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

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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.

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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), 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

[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).

policies). Interestingly, Card, Dobkin and Maestas (2008) 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. Consistent with these patterns, Barcellos and Jacobson (2015) find that Medicare significantly reduces out of pocket medical expenditures.

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).[5] Hence, whether financial risk-taking is affected by increased insurance coverage and generosity through Medicare is ultimately an empirical question.

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.

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[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 (2009), Atella, Brunetti and Maestas (2012).

[5] The intuition for this result is as follows (see Haliassos, 2002 for a more detailed exposition): given that expected returns from stocks exceed those of riskless assets, a household will be discouraged from stock investment only because stockholding increases too much the riskiness of consumption. When the household invests no money in stocks, however, stocks returns are not correlated with consumption, and thus at the margin of zero stock investment the household should prefer to invest in stocks rather than in a riskless asset to take advantage of the equity premium.

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 at least some 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 for this education group, depending on the method used. On the other hand, we find no effect of Medicare on stockholding for those without any college education. 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 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.

The paper that is most similar in spirit to ours is Goldman and Maestas (2013), who also explore the relationship between health insurance coverage and financial risk-taking. While Goldman and Maestas (2013) 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, Goldman and Maestas (2013) 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 Goldman and Maestas (2013) 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

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

health status and risk aversion. Goldman and Maestas (2013) 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 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]

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 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.

[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; Barcellos and Jacobson, 2015).

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, Dobkin 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%

[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.

among 64- and 66-year olds, 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 percentage points) than for non-college educated households (72 percentage points), 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 (Card, Dobkin and Maestas, 2008), 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, Card, Dobkin and Maestas (2008) show that the onset of Medicare facilitates access to care even for better-off population groups like college graduates and whites, who are more likely to have 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, Barcellos and Jacobson (2015) find that, at age 65, out-of-pocket 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

[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).

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

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 more. 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.

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

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[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.

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 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.

[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.

In addition, as Lee and Lemieux (2010, LL henceforth) point out, on 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]

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

[15] De Nardi et al. (2014) provide evidence of substantial such spillovers in couples.

[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.

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 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 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.

[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 analysed 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).

[18] See for example the empirical contributions is Guiso, Haliassos, Jappelli (2002).

3.2 Methodology

Our goal is to estimate the causal impact of Medicare coverage 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 a few individuals below 65 who already have Medicare coverage, even if there is indeed a very large jump in the probability of being covered by Medicare at age 65. Hence, we rely on a fuzzy RD (FRD henceforth) design. A sharp RD design would have been appropriate if the probability of having Medicare had been a deterministic function of age.

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 (TSLS) estimator, with an indicator variable taking the value 1 if age is not below the 65 threshold as the excluded instrument (Imbens and Lemieux, 2008; Hahn et al., 2001).

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

[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.

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.

[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.

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. Researchers often explore whether their results are critically dependent on the particular bandwidth choice (a specific age interval in our context). While it is useful to have some formal guidance in the selection process, the bandwidth selection procedures commonly used in the literature do not focus specifically on the RD setting or lack optimal properties. In a recent contribution, Imbens and Kalyanaraman (2012, henceforth IK) develop a data-dependent method for choosing the bandwidth that is asymptotically optimal and tailored to the specific features of the RD setting. Although IK's proposed bandwidth estimation method has asymptotically optimal properties, it is not unique, as it depends on the range around the discontinuity point of the estimation data used. Hence, IK recommend that researchers experiment with different estimation ranges (i.e., age intervals) to assess sensitivity to range selection. We follow this recommendation and present results based on the IK methodology, but 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 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 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 ownership of stocks either directly or through mutual funds. Table 2 displays results for stocks held directly and through mutual funds, 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 Panel A of Table 2 we show results obtained through the IK method, while in Panel B those obtained through local linear regressions. For robustness, we use five age bands, 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. Note also that the IK method produces for each age band a different optimal bandwidth.[21]

Results using both estimation methods suggest that there is no impact of Medicare coverage on the portfolio decisions of households without any college education: estimates are

[21] The optimal bandwidths produced by the IK 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 each of the age intervals.

often negative, quite small in magnitude and almost always very far from achieving standard levels of statistical significance. These results in general extend to the whole sample, in which the non-college educated form the large majority.[22]

The picture changes completely for college-educated households, where our estimates are sizeable and statistically significant. First, we see that, when using local linear regression (Panel B 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. The median local linear estimate is about 7 percentage points, while the corresponding estimate from the IK method (Panel A of Table 2) is about 13 percentage points.

These estimates are both statistically significant and economically important, especially when considering that the overall prevalence of this form of stockholding for those with some college education is about 44%, as can be seen from Table 1. 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 Barcellos and Jacobson (2015). Moreover, our results are broadly in line with those of Goldman and Maestas (2013). As discussed, they consider the subpopulation of Medicare beneficiaries (among whom there is less heterogeneity both in coverage and in generosity than between Medicare beneficiaries versus non-beneficiaries) and find that HMO participation increases risky asset ownership by 13 percentage points relative to those enrolled in Medicare parts A and B only.

