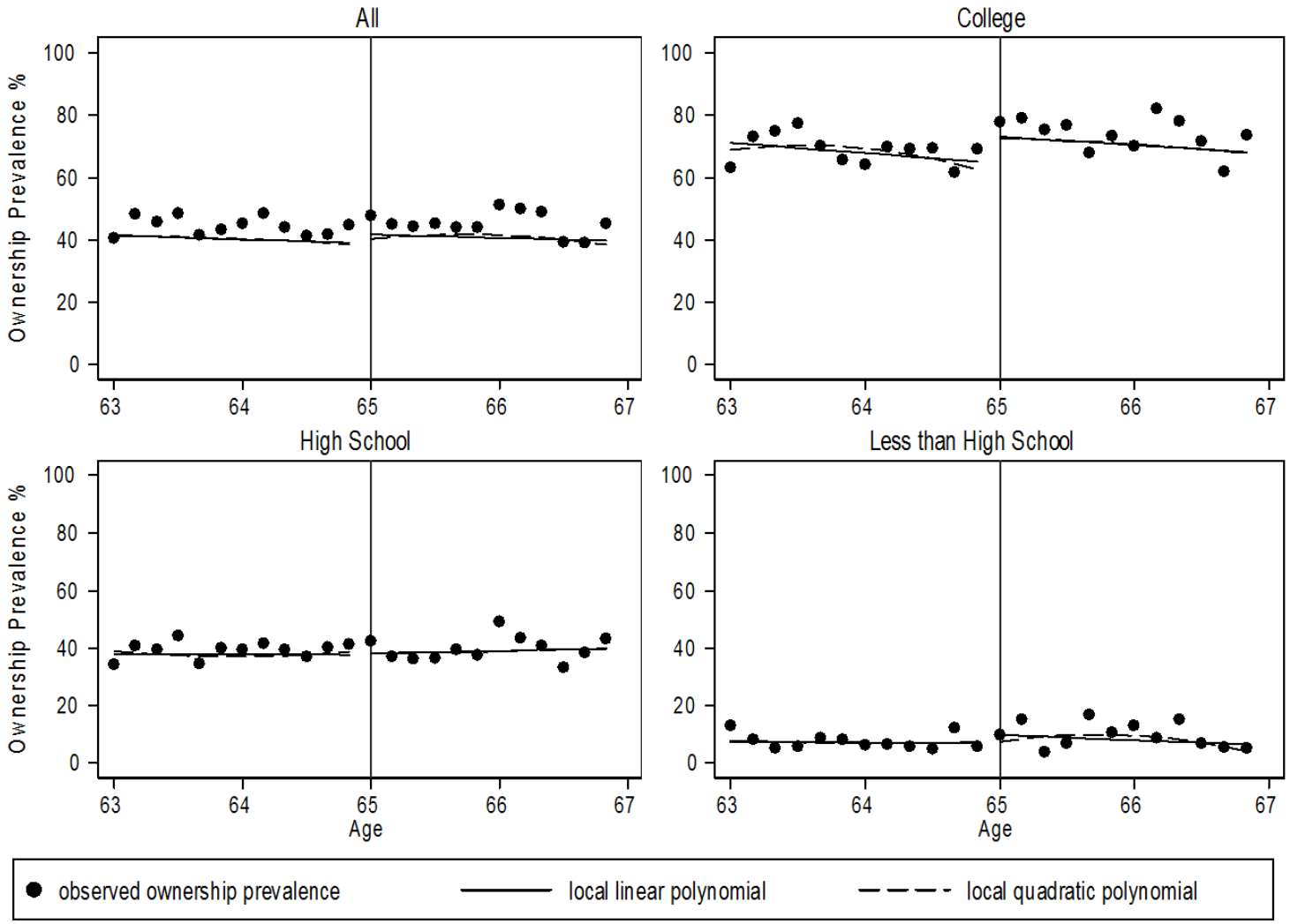

Figure 3. Prevalence of retirement

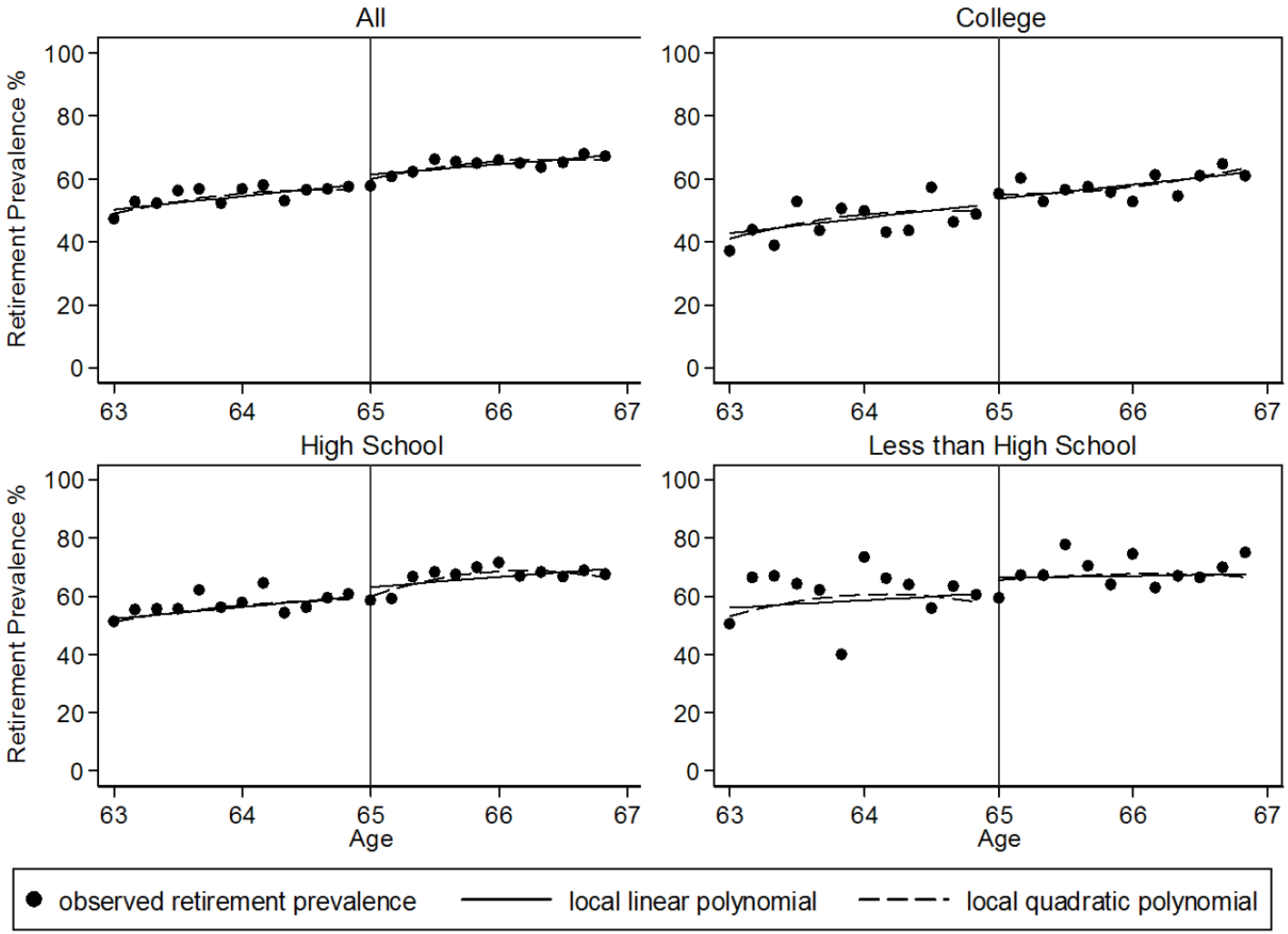

Table 1. Ownership rate of stocks held in different investment vehicles, by education, ages 60-69

Item	Whole Sample	College Graduates	High School Graduates	Less than High School
Stocks held directly or through mutual funds	29.2%	48.7%	24.6%	4.7%
Stocks held in any form	44.9%	71.4%	39.3%	8.8%
Number of observations	32,227	8,078	18,376	5,773

Notes: Ownership rates are calculated using sample weights. All figures are at the household-level. In the case of couples, the education level is defined as the maximum level over the two spouses/partners. The ownership rate of stocks held in any form includes direct stockholding, stocks held through mutual funds, and stocks held through Individual Retirement Accounts. The data come from the 1998, 2000, 2002, 2004, 2008, 2010 and 2012 waves of the HRS.

Table 2. Ownership of stocks, fuzzy RD

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	0.0271	0.0185	0.1437	32,555	0.1111	0.0373	0.0029	5,525	-0.0283	0.0285	0.3203	15,513	0.0177	0.0310	0.5672	5,815
Panel A.2. Local Linear Regression																
64-65	0.0080	0.0125	0.5361	6,474	0.1594	0.0449	0.0045	1,626	-0.0742	0.0301	0.0315	3,702	-0.0627	0.0384	0.1311	1,146
