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

Dimitris Christelis
CSEF, CFS and CEPAR

Dimitris Georgarakos
Goethe University Frankfurt, CFS and University of Leicester

Anna Sanz-de-Galdeano
University of Alicante and IZA

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Abstract

Using data from the US Health and Retirement Study, we study the causal effect of increased health insurance coverage through Medicare and the associated reduction in health-related background risk on financial risk-taking. Given the onset of Medicare at age 65, we identify our effect of interest using a regression discontinuity approach. We find that getting Medicare coverage induces stockholding for those with at least some college education, but not for their less-educated counterparts. Hence, our results indicate that a reduction in background risk induces financial risk-taking in individuals for whom informational and pecuniary stock market participation costs are relatively low.

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Email addresses: dimitris [dot] christelis [at] gmail [dot] com; georgarakos [at] hof [dot] uni-frankfurt [dot] de ; anna [dot] sanzdegaldeano [at] gmail [dot] com

1. Introduction

Much academic, policy and media attention has focused on the relationship between health insurance and labor market outcomes,[1] but much less is known about the potential effects of health insurance programs on financial risk-taking. Nevertheless, medical expenditure and health risks are important sources of background (i.e., not fully diversified) risk, especially among older individuals, and are thus likely to affect their investment choices.[2]

In this paper we investigate, using data from the US Health and Retirement Study (HRS), whether a reduction in background risk due to increased health insurance coverage induces financial risk-taking, as indicated by owning stocks. 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. Medicare eligibility not only affects health insurance coverage (which is nearly universal after age 65), but it also reduces medical expenditure risk (Barcellos and Jacobson, 2014), and it seems reasonable to believe that it might reduce the variance in treatment standards as well. However, the extent to which financial risk-taking is affected by increased insurance coverage through Medicare remains an open question. To fill in this gap, we rely on a regression discontinuity (RD henceforth) design that exploits the Medicare-induced discontinuity in health coverage at age 65 to identify the causal effect of increased health insurance coverage on stockholding under seemingly mild assumptions compared to those needed for other non-experimental approaches (Hahn et al., 2001).

[1] See Gruber and Madrian (2004) and Madrian (2007) for reviews and the references therein.

[2] According to Himmelstein et al. (2009), "62.1% of all bankruptcies in 2007 were medical" in the United States. Moreover, the distribution of health care costs is strongly age dependent, with nearly half of lifetime expenditures being incurred after age 65 (Alemayehu and Warner, 2004). Recent estimates also indicate that, in 2009, a typical married couple age 65 had a 5% probability that the present value of their lifetime uninsured health care costs would exceed $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).

Economic theory suggests 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.[3] A lower background risk, however, may not suffice to induce investment in risky assets. In fact, in a number of 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).[4]

Stock market participation costs 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), and typically vary by education. A higher level of human capital is typically associated with higher financial resources and more efficient information processing, making both aforementioned costs easier to bear. Hence, it is natural to expect the impact of a reduction in background risk on stockholding to differ across education groups due to the education-induced variation in stock market participation costs.

We find that Medicare eligibility induces individuals with at least some college education to invest in stocks. Our preferred estimates suggest an increase in total stockholding, ranging from 12 to about 25 percentage points for this education group, depending on the method used. This is in line with the increase in stockholding prevalence observed in the data for this group. On the other hand, we find no effect of Medicare on

[3] See e.g., Guiso, Jappelli and Terlizzese (1996), Heaton and Lucas (2000), Viceira (2001), Rosen and Wu (2004), Edwards (2008), and Yogo (2009).

[4] 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 in order to take advantage of the equity premium.

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 they are low enough, as is the case for individuals with a higher educational attainment (see Haliassos and Bertaut, 1995). As we discuss in Section 4, however, our estimates likely represent conservative estimates of our effect of interest due to some features of our set-up. As a result, getting health insurance coverage might affect financial risk-taking also for those with less than college education.

While various papers have examined the impact of Medicare on health and health care utilization,[5] this is the first study to assess the impact of Medicare eligibility on stockholding. Interestingly, however, the results of some previous studies indirectly suggest that Medicare eligibility might indeed be relevant for portfolio choice. 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.

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[5] 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).

Finally, Goldman and Maestas (2013) focus on the subpopulation of elderly Medicare beneficiaries and find that being covered by supplemental insurance through Medigap, an employer, or a Medicare HMO has an economically sizeable and statistically significant effect on risky asset ownership. Given that the heterogeneity in terms of health insurance coverage and its characteristics is much wider across the elderly and nonelderly than among Medicare beneficiaries, one would expect that Medicare eligibility would have even larger consequences for portfolio decisions. One challenging issue discussed by Goldman and Maestas (2013) concerns 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. Goldman and Maestas (2013) account for the endogeneity of insurance choice among Medicare beneficiaries by using as instruments geographic variation in the price of Medigap supplemental insurance and non-Medicare HMO market penetration. Hence, their identification strategy relies on the assumption that neither of these factors affects risky asset ownership other than through their effect on supplemental insurance coverage for Medicare beneficiaries.

In this paper, instead, we exploit the abrupt transition to Medicare eligibility that occurs at age 65 and affects the vast majority of individuals in the US in order to estimate the causal effect of health insurance on stockholding. To that effect, we use a regression discontinuity design that is based on Medicare eligibility. 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).

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 a number of 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.[6] 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.[7] Note also that, although Medicare's coverage is quite comprehensive, individuals often choose to supplement it by purchasing Medigap plans, enrolling in a Medicare HMO or obtaining retiree health insurance through employers.

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 percentage points at age 65, from 18.7% to 91.8% among 64 and 66-year olds, respectively. Since Medicare enrollment prior to

[6] Medicare accounts for a substantial and growing share of total health care spending in the US. In particular, 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.

[7] 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.

65 is lower among college educated households, the coverage gap between 64 and 65 is even more pronounced for them (81 percentage points) than for non-college educated households (70 percentage points).

Importantly, there is also evidence that Medicare offers the elderly significant protection against medical expenditure risk and financial strain. In particular, Barcellos and Jacobson (2014) find that, at age 65, out-of-pocket expenditures drop by about 33% at the mean ($326) and 53% ($1730) 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 coverage 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.[8]

[8] 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.

In particular, 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.[9] In particular, 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 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. As a result, 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 most recent available data in the RAND HRS files,[10] namely those from the 2010 wave (i.e., we use seven waves in total).