Subsequently, we also use as our dependent variable total stockholding, i.e. we combine in one variable direct and through mutual funds stock ownership with ownership through IRAs. One important advantage for using this broader definition of stockholding is that it is not affected by any misclassification by the respondents of one form of stock ownership into

[22] Exceptions to this pattern are the local linear estimates for the whole sample based on age bands 61-68 and 60-69. Note, however, that these estimates are small in magnitude, only statistically significant at the 10% level, and they correspond to the two widest age bands, that is, those relatively more prone to yielding biased estimates.

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. Our results are shown in Table 3, and they are similar to those obtained for direct and through mutual funds stock ownership: the median estimate from the IK method implies that Medicare boosts total stockholding by about 14 percentage points, while the corresponding effect obtained through local linear regression is about 7 percentage points. Given that the prevalence of total stockholding is 70.5% for 60-64 households with some college education, these effects are economically important as well.

When interpreting these 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 without any college education, 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.

Finally, we examine whether Medicare induces investment in less risky assets like bonds.[23] 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 asset because of its associated reduction in background risk. Second, since Medicare eligibility significantly reduces out of pocket expenditures (even

[23] These results are available upon request from the authors.

more so for the better educated, as documented by Barcellos and Jacobson, 2015), 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. We find, however, 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 driving our results for stockholding.

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.

First, as discussed in Section 3, we consider other possible factors that might change at age 65 and influence the decision to own stocks. The most salient such factor is 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 do not typically suggest any association between stock ownership and being retired (e.g., see the contributions in Guiso, Haliassos and Jappelli, 2001). 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, 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, and find no statistically significant effect (the local linear regression lines are also shown in Figure 3). Therefore, we find no evidence of a spike in retirement at age 65. Reassuringly, this conclusion has also been reached by other authors using alternative datasets. Specifically, similar smooth employment-related outcomes have been uncovered by Card, Dobkin and Mestas (2008) using both the National Health Interview Survey and the March CPS, and by Barcellos and Jacobson (2015) using both the Medical Expenditure Panel Survey and the Health Tracking Household Survey. Hence, our finding that Medicare increases stockholding for the college educated should not be affected by the retirement choices of the individuals therein.

Another variable that might change at age 65 and might affect stockholding would be income. If such a change occurs, 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. Barcellos and Jacobson (2015) 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.

Next, we 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.

[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.

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 60 and until age 69, i.e., four years to the left and to the right of the age for Medicare eligibility. As suggested by Imbens and Lemieux (2008), we set the placebo thresholds equal to the median age of each age interval considered on both sides of the age 65 cutoff value (that is, avoiding the point where the regression function is known to have a discontinuity). If the effect observed at age 65 is a genuine one, i.e., due to being eligible for 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 (IK and local linear regression). We find that in none of the 16 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 previously shown in Tables 2 and 3 are clearly strong and statistically significant. Hence, we conclude that there is little evidence that our results are due to noisy changes in the data.

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 months and quarterly. The results for directly held stocks are displayed in Table 5A, while those for stocks held in any form in Table 5B. 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 between 7 and 14 percentage points for both directly held stocks and stocks held in any form.

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 race, a measure of whether the household contains a person with health problems as indicated by having any limitations in activities of daily living (ADLs), and whether the household is formed by a couple or whether the single head is divorced or widowed, (the base category for our sample being never married). Our results are shown in Table 6. Consistent with the idea that variation in Medicare coverage near the age 65 threshold is approximately randomized, we find that our point estimates were not affected by the inclusion of these additional covariates.

We also try a sharp RD estimation, which is the procedure that various papers use when dealing with the effects of Medicare (see, e.g., Card, Goldman and Maestas, 2008 and 2009). As is well known, the sharp RD estimate is smaller than the corresponding FRD one because it is not divided by the change in the probability of getting Medicare at age 65. Consequently, we found slightly smaller (by about 2 to 4 percentage points) but still strongly statistically significant effects of Medicare on stockholding.

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 to order five, and our results did not change.

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 households that have at least some college education. In contrast, our results indicate that the onset of Medicare does not significantly alter the financial risk taking behavior of households with less than college education. 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 be manifest itself 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.

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Figure 1. Medicare Coverage Rates