63-66	0.0256	0.0123	0.0485	12,906	0.1162	0.0340	0.0024	3,230	-0.0197	0.0274	0.4797	7,334	0.0107	0.0276	0.7010	2,342
62-67	0.0065	0.0118	0.5889	19,360	0.0642	0.0322	0.0540	4,884	-0.0149	0.0241	0.5406	11,002	-0.0023	0.0263	0.9322	3,474
61-68	0.0239	0.0124	0.0606	25,759	0.0700	0.0280	0.0158	6,453	0.0022	0.0218	0.9184	14,696	0.0125	0.0184	0.5013	4,610
60-69	0.0214	0.0115	0.0690	32,227	0.0511	0.0249	0.0442	8,078	0.0120	0.0199	0.5468	18,376	0.0068	0.0167	0.6850	5,773
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	0.0473	0.0227	0.0371	29,353	0.1477	0.0302	0.0000	6,306	-0.0126	0.0284	0.6577	17,335	0.0800	0.0458	0.0808	5,441
Panel B.2. Local Linear Regression																
64-65	0.0523	0.0283	0.0921	6,474	0.1612	0.0555	0.0144	1,626	-0.0148	0.0314	0.6476	3,702	-0.0333	0.0567	0.5690	1,146
63-66	0.0469	0.0209	0.0348	12,906	0.1176	0.0472	0.0203	3,230	0.0052	0.0309	0.8677	7,334	0.0570	0.0420	0.1885	2,342
62-67	0.0235	0.0192	0.2294	19,360	0.0642	0.0389	0.1074	4,884	0.0121	0.0264	0.6488	11,002	0.0170	0.0371	0.6492	3,474
61-68	0.0363	0.0173	0.0411	25,759	0.0704	0.0337	0.0421	6,453	0.0171	0.0226	0.4539	14,696	0.0399	0.0286	0.1698	4,610
60-69	0.0306	0.0157	0.0564	32,227	0.0552	0.0287	0.0591	8,078	0.0220	0.0212	0.3037	18,376	0.0291	0.0249	0.2479	5,773