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

[9] 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.
[10] 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.

reported for couples. One possibility would then be to carry out the analysis at the household level, i.e., by treating the two partners in a couple as one decision-unit.[11] This is, however, highly problematic in our set-up for various reasons. First, it is not obvious how to define age, which triggers our treatment variable, in the case of couples. One could take the maximum or the minimum age of the two partners, and each option could be appropriate for different couples. Second, 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.

Another possibility would be to treat each partner in a couple as a separate observation. However, in couples reporting stock ownership it is not possible to determine who actually owns the stocks. As a result, one cannot distinguish the three possible ownership patterns (i.e., ownership by the first partner only, the second partner only, or both) from each other. 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 of the assumptions 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 particular treatment assigned to another one. This assumption is unlikely to hold in the case of partners in a couple, given that one partner's portfolio choices following treatment can affect the choices of the untreated partner.[12]

[11] Choosing the financial respondent to represent a couple would not be 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.
[12] De Nardi et al. (2014) provide evidence of substantial such spillovers in couples.

As a result of the above, in the case of couples it is very difficult to link age, and thus treatment status, to stock ownership, regardless of whether one treats them as a single decision unit or whether one treats partners in the couple separately. Therefore, we conduct the main part of our analysis using singles. As discussed in Section 5, however, we also check whether our results change when we add to our sample couples born in the same time interval.

We will examine separately as outcomes the two possible stock ownership modes, i.e., direct or through mutual funds, and through IRAs. In the latter case we will restrict our sample to existing IRA owners because for non-owners investment in stocks through IRAs is not relevant. We will also create a variable that combines the two stockholding modes in one so as to measure stock ownership in any form. We will then also examine this variable as an outcome.

Table 1 shows the prevalence of stock ownership in all forms for all single households aged from 60 to 69 by type of stockholding and level of education. We note that only about 33% 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.[13] In particular, total stockholding rates are remarkably higher (about 63%) in college-educated households than in households with less than high school education (about 8%). This data pattern is consistent, as discussed in the Introduction, with the fact that stock market participation costs vary with education.

[13] 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 risky asset ownership. To this purpose, we use a RD design.[14] 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, 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 and, as Lee (2008) shows, the fact that the variation in treatment (insurance coverage) near the threshold (age 65) is randomized as though from a randomized

[14] 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.

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 are sure 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.[15] 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.

LL also 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

[15] 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.

threshold, is the issue of the sensitivity to the bandwidth choice. Researchers often explore whether their results are critically dependent on a 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 asymptotic 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 try different estimation ranges (i.e., age intervals) to assess sensitivity to range selection. We will follow this recommendation and present results based on IK as our main ones, but we will 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. In our dataset we have age in months, and thus we can also measure it bimonthly, in quarters 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. In order 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 a given 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 in order 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. It is clear that when age is measured in years the F-tests reject the equality of the monthly dummy coefficients within each year, and thus the year is not an appropriate age measurement unit. In contrast, p-values of the F-tests are uniformly high when age is measured in bimonthly intervals. Finally, when age is measured in quarters the pattern is more varied. We notice that there are some scattered low p-values, but these tend to be in age intervals that are further off from the discontinuity threshold. Furthermore, as we will discuss below, we will focus our discussion on the subsample consisting of individuals with some college education, and for this subsample results suggest that quarters are a reasonable choice as an age measurement unit. Hence, in our baseline results we will present results with age measured in quarters. In Section 5, however, we will also perform robustness checks in which age will be measured in months and bimonthly.

As it is customary in the RD literature, we start with some graphical evidence. In particular, we visually check for discontinuities in the distribution of the outcome variable at the threshold point. We checked for the existence of this pattern for the ownership of stocks and mutual funds, and then for stockholding in any form. We plot the results in Fig. 2A and 2B, 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 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 will 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. In particular, 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 more noisy, 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. This bandwidth is displayed in the third column for each sample analyzed and denotes months to the left and to the right of the discontinuity point.[16]

Results using both estimation methods suggest that there is no impact of Medicare coverage on the portfolio decisions of individuals without any college education: estimates are often negative, very small in magnitude and very far from achieving standard levels of statistical significance. These results extend to the whole sample, in which the non-college educated are the large majority.

The picture changes completely for college-educated individuals, where our estimates are sizeable and statistically significant. First, we see that, as the sample size increases as we sequentially depart from narrower age intervals, the optimal bandwidth chosen by the IK method also varies, and the estimated effect of Medicare on stockholding is reduced. If we ignore the first two age intervals, in which we have less than 1,000 observations and for which the estimated coefficients are very large, the median estimate is about 27 percentage points. The corresponding estimate from the local linear regression is about 13 percentage points. These estimates are not only statistically significant but also economically large, when one takes into account 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.

We then used as our dependent variable total stockholding, i.e., we combined 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 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 statistically significant and similar to those obtained for direct and through

[16] Sample sizes displayed in all our tables reflect the number of observations in each of the age intervals.

mutual funds stock ownership: after discarding the first two age bands, the median estimate from the IK method implies that Medicare boosts total stockholding by about 30 percentage points, while the corresponding effect obtained through local linear regression is about 14 percentage points. Given that the prevalence of total stockholding is about 63% for those with some college education, these effects are economically important as well. Finally, we did not find any statistically significant effects for stockownership through IRAs only.

When interpreting our results it is important to keep in mind that, as discussed in Section 4, they likely represent underestimates of the true of effect of Medicare on financial risk-taking due to the possibility of individual anticipating 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 unable to capture this effect due to the fact that 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

We performed a number of specification tests in order to check our results. Due to space constraints we will present only a part of them, but all are available from the authors upon request.

First, as discussed in Section 3, we tried to think of any other factors that might change at age 65 and also 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 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). At any rate, when we graph the data in Fig. 3, we see no spike in the prevalence of retirement at age 65. Moreover, and in order to check whether Medicare also induces retirement at 65, we performed a FRD estimation for the decision to retire, and found no statistically significant effect (the local linear regression lines are also shown in Fig. 3). Therefore, and in accordance with the findings in Card, Goldman and Maestas (2009), we find no evidence of a spike in retirement at age 65. Hence, our finding that Medicare increases stockholding for the college educated subsample should not be affected by the retirement choices of the individuals therein.