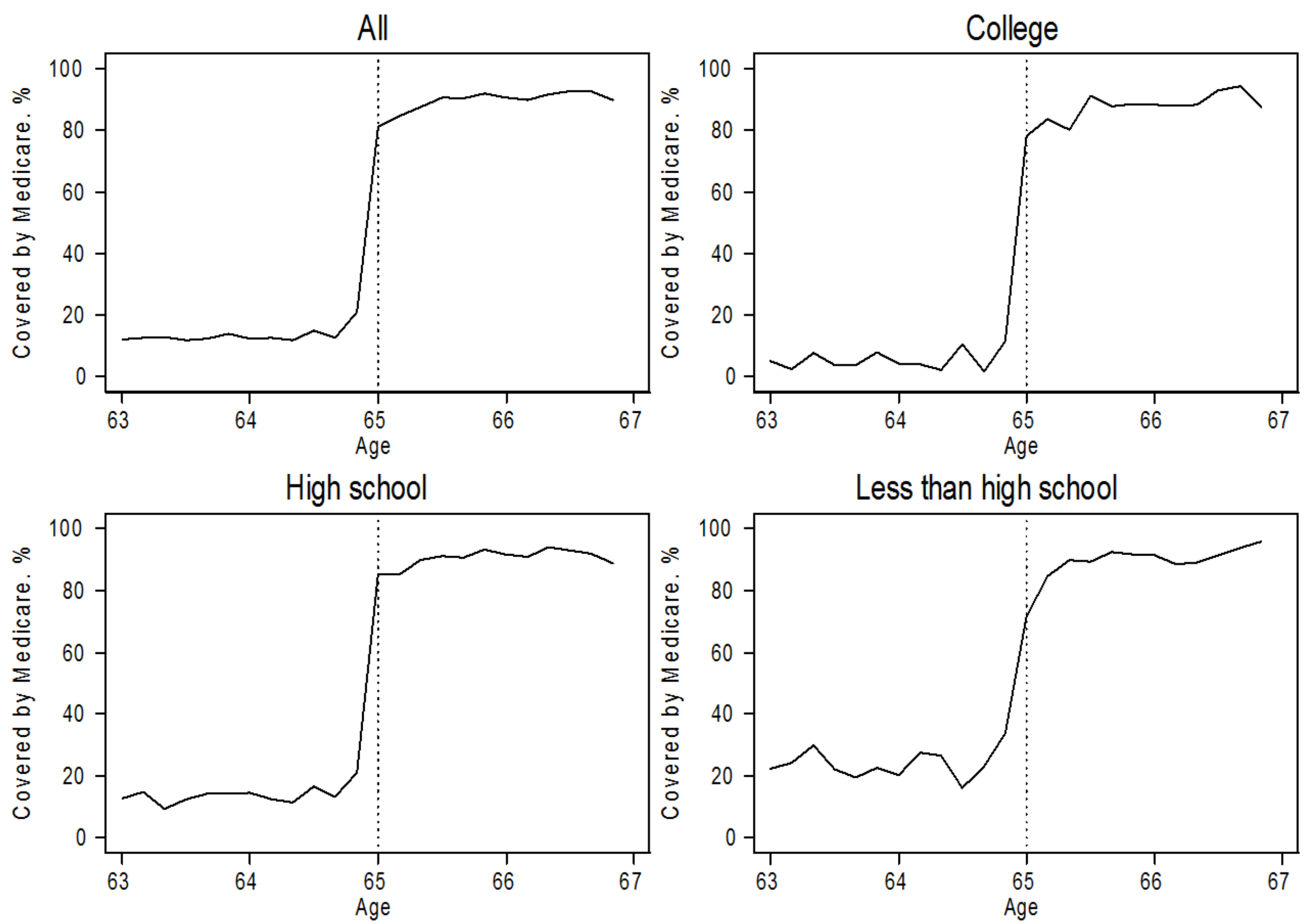

Figure 2A. Rate of ownership of stocks held directly or through mutual funds

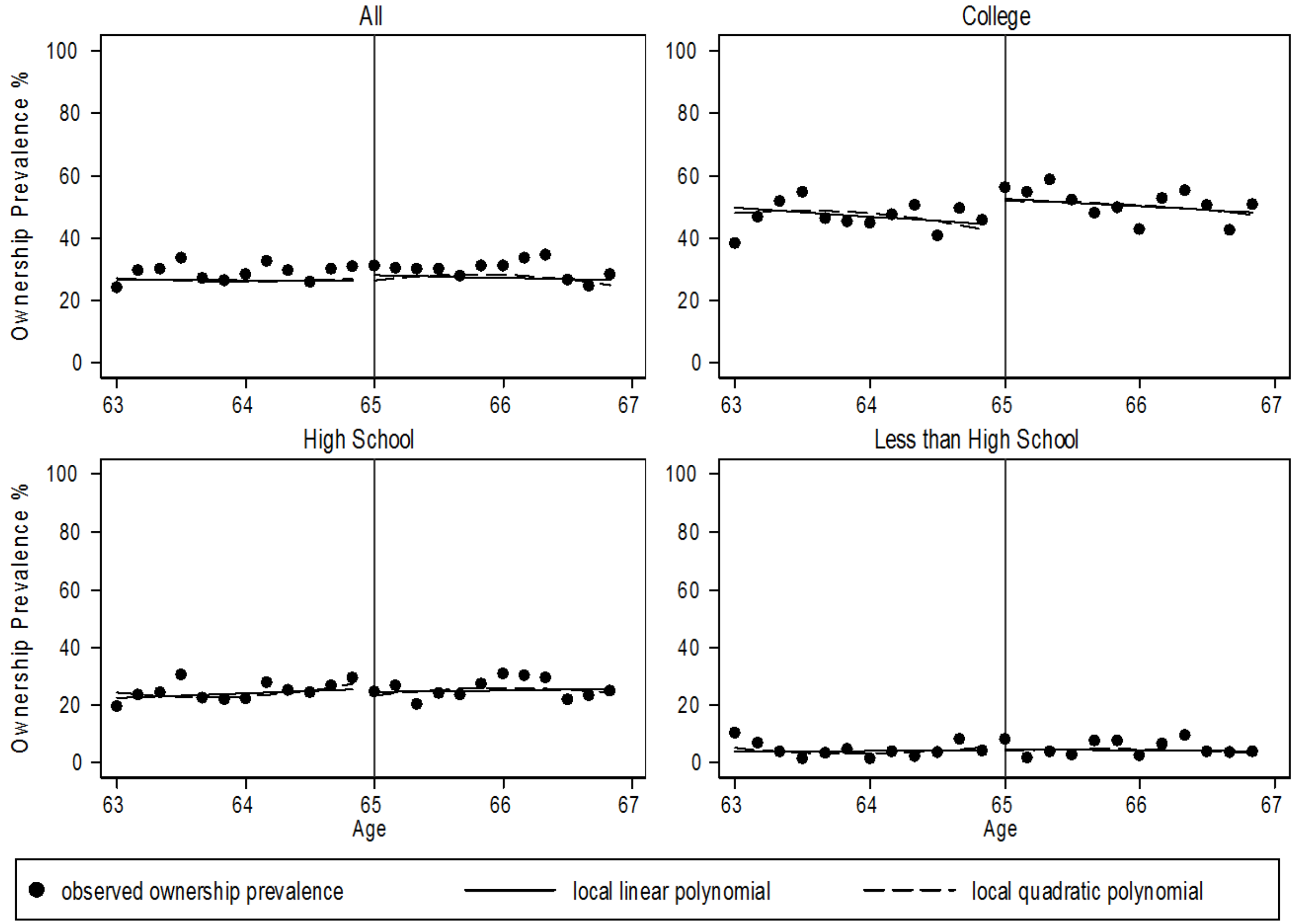

Figure 2B. Rate of ownership of stocks held in any form

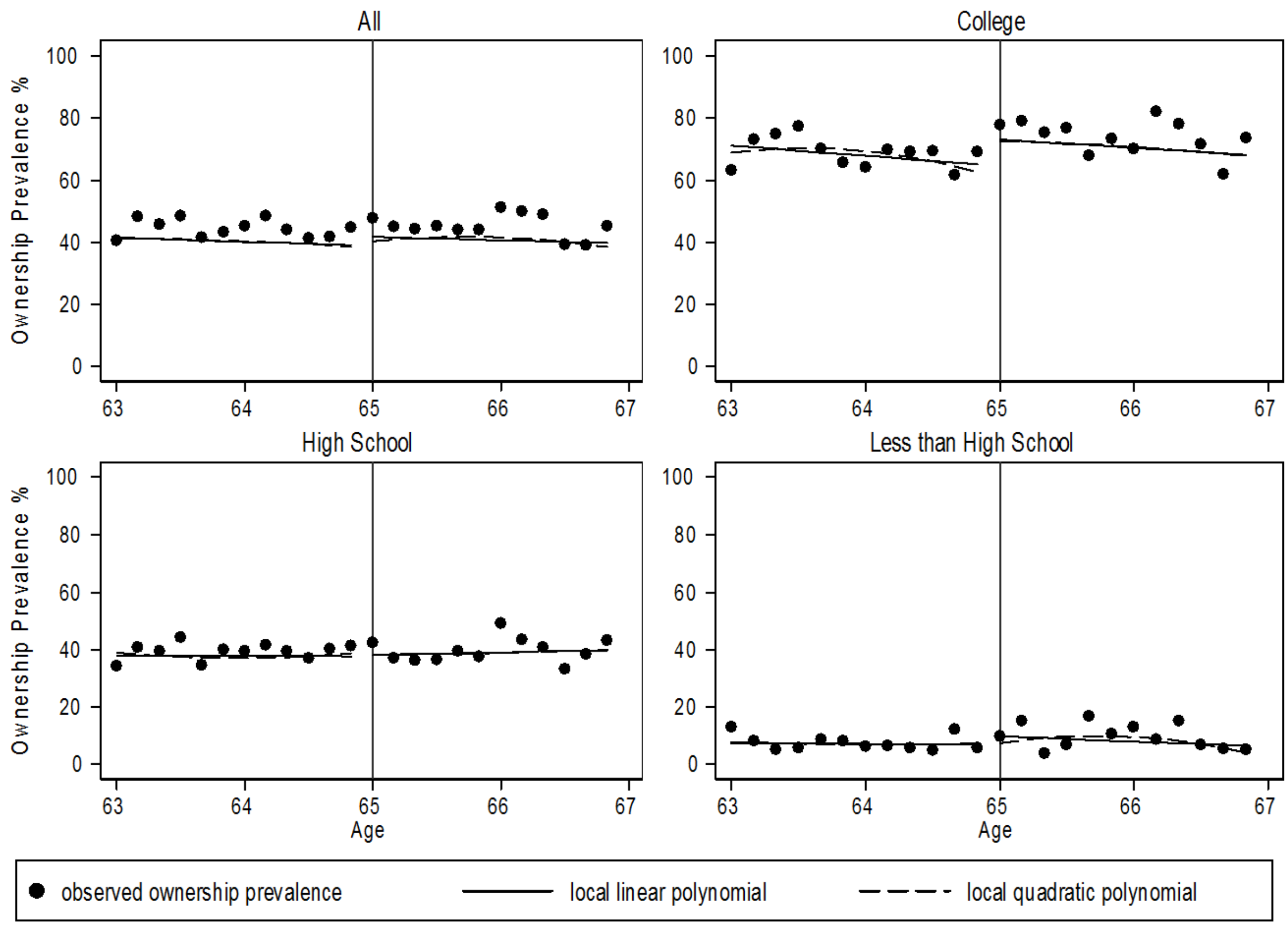

Figure 3. Prevalence of retirement

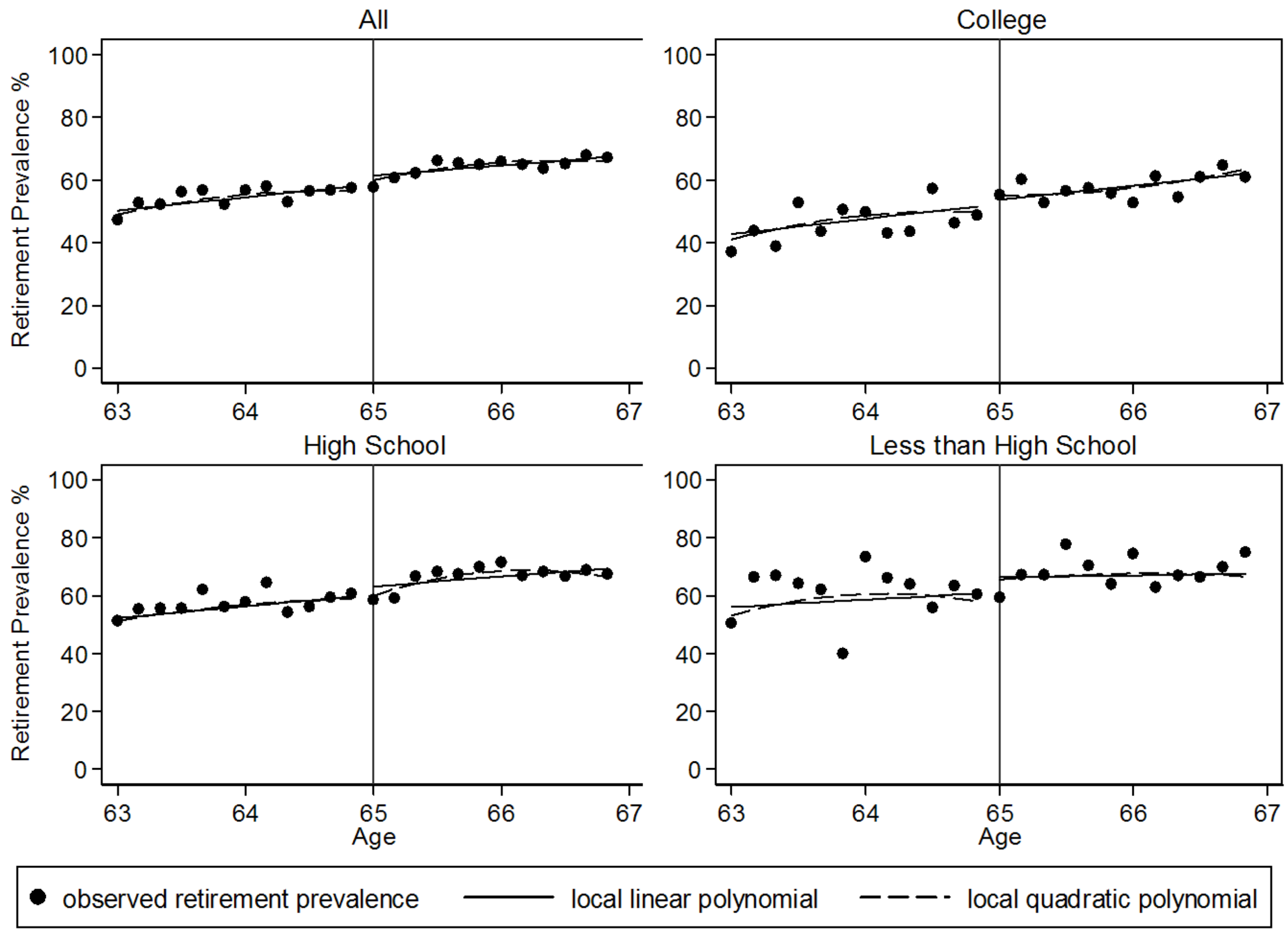

Table 1. Ownership rate of stocks held in different investment vehicles, by education, ages 60-69

Item	Whole Sample	Some college education	High School Graduates	Less than High School Education
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.