Notes: Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. Age is measured in bi-monthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table 3. Ownership of stocks, sharp RD

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	0.0118	0.0130	0.3648	26,161	0.0787	0.0248	0.0015	5,525	-0.0357	0.0189	0.0591	10,624	0.0023	0.0193	0.9069	4,467
Panel A.2. Local Linear Regression																
64-65	0.0047	0.0079	0.5631	6,474	0.1107	0.0294	0.0032	1,626	-0.0453	0.0186	0.0333	3,702	-0.0268	0.0209	0.2249	1,146
63-66	0.0161	0.0083	0.0641	12,906	0.0846	0.0253	0.0028	3,230	-0.0124	0.0176	0.4858	7,334	0.0053	0.0138	0.7035	2,342
62-67	0.0042	0.0078	0.5955	19,360	0.0478	0.0242	0.0564	4,884	-0.0096	0.0158	0.5451	11,002	-0.0011	0.0133	0.9334	3,474
61-68	0.0157	0.0084	0.0669	25,759	0.0528	0.0212	0.0164	6,453	0.0015	0.0145	0.9193	14,696	0.0065	0.0096	0.5008	4,610
60-69	0.0142	0.0078	0.0741	32,227	0.0394	0.0192	0.0443	8,078	0.0080	0.0134	0.5513	18,376	0.0036	0.0088	0.6855	5,773
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	0.0242	0.0157	0.1220	25,073	0.1008	0.0235	0.0000	5,278	-0.0166	0.0194	0.3936	13,722	0.0422	0.0230	0.0663	5,815
Panel B.2. Local Linear Regression																
64-65	0.0309	0.0182	0.1178	6,474	0.1119	0.0413	0.0204	1,626	-0.0090	0.0200	0.6605	3,702	-0.0142	0.0264	0.6005	1,146
63-66	0.0295	0.0136	0.0409	12,906	0.0856	0.0357	0.0250	3,230	0.0033	0.0200	0.8706	7,334	0.0282	0.0211	0.1953	2,342
62-67	0.0151	0.0125	0.2363	19,360	0.0477	0.0295	0.1140	4,884	0.0079	0.0174	0.6537	11,002	0.0084	0.0186	0.6536	3,474
61-68	0.0238	0.0115	0.0449	25,759	0.0531	0.0258	0.0449	6,453	0.0112	0.0151	0.4594	14,696	0.0208	0.0150	0.1729	4,610
60-69	0.0204	0.0106	0.0595	32,227	0.0426	0.0223	0.0607	8,078	0.0147	0.0143	0.3089	18,376	0.0152	0.0131	0.2493	5,773

Notes: Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through sharp RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present sharp RD local linear regression results for each age interval indicated. Age is measured in bi-monthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table 4. Ownership of stocks, placebo tests using alternative age thresholds, fuzzy RD, college-educated subsample

Age thresholds	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Stocks held directly and through mutual funds				Total stockholding			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
				Panel A. Robust RD				
62	-0.296	0.852	0.729	2,586	-0.642	1.570	0.682	2,586
62.5	1.964	2.058	0.340	3,475	0.652	1.857	0.726	3,327
63	2.537	1.640	0.122	3,614	-0.399	0.667	0.550	2,422
63.5	-2.602	1,206.818	0.998	3,140	-59.029	66.034	0.371	2,996
64	-0.654	1.013	0.519	3,795	-1.221	1.810	0.500	3,525
66	-3.604	7.041	0.609	6,893	-1.217	3.146	0.699	4,966
66.5	-2.723	1.697	0.109	5,173	-2.778	3.288	0.398	5,518
67	-0.307	0.492	0.533	3,506	-1.453	0.630	0.021	4,003
67.5	0.462	3.738	0.902	3,873	-0.263	0.448	0.557	4,876
68	-4.025	10.497	0.701	5,221	1.334	2.552	0.601	4,371
				Panel B. Local Linear Regression				
62	7.202	30.794	0.815	5,105	9.425	36.237	0.795	5,105
62.5	-32.610	555.441	0.953	4,205	-13.489	226.779	0.953	4,205
63	-4.416	2.873	0.124	3,353	-4.631	3.558	0.193	3,353
63.5	-0.979	1.286	0.447	2,482	-0.628	1.490	0.674	2,482
64	-1.198	1.807	0.507	1,643	0.010	2.162	0.996	1,643
66	0.089	0.741	0.904	1,584	-0.612	0.930	0.511	1,584
66.5	-0.038	1.186	0.975	2,398	1.396	1.997	0.485	2,398
67	-2.561	4.276	0.549	3,094	-1.404	2.478	0.571	3,094
67.5	-7.539	45.578	0.869	3,862	-0.367	6.528	0.955	3,862
68	-0.394	1.771	0.824	4,609	0.222	1.489	0.882	4,609