Another variable that might change at age 65 and that 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 performed a RD estimation for income, however, we found no evidence of any change at age 65. As a result, we 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 2c) is due to noise in the data. To that effect, we performed “placebo” RD estimations for age thresholds different than 65, starting from age 62 and changing one quarter at a time until age 68, i.e., three years to the left and to the right of the age for Medicare eligibility. 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 observe that, out of 96 possible combinations of age, stockholding mode and estimation method at ages other than 65, only in one case do we obtain a result significant at 5%, and in three more cases results significant at 10%. In contrast, and in line with the impact of Medicare on stockholding being genuine, the results at age 65 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 5 we chose to measure age in quarters for our baseline specifications. We also performed our FRD estimation, however, with age measured in months and bimonthly. The results for the former case are displayed in Table 5A, while those for the latter case in Table 5B. We observe that the IK results produce estimates that are still strongly statistically significant and somewhat smaller in magnitude than the ones discussed in Section 4, thus coming closer to the results obtained from the local linear regression method. The results using the latter method remain essentially the same.

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 added to our specification race, gender, a measure of whether the respondent has any health problems as indicated by having any limitations in activities of daily living (ADLs), whether the respondent is divorced or a widow (the base category for our sample of singles being never married), as well as dummies for each wave in order to capture any time effects. 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 found that our point estimates were not affected by the inclusion of these additional covariates. Moreover, the statistical significance of our results becomes stronger, especially in the case of total stockholding; this is to be expected, given that the inclusion of covariates should make estimates less noisy.

We also tried a sharp RD estimation, which is the procedure that a number of 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. As a result, we found slightly smaller effects of Medicare on stockholding (by about 5 percentage points), but they remained strongly statistically significant.

We then added to our sample of singles the couples in which both partners were born in the same quarter; hence, the discontinuity applies at the same time to both partners. These couples increased our sample by about 4%, and we found that our estimates remained the same.

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.

Furthermore, given that our outcome is a binary variable, we estimated non-linear binary choice models. As Medicare eligibility is also a binary variable that needs to be instrumented for an 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 found that the marginal effects of Medicare on stockholding obtained through this model are very close to those obtained from the local linear regression.

Finally, we wanted to see if Medicare induced investment in less risky assets like bonds. If this were the case, then it would suggest that increased risk tasking due to reduced background risk might not be the only factor driving our results for stocks. We found, however, no effect of Medicare on bondholding, which is congruent with the interpretation of its effect on stockholding as indicative of additional risk-tasking due to reduced risk in another domain of respondents' lives.

6. Discussion and Conclusions

Economic theory predicts that a reduction in health-related background risk should induce financial risk taking, particularly so for individuals subject to relatively low stock market participation costs. We investigate this largely understudied question by looking at 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. In particular, we examine whether the onset of Medicare at age 65 induces stockholding. We use a regression discontinuity design that exploits the discontinuity in health insurance coverage due to the onset of Medicare and thus allows us to identify our causal effect of interest.

We find that Medicare eligibility has a quantitatively and statistically significant impact on stockholding for those who 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 individuals with less than college education. 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.

Importantly, our estimates are likely to be conservative estimates of the true effect of Medicare on financial risk taking. This is so because households might anticipate the stockholding decision before age 65, and also 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 individuals' financial risk taking behavior. Hence, policy-makers may want to take into account this implication when contemplating any such reforms. In addition, 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. Finally, to the extent that our results can be generalized to include any kind of background risk (e.g., with respect to unemployment), they imply that facilitating broader insurance coverage for such risk may enhance financial risk taking.

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Figure 1. Medicare Coverage Rates