Table 2. Ownership of stocks held directly or through mutual funds, Imbens-Kalyanaraman method and local linear regression, age measured in bi-monthly intervals

Ages Included in the Estimation Sample	Full Sample			Some College Education			High School Graduates			Less than High School Education		
	Coeff.	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**
				Panel A. Imbens-Kalyanaraman Method								
64-65	0.0069	0.0419	6,474	0.1766	0.0979 *	1,626	-0.0764	0.0624	3,702	0.2626	0.5507	1,146
63-66	0.0014	0.0387	12,906	0.1281	0.0534 **	3,230	-0.0814	0.0468 *	7,334	-0.0196	0.0534	2,342
62-67	0.0075	0.0219	19,360	0.1156	0.0503 **	4,884	-0.0795	0.0483 *	11,002	0.0001	0.0344	3,474
61-68	0.0097	0.0240	25,759	0.1336	0.0574 **	6,453	-0.0414	0.0350	14,696	-0.0068	0.0397	4,610
60-69	0.0077	0.0217	32,227	0.1298	0.0546 **	8,078	-0.0299	0.0291	18,376	0.0001	0.0294	5,773
				Panel B. Local Linear Regression								
64-65	0.0080	0.0380	6,474	0.1594	0.0740 **	1,626	-0.0742	0.0474	3,702	-0.0627	0.0591	1,146
63-66	0.0256	0.0259	12,906	0.1162	0.0502 **	3,230	-0.0197	0.0332	7,334	0.0107	0.0366	2,342
62-67	0.0065	0.0160	19,360	0.0642	0.0316 **	4,884	-0.0149	0.0208	11,002	-0.0023	0.0250	3,474
61-68	0.0239	0.0143 *	25,759	0.0700	0.0286 **	6,453	0.0022	0.0186	14,696	0.0125	0.0199	4,610
60-69	0.0214	0.0116 *	32,227	0.0511	0.0232 **	8,078	0.0120	0.0153	18,376	0.0068	0.0164	5,773