Notes: The table shows fuzzy RD estimates for the college-educated subsample using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) (Panel A), and local linear regression (Panel B). The following age ranges are used: [59,65), [60,65), [61,65), [62, 65), [63,65), [65,67), [65,68), [65, 69), [65, 70), and [65, 71). In each age range a placebo RD threshold is created at the midpoint. Age is measured in bimonthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table 5. Ownership of stocks, fuzzy RD, with additional covariates

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	0.0213	0.0179	0.2334	28,278	0.0965	0.0339	0.0044	6,572	-0.0188	0.0270	0.4872	15,509	0.0106	0.0316	0.7367	5,249
Panel A.2. Local Linear Regression																
64-65	-0.0117	0.0089	0.2155	6,473	0.1159	0.0410	0.0165	1,626	-0.0663	0.0361	0.0938	3,702	-0.0842	0.0329	0.0263	1,145
63-66	0.0076	0.0102	0.4675	12,902	0.0869	0.0290	0.0065	3,230	-0.0255	0.0276	0.3652	7,333	-0.0017	0.0246	0.9461	2,339
62-67	0.0006	0.0100	0.9561	19,351	0.0533	0.0258	0.0462	4,884	-0.0172	0.0234	0.4687	10,999	-0.0087	0.0249	0.7286	3,468
61-68	0.0128	0.0095	0.1855	25,745	0.0525	0.0230	0.0269	6,453	-0.0017	0.0200	0.9345	14,692	0.0063	0.0175	0.7221	4,600
60-69	0.0124	0.0093	0.1844	32,210	0.0394	0.0196	0.0493	8,078	0.0064	0.0187	0.7317	18,371	0.0031	0.0162	0.8462	5,761
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	0.0308	0.0201	0.1256	20,887	0.1349	0.0281	0.0000	7,387	-0.0064	0.0242	0.7917	16,123	0.0687	0.0427	0.1077	5,048
Panel B.2. Local Linear Regression																
64-65	0.0281	0.0217	0.2223	6,473	0.1299	0.0488	0.0221	1,626	0.0001	0.0328	0.9980	3,702	-0.0712	0.0450	0.1416	1,145
63-66	0.0232	0.0169	0.1837	12,902	0.0889	0.0393	0.0336	3,230	-0.0021	0.0285	0.9431	7,333	0.0366	0.0385	0.3520	2,339
62-67	0.0158	0.0154	0.3131	19,351	0.0546	0.0316	0.0927	4,884	0.0084	0.0232	0.7189	10,999	0.0068	0.0348	0.8461	3,468
61-68	0.0205	0.0136	0.1379	25,745	0.0506	0.0272	0.0688	6,453	0.0102	0.0197	0.6078	14,692	0.0283	0.0271	0.3007	4,600
60-69	0.0182	0.0124	0.1488	32,210	0.0409	0.0228	0.0781	8,078	0.0132	0.0185	0.4781	18,371	0.0219	0.0238	0.3613	5,761

Notes: Panel A reports results for Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. The specification includes the following additional covariates, other than age-related terms and an indicator for having Medicare: time dummies, being white, being in a couple, having at least one limitation in daily living activities, and income quartiles. Age is measured in bi-monthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table 6. Additional outcomes

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Bond ownership				Amounts of stocks held directly or through mutual funds, conditional on ownership (in logarithms)				Amounts of all stocks, conditional on ownership (in logarithms)				Household income				Retirement			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Robust RD																				
Selected by the optimal bandwidth	0.0728	0.0533	0.1719	4,996	0.0493	0.2643	0.8521	3,804	-0.0362	0.1832	0.8435	4,182	-0.1363	0.2005	0.4965	5,525	0.0029	0.0391	0.9400	5,814
Panel B. Local linear regression																				
64-65	0.0749	0.0612	0.2461	1,626	0.3125	0.3675	0.4133	795	-0.1035	0.2578	0.6956	1,123	0.1954	0.1219	0.1371	1,626	0.0615	0.0390	0.1428	1,626
63-66	0.0350	0.0440	0.4342	3,230	0.0107	0.2893	0.9709	1,576	-0.0278	0.1887	0.8843	2,243	0.0734	0.1321	0.5837	3,230	0.0139	0.0314	0.6623	3,230
62-67	0.0399	0.0362	0.2776	4,884	0.0987	0.2358	0.6781	2,360	-0.0080	0.1607	0.9608	3,362	-0.0677	0.1206	0.5781	4,884	0.0115	0.0251	0.6490	4,884
61-68	0.0247	0.0291	0.3998	6,453	-0.0019	0.2054	0.9926	3,111	0.0124	0.1276	0.9233	4,442	0.0668	0.1087	0.5417	6,453	-0.0060	0.0222	0.7869	6,453
60-69	0.0307	0.0264	0.2497	8,078	-0.0288	0.1709	0.8668	3,879	-0.0015	0.1107	0.9891	5,538	0.1306	0.0988	0.1916	8,078	0.0053	0.0191	0.7817	8,078