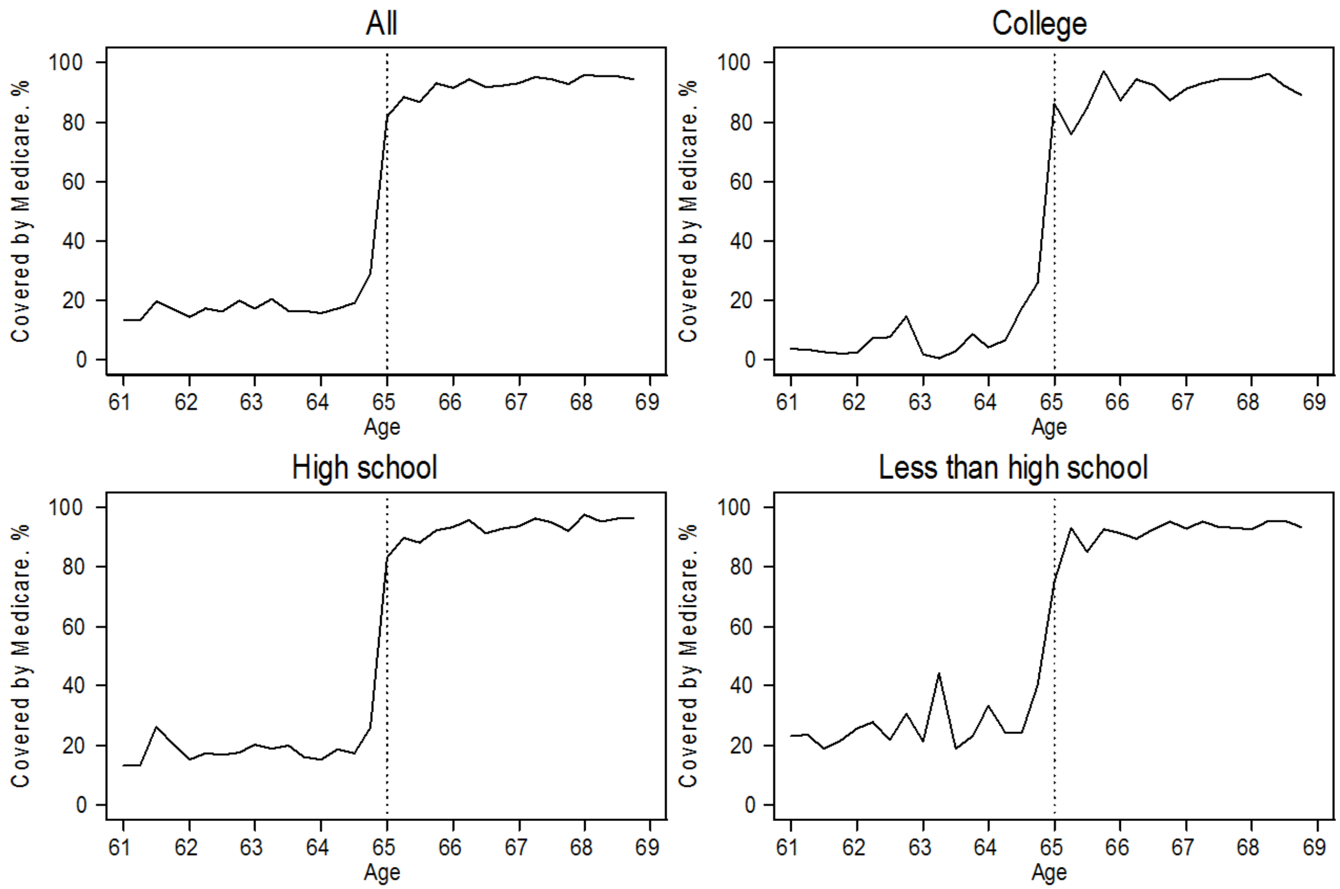

Figure 2A. Rate of ownership of stocks held directly or through mutual funds

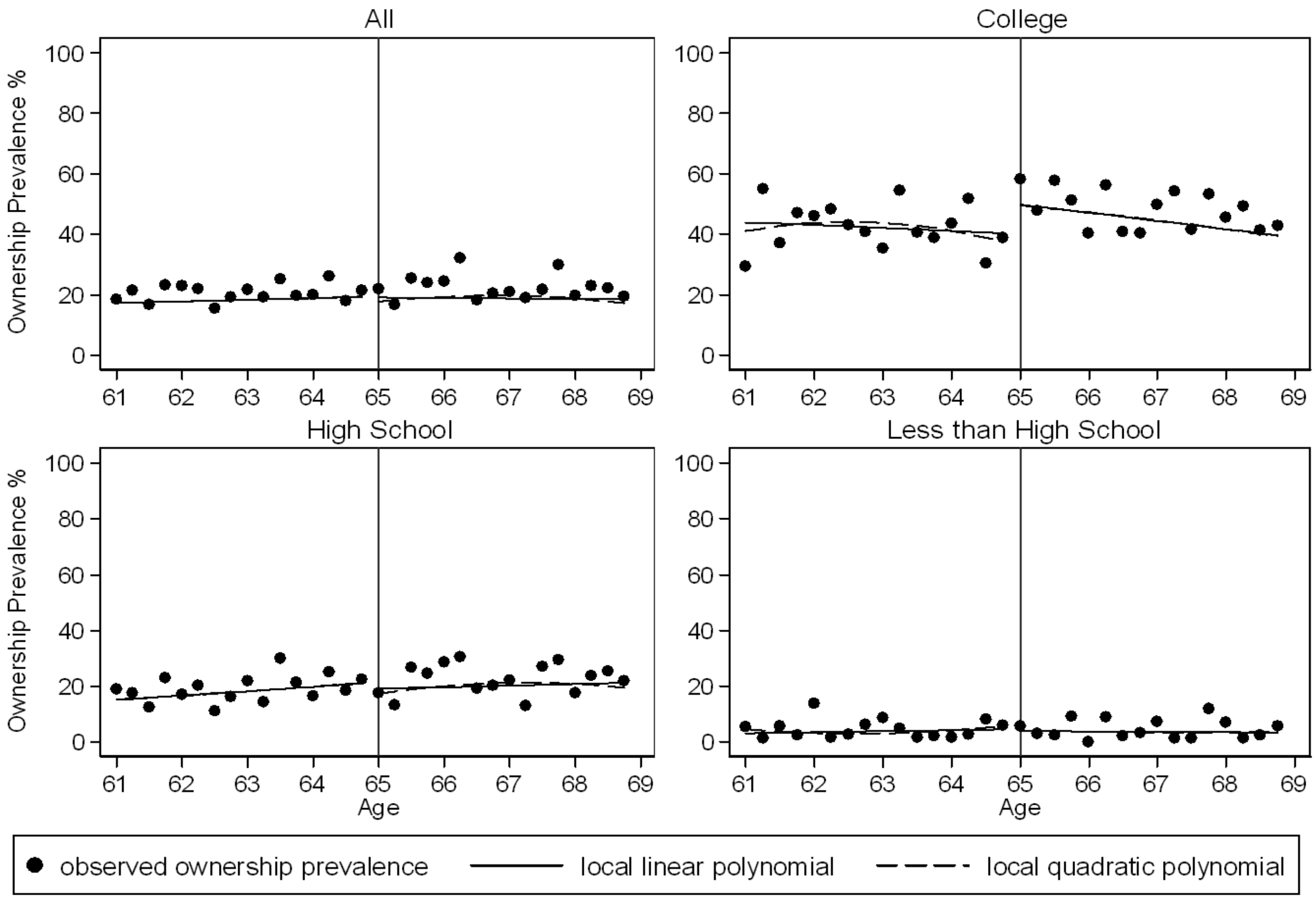

Figure 2B. Rate of ownership of stocks held in any form

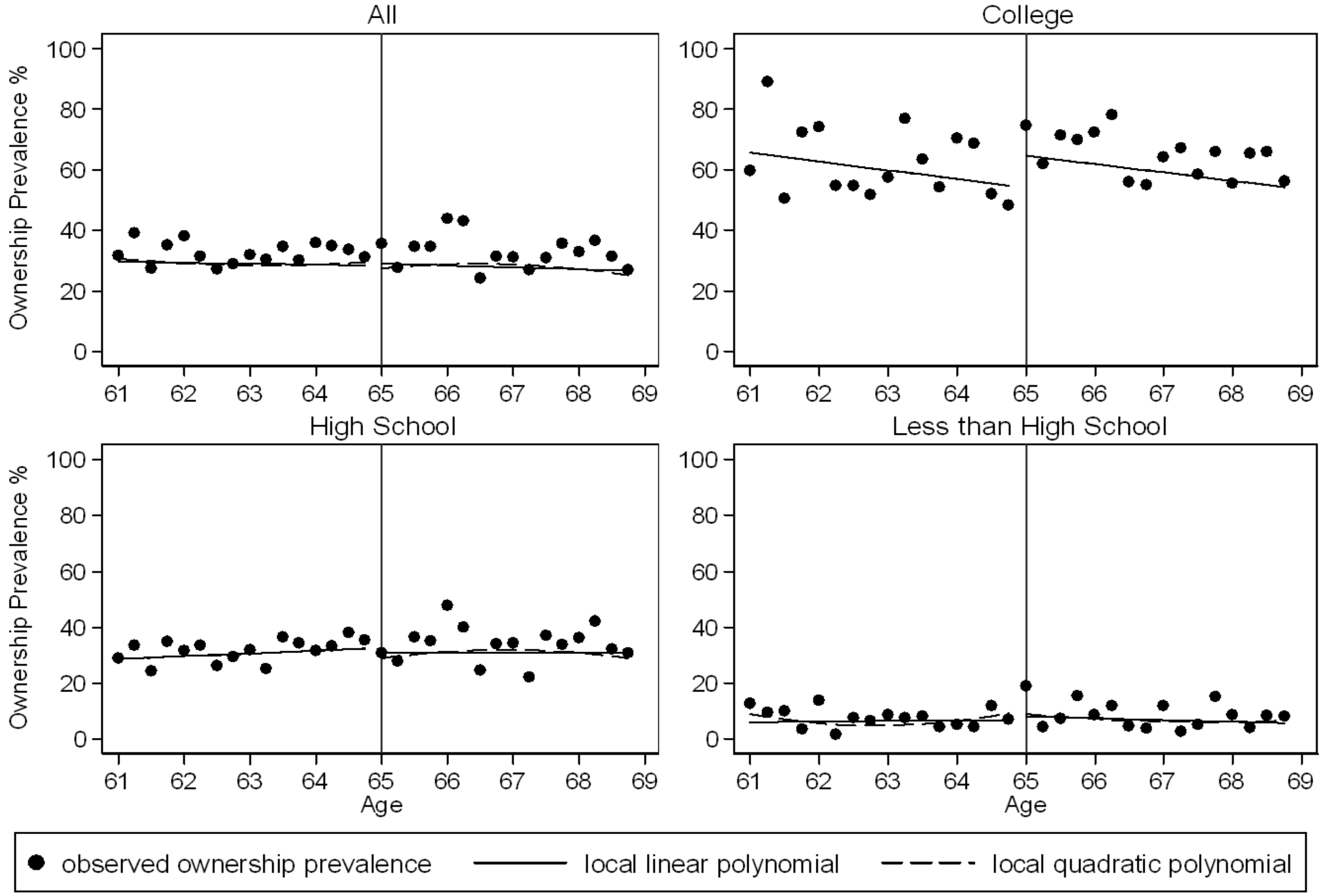

Figure 3. Proportion of retirees

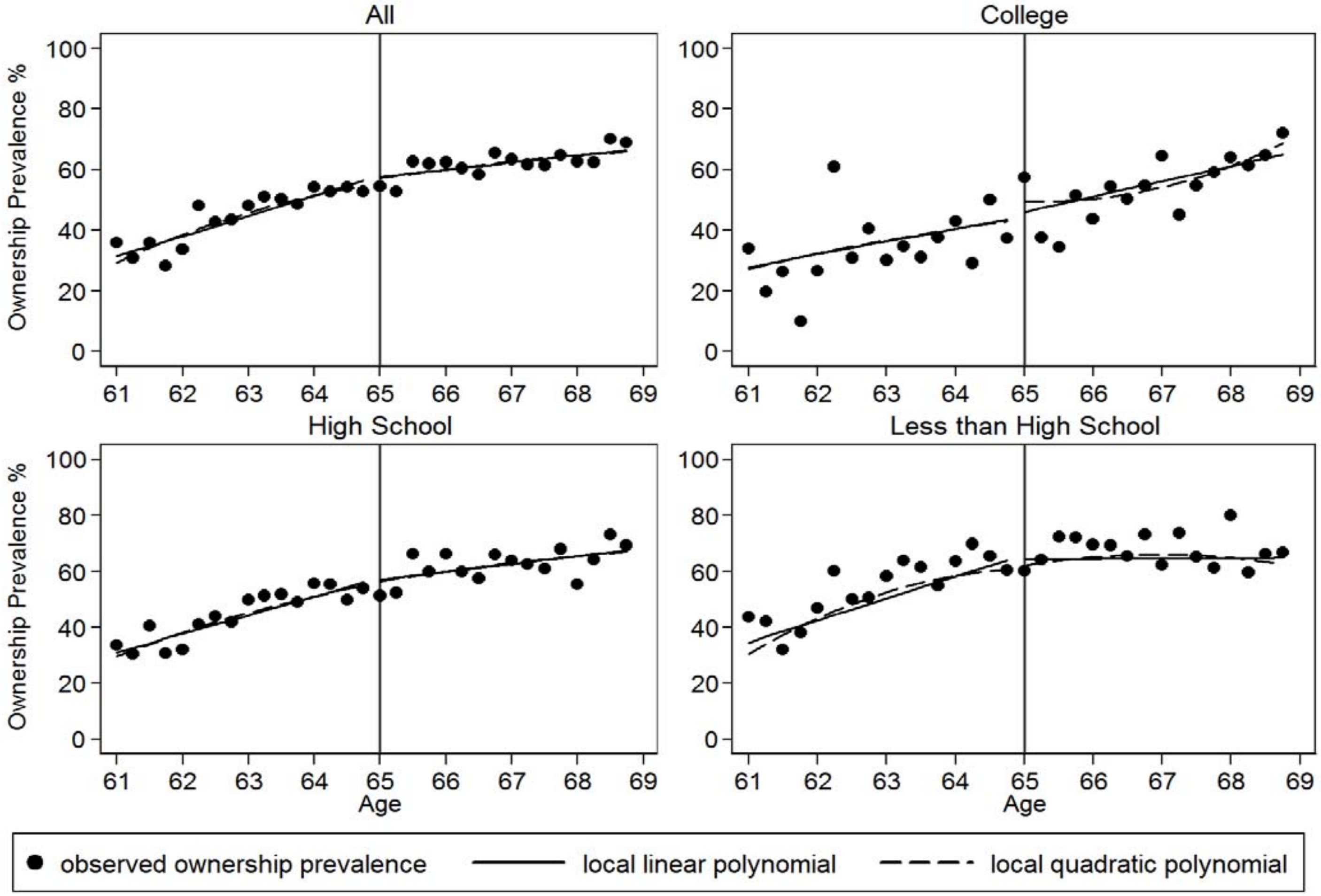

Table 1. Ownership rate of stocks held in different investment vehicles, by education, singles aged 60-69

Item	Whole Sample	Some college education	High School Graduates	Less than High School Education
Stocks held directly or through mutual funds	21.4%	43.9%	21.2%	4.6%
Stocks held through IRAs	22.2%	44.5%	22.2%	4.9%
Stocks held in any form	32.9%	62.9%	33.3%	8.3%
Number of observations	11,584	1,802	6,469	3,313

Notes: Ownership rates are calculated using sample weights.