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table 3. Ownership of stocks held in any form, Imbens-Kalyanaraman method and local linear regression, age measured in bi-monthly intervals

Ages Included in the Estimation Sample	Full Sample			Some College Education			High School Graduates			Less than High School Education		
	Coeff.	Std. Error	Number of obs	Coeff.	Std. Error	Number of obs	Coeff.	Std. Error	Number of obs	Coeff.	Std. Error	Number of obs
	Panel A. Imbens-Kalyanaraman Method											
64-65	0.0337	0.0757	6,474	0.2481	0.1143 **	1,626	-0.0353	0.0902	3,702	-0.0451	0.1064	1,146
63-66	0.0377	0.0421	12,906	0.1705	0.0701 **	3,230	-0.0100	0.0429	7,334	-0.0098	0.0817	2,342
62-67	0.0250	0.0227	19,360	0.1420	0.0561 **	4,884	-0.0082	0.0421	11,002	0.0163	0.0699	3,474
61-68	0.0266	0.0234	25,759	0.1424	0.0555 **	6,453	0.0006	0.0309	14,696	0.0383	0.0487	4,610
60-69	0.0288	0.0252	32,227	0.1358	0.0508 ***	8,078	0.0043	0.0274	18,376	0.0316	0.0315	5,773
	Panel B. Local Linear Regression											
64-65	0.0523	0.0422	6,474	0.1612	0.0699 **	1,626	-0.0148	0.0531	3,702	-0.0333	0.0757	1,146
63-66	0.0469	0.0288	12,906	0.1176	0.0471 **	3,230	0.0052	0.0374	7,334	0.0570	0.0460	2,342
62-67	0.0235	0.0176	19,360	0.0642	0.0298 **	4,884	0.0121	0.0233	11,002	0.0170	0.0321	3,474
61-68	0.0363	0.0158 **	25,759	0.0704	0.0269 ***	6,453	0.0171	0.0209	14,696	0.0399	0.0272	4,610
60-69	0.0306	0.0128 **	32,227	0.0552	0.0223 **	8,078	0.0220	0.0171	18,376	0.0291	0.0220	5,773

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table 4. Placebo tests using alternative age thresholds, college educated subsample, age measured in bi-monthly intervals

Ages Included in the Estimation Sample	Stocks held directly and through Mutual Funds		Stocks held in any Form		Number of obs
	Coeff.	Std. Error	Coeff.	Std. Error	
	Panel A. Imbens-Kalyanaraman Method				
60-64	-8.221	58.341	-1.316	13.517	4,211
61-64	-2.861	3.929	-3.247	8.500	3,358
62-64	-1.897	2.066	-3.333	3.445	2,485
63-64	-5.794	30.763	-5.492	23.045	1,646
65-66	0.070	1.164	-0.646	1.007	1,584
65-67	-1.562	2.692	-2.768	2.988	2,399
65-68	13.654	88.718	24.548	341.864	3,095
65-69	-1.670	3.332	0.148	2.468	3,867
	Panel B. Local Linear Regression				
60-64	-7.506	38.949	-3.346	18.821	4,211
61-64	-4.479	6.525	-4.782	6.777	3,358
62-64	-0.822	1.899	-0.612	1.693	2,485
63-64	-1.892	6.980	0.031	4.774	1,646
65-66	0.089	0.756	-0.612	0.752	1,584
65-67	-0.023	1.412	1.420	1.772	2,399
65-68	-2.523	3.902	-1.336	2.600	3,095
65-69	-7.531	40.769	0.008	9.033	3,867

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% respectively. The placebo thresholds are equal to the median age of each age interval.

Table 5A. Ownership of stocks held directly or through mutual funds, age measured in months and in quarters