Notes: The outcomes shown include i) bond ownership; ii) amount (in logs) of stocks held directly or through mutual funds, conditional on ownership; iii) amount (in logs) of stocks held in any form, conditional on ownership; iv) household income (transformed using the inverse hyperbolic sine transformation); v) retirement, denoted by a binary variable indicating whether any of the two partners is retired. Estimates in Panel A are derived using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panel B presents local linear regression results for each age interval indicated. We use fuzzy RD for outcomes i), ii) and iii), while sharp RD for outcomes iv) and v) above. Age is measured in bi-monthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table A.1. P values of F tests of different age measurement units

Ages Included in the Estimation Sample	Age measured in bimonthly intervals				Age measured in quarters				Age measured in six-month intervals				Age measured in years			
	Full Sample	College Graduates	High School Graduates	Less than High School Education	Full Sample	College Graduates	High School Graduates	Less than High School Education	Full Sample	College Graduates	High School Graduates	Less than High School Education	Full Sample	College Graduates	High School Graduates	Less than High School Education
	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value	P-value
Panel A. Stocks held directly or through mutual funds																
64-65	0.2324	0.2510	0.4870	0.2313	0.5128	0.3154	0.5907	0.3000	0.5667	0.4255	0.5038	0.0047 ***	0.6793	0.4534	0.5238	0.0001 ***
63-66	0.4001	0.2149	0.7991	0.4116	0.6740	0.1825	0.8606	0.7039	0.7052	0.3005	0.7483	0.0027 ***	0.4414	0.3655	0.6349	0.0000 ***
62-67	0.5725	0.2096	0.9012	0.4909	0.8091	0.2282	0.4794	0.1308	0.8093	0.4341	0.5232	0.0000 ***	0.6020	0.5028	0.3988	0.0000 ***
61-68	0.5216	0.0488 **	0.6642	0.6119	0.8273	0.0794 *	0.3022	0.1099	0.7891	0.1335	0.3251	0.0001 ***	0.6187	0.2098	0.2596	0.0000 ***
60-69	0.6184	0.0100 **	0.5877	0.6082	0.9068	0.0536 *	0.2987	0.1397	0.9062	0.0838 *	0.3400	0.0002 ***	0.8269	0.1574	0.3028	0.0000 ***
Panel B. Stocks held in any form																
64-65	0.8386	0.0664 *	0.5811	0.2463	0.9150	0.0235 **	0.5451	0.0405 **	0.9170	0.0144 **	0.6471	0.0005 ***	0.9438	0.0269 **	0.7426	0.0000 ***
63-66	0.9014	0.1170	0.6345	0.2111	0.8083	0.0279 **	0.3602	0.0782 *	0.8326	0.0172 **	0.4042	0.0020 ***	0.5123	0.0226 **	0.4855	0.0000 ***
62-67	0.9123	0.1070	0.8015	0.1060	0.9145	0.0401 **	0.3677	0.0017 ***	0.7853	0.0404 **	0.4066	0.0000 ***	0.4201	0.0664 *	0.4459	0.0000 ***
61-68	0.9519	0.2195	0.6722	0.2644	0.9391	0.1150	0.4626	0.0018 ***	0.8279	0.0711 *	0.5228	0.0000 ***	0.4891	0.1234	0.5353	0.0000 ***
60-69	0.9682	0.1807	0.8550	0.2615	0.9420	0.1864	0.5361	0.0029 ***	0.8854	0.1200	0.6266	0.0000 ***	0.6458	0.1977	0.6639	0.0000 ***

Notes: The table shows p-values of the F-tests of coefficients of monthly dummies in regressions in which the dependent variable is stockholding. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table A.2. Ownership of stocks, fuzzy RD, age measured in quarters

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	0.0136	0.0277	0.6241	23,278	0.1099	0.0440	0.0125	5,456	-0.0368	0.0291	0.2064	15,068	0.0170	0.0319	0.5951	5,859
Panel A.2. Local Linear Regression																
64-65	0.0059	0.0294	0.8464	6,474	0.1699	0.0360	0.0022	1,626	-0.0916	0.0257	0.0092	3,702	-0.0727	0.0294	0.0427	1,146
63-66	0.0237	0.0192	0.2374	12,906	0.1190	0.0220	0.0001	3,230	-0.0254	0.0299	0.4091	7,334	0.0083	0.0291	0.7808	2,342
62-67	0.0056	0.0168	0.7409	19,360	0.0628	0.0269	0.0286	4,884	-0.0171	0.0255	0.5084	11,002	-0.0042	0.0254	0.8688	3,474
61-68	0.0235	0.0153	0.1346	25,759	0.0678	0.0241	0.0085	6,453	0.0020	0.0242	0.9352	14,696	0.0114	0.0217	0.6041	4,610
60-69	0.0209	0.0137	0.1356	32,227	0.0484	0.0228	0.0407	8,078	0.0122	0.0214	0.5712	18,376	0.0054	0.0197	0.7852	5,773
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	0.0416	0.0255	0.1029	24,797	0.1599	0.0309	0.0000	3,854	-0.0192	0.0249	0.4415	16,887	0.0780	0.0454	0.0856	5,317
Panel B.2. Local Linear Regression																
64-65	0.0567	0.0202	0.0260	6,474	0.1769	0.0329	0.0010	1,626	-0.0288	0.0203	0.2000	3,702	-0.0375	0.0420	0.4013	1,146
63-66	0.0461	0.0163	0.0128	12,906	0.1194	0.0360	0.0047	3,230	0.0021	0.0240	0.9300	7,334	0.0533	0.0351	0.1494	2,342
62-67	0.0226	0.0207	0.2863	19,360	0.0630	0.0332	0.0708	4,884	0.0100	0.0237	0.6781	11,002	0.0118	0.0305	0.7020	3,474
61-68	0.0363	0.0170	0.0411	25,759	0.0692	0.0291	0.0235	6,453	0.0169	0.0205	0.4157	14,696	0.0378	0.0272	0.1740	4,610
60-69	0.0300	0.0156	0.0623	32,227	0.0536	0.0257	0.0438	8,078	0.0212	0.0183	0.2536	18,376	0.0274	0.0237	0.2531	5,773