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

Ages Included in the Estimation Sample	Full Sample				Some College Education				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs
								Panel A. Imbens-Kalyanaraman Method								
64-65	-0.0448	0.0654	14.29	2,327	0.3867	0.1961 **	30.15	350	-0.2030	0.1271	8.13	1,291	-0.0572	0.2466	9.06	686
63-66	-0.0439	0.0538	17.89	4,689	0.3881	0.2011 *	13.96	726	-0.1289	0.0683 *	16.92	2,604	-0.0653	0.0568	25.40	1,359
62-67	-0.0439	0.0539	17.82	6,996	0.2997	0.1456 **	20.72	1,082	-0.1269	0.0918	11.79	3,887	-0.0347	0.0400	52.26	2,027
61-68	-0.0187	0.0373	29.28	9,287	0.2675	0.1220 **	26.61	1,454	-0.0998	0.0613	19.88	5,177	-0.0376	0.0407	41.21	2,656
60-69	-0.0181	0.0294	43.87	11,584	0.1828	0.0956 *	36.31	1,802	-0.0527	0.0409	37.53	6,469	-0.0424	0.0451	35.34	3,313
								Panel B. Local Linear Regression								
64-65	-0.0515	0.0596	-..-	2,327	0.3904	0.1965 **	-..-	350	-0.1511	0.0724 **	-..-	1,291	-0.1223	0.0825	-..-	686
63-66	-0.0101	0.0375	-..-	4,689	0.2309	0.1145 **	-..-	726	-0.0454	0.0474	-..-	2,604	-0.0435	0.0499	-..-	1,359
62-67	-0.0182	0.0243	-..-	6,996	0.1281	0.0683 *	-..-	1,082	-0.0430	0.0315	-..-	3,887	-0.0306	0.0333	-..-	2,027
61-68	-0.0038	0.0213	-..-	9,287	0.1261	0.0597 **	-..-	1,454	-0.0332	0.0279	-..-	5,177	-0.0161	0.0261	-..-	2,656
60-69	0.0103	0.0177	-..-	11,584	0.0791	0.0493	-..-	1,802	0.0033	0.0235	-..-	6,469	-0.0120	0.0217	-..-	3,313

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 quarters

Ages Included in the Estimation Sample	Full Sample				Some College Education				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs
							Panel A. Imbens-Kalyanaraman Method									
64-65	-0.0061	0.0837	12.52	2,327	0.5221	0.2684 *	11.44	350	-0.1181	0.0868	22.44	1,291	0.1975	0.3353	7.23	686
63-66	-0.0219	0.0579	19.25	4,689	0.3242	0.1499 **	20.71	726	-0.0955	0.0733	19.21	2,604	-0.0672	0.0969	17.13	1,359
62-67	-0.0243	0.0600	18.52	6,996	0.5034	0.2175 **	13.51	1,082	-0.1168	0.0809	16.45	3,887	-0.0271	0.0739	23.64	2,027
61-68	-0.0173	0.0409	32.01	9,287	0.3046	0.1362 **	23.66	1,454	-0.0655	0.0577	27.49	5,177	-0.0072	0.0558	36.04	2,656
60-69	-0.0146	0.0349	42.26	11,584	0.1587	0.0937 *	37.59	1,802	-0.0412	0.0434	45.18	6,469	-0.0064	0.0519	40.33	3,313
							Panel B. Local Linear Regression									
64-65	-0.0109	0.0697	-..-	2,327	0.4831	0.2036 **	-..-	350	-0.1145	0.0856	-..-	1,291	-0.1159	0.1013	-..-	686
63-66	-0.0101	0.0432	-..-	4,689	0.2170	0.1134 *	-..-	726	-0.0507	0.0554	-..-	2,604	0.0013	0.0628	-..-	1,359
62-67	-0.0031	0.0278	-..-	6,996	0.1238	0.0655 *	-..-	1,082	-0.0188	0.0368	-..-	3,887	-0.0075	0.0404	-..-	2,027
61-68	0.0105	0.0240	-..-	9,287	0.1380	0.0573 **	-..-	1,454	-0.0264	0.0321	-..-	5,177	0.0229	0.0327	-..-	2,656
60-69	0.0231	0.0200	-..-	11,584	0.0989	0.0482 **	-..-	1,802	0.0082	0.0269	-..-	6,469	0.0200	0.0263	-..-	3,313

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

Table 4. Placebo tests of alternative age thresholds, college educated subsample

Threshold age	Stocks held directly or through mutual funds				Stocks held in any form			
	Imbens - Kalyanaraman method		Local linear regression		Imbens - Kalyanaraman method		Local linear regression	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
62 years	11.343	81.495	0.364	0.750	1.367	9.973	0.346	0.702
62 years, 1 quarter	-1.272	2.888	0.264	1.074	-4.424	4.468	1.351	1.099
62 years, 2 quarters	-2.157	4.592	0.361	1.524	-3.589	5.863	0.493	1.498
62 years, 3 quarters	-1.345	8.326	-0.776	2.198	-5.603	40.971	-1.986	2.772
63 years	-0.917	0.866	-4.810	12.126	-2.239	1.936	-9.289	22.762
63 years, 1 quarter	-0.330	0.385	1.051	0.998	-0.768	0.410 *	2.195	1.289 *
63 years, 2 quarters	0.385	0.533	-0.042	0.364	-0.155	0.571	0.455	0.397
63 years, 3 quarters	-0.774	4.965	0.144	0.227	-0.275	0.682	0.323	0.237
64 years	0.097	0.954	0.099	0.157	-0.334	0.796	0.254	0.166
64 years, 1 quarter	39.884	638.122	-0.009	0.109	-5.021	7.545	0.010	0.110
64 years, 2 quarters	-0.386	0.308	-0.013	0.084	-1.248	0.775	-0.018	0.084
64 years, 3 quarters	0.077	0.093	0.080	0.070	-0.082	0.178	0.052	0.068
65 years	**0.267**	**0.122 ****	**0.126**	**0.060 ****	**0.305**	**0.136 ****	**0.138**	**0.057 ****
65 years, 1 quarter	0.092	0.154	0.086	0.075	0.078	0.152	0.105	0.071
65 years, 2 quarters	0.440	0.345	0.153	0.086 *	0.416	0.330	0.175	0.081 **
65 years, 3 quarters	0.419	0.507	0.036	0.108	-0.740	1.240	0.156	0.101
66 years	0.413	0.252	-0.072	0.173	0.096	0.260	0.110	0.154
66 years, 1 quarter	-0.170	0.754	0.129	0.240	0.012	0.329	0.145	0.215
66 years, 2 quarters	0.609	0.693	-0.198	0.449	2.442	2.168	-0.427	0.443
66 years, 3 quarters	0.022	0.402	0.114	1.138	1.981	3.498	-0.782	1.273
67 years	-0.150	0.323	-6.517	52.452	-0.212	0.514	-6.382	50.787
67 years, 1 quarter	-0.213	0.422	-0.956	2.368	-0.387	1.282	-0.599	2.173
67 years, 2 quarters	-0.038	5.021	0.170	0.976	2.352	6.283	-0.322	0.974
67 years, 3 quarters	-0.282	9.741	0.146	0.604	2.993	11.530	-0.143	0.598
68 years	0.236	3.815	0.192	0.434	1.013	4.090	0.060	0.431