Ages Included in the Estimation Sample	Full Sample			Some College Education			High School Graduates			Less than High School Education		
	Coeff.	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**
Panel A.1. Age measured in months, Imbens-Kalyaranaman Method												
64-65	-0.0405	0.0681	6,474	0.1488	0.1022	1,626	-0.0825	0.0510	3,702	0.0024	0.2693	1,146
63-66	-0.0094	0.0363	12,906	0.1468	0.0672 **	3,230	-0.0891	0.0455 *	7,334	-0.0293	0.0578	2,342
62-67	0.0091	0.0254	19,360	0.1343	0.0572 **	4,884	-0.0874	0.0494 *	11,002	-0.0039	0.0354	3,474
61-68	0.0099	0.0260	25,759	0.1345	0.0575 **	6,453	-0.0536	0.0368	14,696	-0.0214	0.0467	4,610
60-69	0.0071	0.0216	32,227	0.1074	0.0482 **	8,078	-0.0278	0.0281	18,376	-0.0022	0.0313	5,773
Panel A.2. Age measured in months, Local Linear Regression												
64-65	0.0054	0.0380	6,474	0.1637	0.0736 **	1,626	-0.0765	0.0474	3,702	-0.0721	0.0609	1,146
63-66	0.0243	0.0259	12,906	0.1142	0.0501 **	3,230	-0.0216	0.0333	7,334	0.0081	0.0367	2,342
62-67	0.0067	0.0160	19,360	0.0637	0.0315 **	4,884	-0.0144	0.0208	11,002	-0.0036	0.0251	3,474
61-68	0.0241	0.0143 *	25,759	0.0686	0.0285 **	6,453	0.0030	0.0186	14,696	0.0117	0.0199	4,610
60-69	0.0213	0.0116 *	32,227	0.0497	0.0231 **	8,078	0.0126	0.0153	18,376	0.0058	0.0164	5,773
Panel B.1. Age measured in quarterly intervals, Imbens-Kalyaranaman Method												
64-65	-0.0412	0.0524	6,474	0.0962	0.1011	1,626	-0.1080	0.0576 *	3,702	-0.0393	0.1367	1,146
63-66	-0.0136	0.0370	12,906	0.1315	0.0554 **	3,230	-0.1152	0.0625 *	7,334	-0.0270	0.0523	2,342
62-67	0.0047	0.0222	19,360	0.1331	0.0580 **	4,884	-0.1069	0.0519 **	11,002	-0.0152	0.0411	3,474
61-68	0.0073	0.0238	25,759	0.1311	0.0556 **	6,453	-0.0473	0.0347	14,696	-0.0227	0.0481	4,610
60-69	0.0056	0.0230	32,227	0.1328	0.0569 **	8,078	-0.0306	0.0276	18,376	-0.0025	0.0304	5,773
Panel B.2. Age measured in quarterly intervals, Local Linear Regression												
64-65	0.0059	0.0391	6,474	0.1699	0.0758 **	1,626	-0.0916	0.0490 *	3,702	-0.0727	0.0578	1,146
63-66	0.0237	0.0260	12,906	0.1190	0.0504 **	3,230	-0.0254	0.0335	7,334	0.0083	0.0368	2,342
62-67	0.0056	0.0160	19,360	0.0628	0.0316 **	4,884	-0.0171	0.0209	11,002	-0.0042	0.0251	3,474
61-68	0.0235	0.0143	25,759	0.0678	0.0285 **	6,453	0.0020	0.0187	14,696	0.0114	0.0200	4,610
60-69	0.0209	0.0116 *	32,227	0.0484	0.0232 **	8,078	0.0122	0.0153	18,376	0.0054	0.0164	5,773

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% respectively

Table 5B. Ownership of stocks held in any form, age measured in months and in quarters

Ages Included in the Estimation Sample	Full Sample			Some College Education			High School Graduates			Less than High School Education		
	Coeff.	Std. Error	Number of obs	Coeff.	Std. Error	Number of obs	Coeff.	Std. Error	Number of obs	Coeff.	Std. Error	Number of obs
	Panel A.1. Age measured in months, Imbens-Kalyaranaman Method											
64-65	0.0427	0.0755	6,474	0.2700	0.1175 **	1,626	-0.0417	0.0767	3,702	0.0217	0.2206	1,146
63-66	0.0408	0.0308	12,906	0.1974	0.0783 **	3,230	-0.0309	0.0540	7,334	0.0025	0.0697	2,342
62-67	0.0259	0.0238	19,360	0.1531	0.0629 **	4,884	-0.0196	0.0454	11,002	-0.0372	0.0867	3,474
61-68	0.0255	0.0231	25,759	0.1430	0.0573 **	6,453	-0.0043	0.0324	14,696	0.0325	0.0497	4,610
60-69	0.0286	0.0256	32,227	0.1374	0.0512 **	8,078	0.0034	0.0274	18,376	0.0296	0.0284	5,773
	Panel A.2. Age measured in months, Local Linear Regression											
64-65	0.0505	0.0421	6,474	0.1650	0.0692 **	1,626	-0.0120	0.0532	3,702	-0.0517	0.0757	1,146
63-66	0.0456	0.0288	12,906	0.1174	0.0469 **	3,230	0.0022	0.0374	7,334	0.0545	0.0462	2,342
62-67	0.0234	0.0176	19,360	0.0639	0.0297 **	4,884	0.0120	0.0233	11,002	0.0149	0.0322	3,474
61-68	0.0367	0.0158 **	25,759	0.0697	0.0269 **	6,453	0.0179	0.0209	14,696	0.0387	0.0273	4,610
60-69	0.0307	0.0128 **	32,227	0.0548	0.0223 **	8,078	0.0224	0.0171	18,376	0.0282	0.0221	5,773
	Panel B.1. Age measured in quarterly intervals, Imbens-Kalyaranaman Method											
64-65	0.0381	0.0636	6,474	0.2630	0.1289 **	1,626	-0.0846	0.0913	3,702	0.0056	0.1335	1,146
63-66	0.0426	0.0451	12,906	0.1444	0.0534 **	3,230	-0.0396	0.0504	7,334	0.0302	0.0625	2,342
62-67	0.0431	0.0314	19,360	0.1464	0.0597 **	4,884	-0.0150	0.0421	11,002	0.0184	0.0660	3,474
61-68	0.0271	0.0251	25,759	0.1441	0.0559 **	6,453	-0.0063	0.0324	14,696	0.0391	0.0486	4,610
60-69	0.0432	0.0317	32,227	0.1439	0.0570 **	8,078	0.0020	0.0271	18,376	0.0280	0.0315	5,773
	Panel B.2. Age measured in quarterly intervals, Local Linear Regression											
64-65	0.0567	0.0433	6,474	0.1769	0.0712 **	1,626	-0.0288	0.0548	3,702	-0.0375	0.0719	1,146
63-66	0.0461	0.0289	12,906	0.1194	0.0472 **	3,230	0.0021	0.0376	7,334	0.0533	0.0457	2,342
62-67	0.0226	0.0176	19,360	0.0630	0.0297 **	4,884	0.0100	0.0234	11,002	0.0118	0.0318	3,474
61-68	0.0363	0.0159 **	25,759	0.0692	0.0269 **	6,453	0.0169	0.0210	14,696	0.0378	0.0272	4,610
60-69	0.0300	0.0128 **	32,227	0.0536	0.0223 **	8,078	0.0212	0.0171	18,376	0.0274	0.0219	5,773