Notes: Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. Age is measured in quarterly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table A.3. Ownership of stocks, fuzzy RD, age measured in months

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	0.0259	0.0217	0.2315	30,685	0.1174	0.0491	0.0168	5,754	-0.0255	0.0275	0.3538	15,953	0.0176	0.0313	0.5736	6,192
Panel A.2. Local Linear Regression																
64-65	0.0059	0.0294	0.8464	6,474	0.1699	0.0360	0.0022	1,626	-0.0916	0.0257	0.0092	3,702	-0.0727	0.0294	0.0427	1,146
63-66	0.0237	0.0192	0.2374	12,906	0.1190	0.0220	0.0001	3,230	-0.0254	0.0299	0.4091	7,334	0.0083	0.0291	0.7808	2,342
62-67	0.0056	0.0168	0.7409	19,360	0.0628	0.0269	0.0286	4,884	-0.0171	0.0255	0.5084	11,002	-0.0042	0.0254	0.8688	3,474
61-68	0.0235	0.0153	0.1346	25,759	0.0678	0.0241	0.0085	6,453	0.0020	0.0242	0.9352	14,696	0.0114	0.0217	0.6041	4,610
60-69	0.0209	0.0137	0.1356	32,227	0.0484	0.0228	0.0407	8,078	0.0122	0.0214	0.5712	18,376	0.0054	0.0197	0.7852	5,773
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	0.0462	0.0221	0.0365	27,487	0.1474	0.0440	0.0008	6,130	-0.0143	0.0300	0.6326	16,573	0.0802	0.0493	0.1039	5,488
Panel B.2. Local Linear Regression																
64-65	0.0567	0.0202	0.0260	6,474	0.1769	0.0329	0.0010	1,626	-0.0288	0.0203	0.2000	3,702	-0.0375	0.0420	0.4013	1,146
63-66	0.0461	0.0163	0.0128	12,906	0.1194	0.0360	0.0047	3,230	0.0021	0.0240	0.9300	7,334	0.0533	0.0351	0.1494	2,342
62-67	0.0226	0.0207	0.2863	19,360	0.0630	0.0332	0.0708	4,884	0.0100	0.0237	0.6781	11,002	0.0118	0.0305	0.7020	3,474
61-68	0.0363	0.0170	0.0411	25,759	0.0692	0.0291	0.0235	6,453	0.0169	0.0205	0.4157	14,696	0.0378	0.0272	0.1740	4,610
60-69	0.0300	0.0156	0.0623	32,227	0.0536	0.0257	0.0438	8,078	0.0212	0.0183	0.2536	18,376	0.0274	0.0237	0.2531	5,773

Notes: Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. Age is measured in months. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table A.4. Ownership of stocks, households with at least one of the two partners having neither Medicare nor other health insurance before age 65, fuzzy RD

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	-0.0023	0.0659	0.9722	4,700	0.2573	0.1345	0.0558	572	-0.0806	0.0949	0.3957	2,395	-0.0184	0.0686	0.7889	1,443
Panel A.2. Local Linear Regression																
64-65	-0.0022	0.0767	0.9780	1,122	0.4065	0.1188	0.0057	124	-0.1599	0.1140	0.1884	633	0.0000	0.0529	0.9997	365
63-66	0.0272	0.0512	0.6006	2,236	0.2648	0.1305	0.0542	253	-0.0263	0.0751	0.7294	1,219	0.0058	0.0330	0.8612	764
62-67	0.0327	0.0397	0.4156	3,355	0.1629	0.1225	0.1921	378	0.0148	0.0581	0.8009	1,855	0.0078	0.0283	0.7853	1,122
61-68	0.0394	0.0351	0.2673	4,444	0.1879	0.1048	0.0795	484	0.0184	0.0493	0.7101	2,479	0.0234	0.0227	0.3095	1,481
60-69	0.0389	0.0285	0.1768	5,544	0.1814	0.0944	0.0595	607	0.0171	0.0394	0.6655	3,085	0.0255	0.0193	0.1913	1,852
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	-0.0110	0.0558	0.8442	3,608	0.3044	0.1387	0.0282	646	-0.1007	0.0922	0.2744	2,395	0.0723	0.0649	0.2658	1,752
Panel B.2. Local Linear Regression																
64-65	0.0246	0.0580	0.6799	1,122	0.2470	0.1181	0.0605	124	-0.1170	0.1312	0.3916	633	0.0468	0.0493	0.3637	365
63-66	0.0138	0.0379	0.7193	2,236	0.1489	0.1109	0.1926	253	-0.0617	0.0785	0.4398	1,219	0.0547	0.0321	0.1015	764
62-67	0.0187	0.0325	0.5685	3,355	0.1119	0.1001	0.2714	378	-0.0002	0.0604	0.9976	1,855	0.0080	0.0333	0.8104	1,122
61-68	0.0232	0.0291	0.4276	4,444	0.1318	0.0928	0.1619	484	-0.0050	0.0477	0.9168	2,479	0.0395	0.0266	0.1444	1,481
60-69	0.0294	0.0246	0.2360	5,544	0.1567	0.0840	0.0670	607	0.0072	0.0405	0.8595	3,085	0.0267	0.0246	0.2816	1,852