Notes: ***, **, * denote statistical significance at 1%, 5% and 10% respectively. The estimation sample includes those aged from 61 to 68 years. Age is measured in years and quarters completed.

Table 5A. Ownership of stocks held directly or through mutual funds, Imbens-Kalyanaraman method, age measured in months and in bimonthly intervals

Ages Included in the Estimation Sample	Full Sample				Some College Education				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs
Panel A.1. Age measured in months, Imbens-Kalyanaraman Method																
64-65	-0.0341	0.0897	7.91	2,327	0.2762	0.2322	7.18	350	-0.0976	0.0844	10.80	1,291	-0.1701	0.3040	6.78	686
63-66	-0.0374	0.0493	18.87	4,689	0.3391	0.1693 **	14.39	726	-0.0987	0.0621	18.21	2,604	-0.0905	0.0760	18.55	1,359
62-67	-0.0195	0.0330	35.20	6,996	0.2817	0.1326 **	21.88	1,082	-0.1019	0.0634	17.54	3,887	-0.0757	0.0646	21.65	2,027
61-68	-0.0264	0.0408	24.81	9,287	0.1703	0.0865 **	41.12	1,454	-0.0816	0.0541	22.95	5,177	-0.0397	0.0439	36.23	2,656
60-69	-0.0166	0.0296	42.91	11,584	0.2133	0.1045 **	31.01	1,802	-0.0480	0.0393	39.82	6,469	-0.0393	0.0432	37.07	3,313
Panel A.2. Age measured in months, Local Linear Regression																
64-65	-0.0450	0.0570	-..-	2,327	0.3367	0.1748 *	-..-	350	-0.1234	0.0693 *	-..-	1,291	-0.1236	0.0839	-..-	686
63-66	-0.0102	0.0370	-..-	4,689	0.2369	0.1126 **	-..-	726	-0.0459	0.0470	-..-	2,604	-0.0423	0.0489	-..-	1,359
62-67	-0.0179	0.0241	-..-	6,996	0.1346	0.0683 **	-..-	1,082	-0.0424	0.0313	-..-	3,887	-0.0304	0.0328	-..-	2,027
61-68	-0.0038	0.0211	-..-	9,287	0.1282	0.0596 **	-..-	1,454	-0.0327	0.0277	-..-	5,177	-0.0151	0.0259	-..-	2,656
60-69	0.0105	0.0176	-..-	11,584	0.0837	0.0492 *	-..-	1,802	0.0031	0.0233	-..-	6,469	-0.0116	0.0215	-..-	3,313
Panel B.1. Age measured in bimonthly intervals, Imbens-Kalyanaraman Method																
64-65	-0.1955	0.1646	4.87	2,327	0.1262	0.4149	5.94	350	-0.0894	0.0829	12.21	1,291	0.0284	0.8519	6.04	686
63-66	-0.0351	0.0517	18.10	4,689	0.3587	0.1963 *	13.50	726	-0.0910	0.0631	18.18	2,604	-0.0734	0.0646	21.92	1,359
62-67	-0.0178	0.0384	27.58	6,996	0.2823	0.1363 **	21.98	1,082	-0.0896	0.0625	18.37	3,887	-0.0692	0.0608	23.21	2,027
61-68	-0.0180	0.0385	27.40	9,287	0.1822	0.0952 *	36.02	1,454	-0.0720	0.0549	22.55	5,177	-0.0395	0.0426	38.03	2,656
60-69	-0.0189	0.0311	39.09	11,584	0.1796	0.0941 *	36.50	1,802	-0.0459	0.0396	39.17	6,469	-0.0400	0.0434	36.77	3,313
Panel B.2. Age measured in bimonthly intervals, Local Linear Regression																
64-65	-0.0410	0.0575	-..-	2,327	0.3449	0.1825 *	-..-	350	-0.1149	0.0692 *	-..-	1,291	-0.1234	0.0851	-..-	686
63-66	-0.0098	0.0369	-..-	4,689	0.2370	0.1134 **	-..-	726	-0.0419	0.0467	-..-	2,604	-0.0423	0.0492	-..-	1,359
62-67	-0.0185	0.0241	-..-	6,996	0.1350	0.0683 **	-..-	1,082	-0.0425	0.0312	-..-	3,887	-0.0292	0.0328	-..-	2,027
61-68	-0.0038	0.0211	-..-	9,287	0.1302	0.0596 **	-..-	1,454	-0.0330	0.0277	-..-	5,177	-0.0139	0.0259	-..-	2,656
60-69	0.0105	0.0176	-..-	11,584	0.0839	0.0491 *	-..-	1,802	0.0031	0.0234	-..-	6,469	-0.0102	0.0215	-..-	3,313

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

Table 5B. Ownership of stocks held in any form, Imbens-Kalyanaraman method, age measured in months and in bimonthly intervals