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% respectively.

Table 6. Results using Additional Covariates

Ages Included in the Estimation	Full Sample			Some College Education			High School Graduates			Less than High School Education		
	Coeff.	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**	**Coeff.**	**Std. Error**	**Number of obs**
Panel A. Stocks Held Directly and through Mutual Funds												
A.1. Imbens-Kalyanaraman Method												
64-65	-0.0513	0.0503	6,473	0.0734	0.0979	1,626	-0.0968	0.0565 *	3,702	-0.0454	0.1332	1,145
63-66	-0.0254	0.0353	12,901	0.1066	0.0541 **	3,229	-0.1035	0.0615 *	7,333	-0.0386	0.0516	2,339
62-67	-0.0066	0.0211	19,350	0.1086	0.0565 *	4,883	-0.0969	0.0508 *	10,998	-0.0251	0.0404	3,469
61-68	-0.0055	0.0227	25,744	0.1060	0.0541 **	6,452	-0.0496	0.0336	14,691	-0.0337	0.0475	4,601
60-69	-0.0063	0.0218	32,209	0.1078	0.0554 *	8,077	-0.0359	0.0266	18,370	-0.0092	0.0298	5,762
A.2. Local Linear Regression												
64-65	-0.0019	0.0364	6,472	0.1377	0.0724 *	1,626	-0.0646	0.0465	3,701	-0.0745	0.0585	1,145
63-66	0.0102	0.0246	12,901	0.1003	0.0493 **	3,230	-0.0278	0.0321	7,332	0.0017	0.0355	2,339
62-67	-0.0020	0.0155	19,349	0.0585	0.0312 *	4,884	-0.0214	0.0204	10,997	-0.0087	0.0246	3,468
61-68	0.0146	0.0138	25,743	0.0586	0.0281 **	6,453	-0.0037	0.0181	14,690	0.0089	0.0196	4,600
60-69	0.0138	0.0113	32,208	0.0434	0.0230 *	8,078	0.0051	0.0149	18,369	0.0044	0.0162	5,761
Panel B. Stocks Held in any Form												
B.1. Imbens-Kalyanaraman Method												
64-65	0.0247	0.0592	6,473	0.2358	0.1199 **	1,626	-0.0713	0.0892	3,702	-0.0184	0.1302	1,145
63-66	0.0235	0.0420	12,901	0.1140	0.0510 **	3,229	-0.0309	0.0488	7,333	0.0091	0.0612	2,339
62-67	0.0219	0.0292	19,350	0.1188	0.0569 **	4,883	-0.0157	0.0405	10,998	-0.0030	0.0646	3,469
61-68	0.0101	0.0234	25,744	0.1152	0.0532 **	6,452	-0.0143	0.0308	14,691	0.0225	0.0474	4,601
60-69	0.0221	0.0295	32,209	0.1157	0.0543 **	8,077	-0.0057	0.0257	18,370	0.0200	0.0308	5,762
B.2. Local Linear Regression												
64-65	0.0376	0.0395	6,472	0.1358	0.0675 **	1,626	-0.0011	0.0512	3,701	-0.0530	0.0740	1,145
63-66	0.0246	0.0265	12,901	0.0960	0.0451 **	3,230	-0.0072	0.0356	7,332	0.0418	0.0443	2,339
62-67	0.0117	0.0167	19,349	0.0574	0.0292 **	4,884	0.0025	0.0225	10,997	0.0073	0.0313	3,468
61-68	0.0230	0.0149	25,743	0.0561	0.0261 **	6,453	0.0083	0.0201	14,690	0.0332	0.0265	4,600
60-69	0.0199	0.0122	32,208	0.0458	0.0219 **	8,078	0.0119	0.0165	18,369	0.0249	0.0217	5,761

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% respectively. Additional covariates included are race, marital status and number of limitations in activities of daily living.

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	Some College Education	High School Graduates	Less than High School Education	Full Sample	Some College Education	High School Graduates	Less than High School Education	Full Sample	Some College Education	High School Graduates	Less than High School Education	Full Sample	Some College Education	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: ***, **, * denote statistical significance at 1%, 5% and 10% respectively.