Notes: The sample consists of households with at least one of the two partners having neither Medicare nor other health insurance before age 65. Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. Age is measured in bimonthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table A.5. Ownership of stocks, households with both partners having health insurance (but not Medicare) before age 65, fuzzy RD

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	0.0124	0.0209	0.5510	13,535	0.1085	0.0369	0.0033	5,060	-0.0424	0.0307	0.1671	7,006	0.0268	0.0365	0.4630	1,757
Panel A.2. Local Linear Regression																
64-65	0.0338	0.0130	0.0245	4,785	0.1466	0.0588	0.0299	1,449	-0.0366	0.0316	0.2708	2,766	-0.0826	0.0604	0.1985	570
63-66	0.0296	0.0145	0.0529	9,457	0.1082	0.0405	0.0136	2,856	-0.0205	0.0280	0.4709	5,462	0.0141	0.0412	0.7358	1,139
62-67	0.0140	0.0125	0.2712	13,999	0.0701	0.0352	0.0541	4,259	-0.0152	0.0250	0.5490	8,075	-0.0095	0.0328	0.7730	1,665
61-68	0.0250	0.0119	0.0407	18,411	0.0607	0.0316	0.0605	5,590	-0.0019	0.0213	0.9289	10,641	-0.0033	0.0250	0.8944	2,180
60-69	0.0210	0.0124	0.0948	22,731	0.0415	0.0273	0.1342	6,922	0.0077	0.0208	0.7129	13,145	-0.0157	0.0237	0.5108	2,664
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	0.0413	0.0313	0.1861	12,083	0.1374	0.0332	0.0000	5,060	-0.0254	0.0413	0.5382	8,259	0.0528	0.0566	0.3508	1,937
Panel B.2. Local Linear Regression																
64-65	0.0764	0.0315	0.0338	4,785	0.1697	0.0553	0.0107	1,449	0.0136	0.0411	0.7474	2,766	-0.0865	0.1105	0.4499	570
63-66	0.0549	0.0271	0.0549	9,457	0.1254	0.0505	0.0209	2,856	0.0104	0.0397	0.7958	5,462	0.0199	0.0654	0.7633	1,139
62-67	0.0311	0.0217	0.1604	13,999	0.0732	0.0400	0.0761	4,259	0.0108	0.0342	0.7536	8,075	-0.0035	0.0504	0.9456	1,665
61-68	0.0412	0.0189	0.0344	18,411	0.0693	0.0360	0.0606	5,590	0.0140	0.0297	0.6401	10,641	0.0144	0.0386	0.7113	2,180
60-69	0.0335	0.0183	0.0718	22,731	0.0535	0.0317	0.0967	6,922	0.0163	0.0273	0.5518	13,145	0.0025	0.0348	0.9430	2,664

Notes: The sample consists of households with both partners having health insurance (but not Medicare) before age 65. Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. Age is measured in bimonthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table A.6. Ownership of stocks, households with a maximum (between the two partners) delayed recall score equal to 5 or above, fuzzy RD

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	0.0192	0.0227	0.3974	14,858	0.1108	0.0443	0.0124	4,039	-0.0591	0.0400	0.1392	8,226	0.0689	0.0502	0.1705	2,205
Panel A.2. Local Linear Regression																
64-65	0.0257	0.0205	0.2358	4,386	0.1770	0.0507	0.0051	1,399	-0.0867	0.0409	0.0574	2,544	0.0263	0.1068	0.8100	443
63-66	0.0484	0.0183	0.0146	8,725	0.1207	0.0399	0.0060	2,773	-0.0099	0.0381	0.7976	5,059	0.0758	0.0665	0.2660	893
62-67	0.0266	0.0155	0.0955	13,054	0.0841	0.0373	0.0306	4,172	-0.0095	0.0319	0.7664	7,567	0.0371	0.0574	0.5218	1,315
61-68	0.0410	0.0153	0.0103	17,337	0.0754	0.0321	0.0232	5,515	0.0069	0.0278	0.8045	10,082	0.0677	0.0405	0.1007	1,740
60-69	0.0341	0.0142	0.0198	21,537	0.0464	0.0286	0.1102	6,857	0.0211	0.0258	0.4162	12,502	0.0420	0.0346	0.2298	2,178
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	0.0659	0.0334	0.0481	12,672	0.1476	0.0404	0.0003	4,721	-0.0006	0.0451	0.9893	8,226	0.1566	0.0603	0.0094	2,134
Panel B.2. Local Linear Regression																
64-65	0.0861	0.0457	0.0859	4,386	0.1909	0.0647	0.0132	1,399	-0.0144	0.0488	0.7731	2,544	0.1371	0.0513	0.0217	443
63-66	0.0911	0.0320	0.0091	8,725	0.1210	0.0574	0.0462	2,773	0.0469	0.0425	0.2813	5,059	0.1888	0.0508	0.0011	893
62-67	0.0699	0.0252	0.0089	13,054	0.0987	0.0456	0.0372	4,172	0.0493	0.0335	0.1509	7,567	0.0885	0.0515	0.0943	1,315
61-68	0.0718	0.0232	0.0034	17,337	0.0894	0.0398	0.0295	5,515	0.0398	0.0290	0.1769	10,082	0.1325	0.0379	0.0010	1,740
60-69	0.0584	0.0199	0.0047	21,537	0.0610	0.0342	0.0799	6,857	0.0470	0.0266	0.0826	12,502	0.0884	0.0360	0.0170	2,178

Notes: The sample consists of households with a maximum (between the two partners) delayed recall score equal to 5 or above (out of 10). Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. Age is measured in bimonthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table A.7. Ownership of stocks, households with a maximum (between the two partners) delayed recall score below 5, fuzzy RD

Ages included in the estimation sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Full Sample				College Graduates				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs	Coeff.	Std. Error	p-value	Number of obs
Panel A. Direct Stockholding																
Panel A.1. Robust RD																
Selected by the optimal bandwidth	-0.0050	0.0419	0.9059	7,544	0.1247	0.0706	0.0775	1,039	-0.0221	0.0481	0.6459	5,773	-0.0443	0.0623	0.4774	2,838
Panel A.2. Local Linear Regression																
64-65	-0.0589	0.0334	0.1056	2,003	0.0513	0.0976	0.6096	225	-0.0745	0.0438	0.1167	1,127	-0.1120	0.0501	0.0471	651
63-66	-0.0295	0.0273	0.2919	4,009	0.0659	0.0688	0.3476	453	-0.0481	0.0321	0.1481	2,211	-0.0288	0.0415	0.4949	1,345
62-67	-0.0264	0.0254	0.3070	6,049	-0.0283	0.0511	0.5836	704	-0.0219	0.0358	0.5439	3,345	-0.0251	0.0338	0.4630	2,000
61-68	-0.0093	0.0238	0.6973	8,072	0.0326	0.0472	0.4937	926	-0.0087	0.0356	0.8071	4,487	-0.0138	0.0256	0.5924	2,659
60-69	0.0046	0.0212	0.8303	10,247	0.0930	0.0507	0.0719	1,200	-0.0039	0.0301	0.8968	5,711	-0.0085	0.0231	0.7125	3,336
Panel B. Total Stockholding																
Panel B.1. Robust RD																
Selected by the optimal bandwidth	-0.0698	0.0774	0.3672	6,852	0.1479	0.0985	0.1333	992	-0.0868	0.0595	0.1448	4,945	-0.0115	0.0894	0.8980	2,713
Panel B.2. Local Linear Regression																
64-65	-0.0652	0.0673	0.3534	2,003	0.0124	0.0743	0.8706	225	-0.0658	0.0607	0.3020	1,127	-0.1362	0.0965	0.1859	651
63-66	-0.0661	0.0504	0.2024	4,009	0.1206	0.0727	0.1108	453	-0.1139	0.0509	0.0352	2,211	-0.0290	0.0733	0.6962	1,345
62-67	-0.0741	0.0422	0.0875	6,049	-0.0928	0.0548	0.0993	704	-0.0851	0.0476	0.0825	3,345	-0.0277	0.0619	0.6577	2,000
61-68	-0.0440	0.0339	0.2016	8,072	-0.0251	0.0493	0.6126	926	-0.0508	0.0408	0.2199	4,487	-0.0094	0.0471	0.8419	2,659
60-69	-0.0231	0.0312	0.4620	10,247	0.0448	0.0512	0.3851	1,200	-0.0410	0.0386	0.2917	5,711	-0.0001	0.0408	0.9971	3,336

Notes: The sample consists of households with a maximum (between the two partners) delayed recall score below 5 (out of 10). Panel A reports results for direct stockholding (that is, stocks held directly or through mutual funds), while Panel B reports results for total stockholding or stocks held in any form (that is, direct stockholding plus stocks held through Investment Retirement Accounts). Estimates in Panels A.1. and B.1 are derived through fuzzy RD using the methodology proposed by Calonico, Cattaneo, and Titiunik (2014) to choose the optimal bandwidth, while Panels A.2 and B.2 present fuzzy RD local linear regression results for each age interval indicated. Age is measured in bimonthly intervals. ***, **, * denote statistical significance at 1%, 5% and 10% respectively.