Ages Included in the Estimation Sample	Full Sample				Some College Education				High School Graduates				Less than High School Education			
	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs	Coeff.	Std. Error	Optimal Bandwidth (months)	Number of obs
Panel A.1. Age measured in months, Imbens-Kalyanaraman Method																
64-65	-0.0104	0.0924	9.43	2,327	0.3477	0.2625	6.70	350	-0.0952	0.1109	9.06	1,291	0.2112	0.4174	5.88	686
63-66	-0.0373	0.0598	17.69	4,689	0.2939	0.1458 **	19.19	726	-0.0925	0.0713	19.20	2,604	-0.0391	0.0781	21.93	1,359
62-67	-0.0214	0.0418	30.43	6,996	0.2985	0.1473 **	18.89	1,082	-0.0933	0.0718	19.01	3,887	-0.0828	0.1000	16.82	2,027
61-68	-0.0209	0.0411	31.33	9,287	0.1487	0.0819 *	44.56	1,454	-0.0655	0.0566	27.80	5,177	-0.0072	0.0575	33.74	2,656
60-69	-0.0164	0.0364	38.69	11,584	0.1603	0.0925 *	37.43	1,802	-0.0555	0.0529	31.34	6,469	-0.0023	0.0486	44.12	3,313
Panel A.2. Age measured in months, Local Linear Regression																
64-65	-0.0257	0.0666	-..-	2,327	0.3831	0.1796 **	-..-	350	-0.0998	0.0822	-..-	1,291	-0.1278	0.1034	-..-	686
63-66	-0.0115	0.0429	-..-	4,689	0.2208	0.1117 **	-..-	726	-0.0507	0.0552	-..-	2,604	0.0012	0.0619	-..-	1,359
62-67	-0.0035	0.0276	-..-	6,996	0.1264	0.0655 *	-..-	1,082	-0.0179	0.0365	-..-	3,887	-0.0062	0.0400	-..-	2,027
61-68	0.0097	0.0238	-..-	9,287	0.1376	0.0573 **	-..-	1,454	-0.0255	0.0319	-..-	5,177	0.0237	0.0326	-..-	2,656
60-69	0.0229	0.0199	-..-	11,584	0.1018	0.0480 **	-..-	1,802	0.0088	0.0268	-..-	6,469	0.0202	0.0263	-..-	3,313
Panel B.1. Age measured in bimonthly intervals, Imbens-Kalyanaraman Method																
64-65	-0.1198	0.1878	5.08	2,327	0.1842	0.2086	3.93	350	-0.0765	0.1137	9.82	1,291	0.0010	0.2354	9.52	686
63-66	-0.0308	0.0564	19.70	4,689	0.2496	0.1209 **	28.66	726	-0.0844	0.0813	15.78	2,604	-0.0451	0.0823	20.86	1,359
62-67	-0.0231	0.0503	22.93	6,996	0.2838	0.1409 **	21.48	1,082	-0.0813	0.0711	19.37	3,887	-0.0339	0.0766	22.49	2,027
61-68	-0.0181	0.0423	30.02	9,287	0.1589	0.0924 *	37.85	1,454	-0.0576	0.0566	27.72	5,177	-0.0078	0.0564	34.83	2,656
60-69	-0.0151	0.0354	40.59	11,584	0.1609	0.0935 *	37.14	1,802	-0.0390	0.0461	39.97	6,469	0.0076	0.0422	53.57	3,313
Panel B.2. Age measured in bimonthly intervals, Local Linear Regression																
64-65	-0.0172	0.0672	-..-	2,327	0.4113	0.1893 **	-..-	350	-0.0906	0.0818	-..-	1,291	-0.1263	0.1036	-..-	686
63-66	-0.0109	0.0428	-..-	4,689	0.2243	0.1128 **	-..-	726	-0.0465	0.0549	-..-	2,604	0.0004	0.0618	-..-	1,359
62-67	-0.0040	0.0276	-..-	6,996	0.1269	0.0655 *	-..-	1,082	-0.0177	0.0365	-..-	3,887	-0.0047	0.0399	-..-	2,027
61-68	0.0097	0.0239	-..-	9,287	0.1385	0.0573 **	-..-	1,454	-0.0257	0.0319	-..-	5,177	0.0253	0.0325	-..-	2,656
60-69	0.0227	0.0199	-..-	11,584	0.1009	0.0480 **	-..-	1,802	0.0087	0.0268	-..-	6,469	0.0216	0.0262	-..-	3,313

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

Table 6. Results using Additional Covariates

Ages Included in the Estimation Sample	Full Sample				Some College Education				High School Graduates				Less than High School Education			
	Coeff.	**Std. Error**	**Optimal Bandwidth (months)**	**Number of obs**	**Coeff.**	**Std. Error**	**Optimal Bandwidth (months)**	**Number of obs**	**Coeff.**	**Std. Error**	**Optimal Bandwidth (months)**	**Number of obs**	**Coeff.**	**Std. Error**	**Optimal Bandwidth (months)**	**Number of obs**
								Panel A. Stocks Held Directly and through Mutual Funds								
								A.1. Imbens-Kalyanaraman Method								
64-65	-0.0502	0.0614	14.29	2,327	0.2680	0.1885	30.15	350	-0.1636	0.1164	8.13	1,291	-0.0920	0.2592	9.06	686
63-66	-0.0471	0.0509	17.89	4,689	0.2919	0.1852	13.96	726	-0.1147	0.0651 *	16.92	2,604	-0.0698	0.0527	25.40	1,359
62-67	-0.0470	0.0510	17.82	6,996	0.2487	0.1362 *	20.72	1,082	-0.0959	0.0866	11.79	3,887	-0.0391	0.0378	52.26	2,027
61-68	-0.0213	0.0357	29.28	9,287	0.2425	0.1154 **	26.61	1,454	-0.0902	0.0587	19.88	5,177	-0.0422	0.0383	41.21	2,656
60-69	-0.0174	0.0282	43.87	11,584	0.1844	0.0919 **	36.31	1,802	-0.0436	0.0398	37.53	6,469	-0.0471	0.0422	35.34	3,313
								A.2. Local Linear Regression								
64-65	-0.0597	0.0569	-..-	2,327	0.3336	0.1933 *	-..-	350	-0.1395	0.0706 **	-..-	1,291	-0.1228	0.0795	-..-	686
63-66	-0.0133	0.0359	-..-	4,689	0.2186	0.1120 *	-..-	726	-0.0381	0.0462	-..-	2,604	-0.0497	0.0465	-..-	1,359
62-67	-0.0234	0.0237	-..-	6,996	0.1336	0.0690 *	-..-	1,082	-0.0420	0.0311	-..-	3,887	-0.0364	0.0322	-..-	2,027
61-68	-0.0060	0.0207	-..-	9,287	0.1389	0.0598 **	-..-	1,454	-0.0279	0.0275	-..-	5,177	-0.0207	0.0251	-..-	2,656
60-69	0.0106	0.0174	-..-	11,584	0.0934	0.0493 *	-..-	1,802	0.0082	0.0232	-..-	6,469	-0.0160	0.0210	-..-	3,313
								Panel B. Stocks Held in any Form								
								B.1. Imbens-Kalyanaraman Method								
64-65	-0.0077	0.0778	12.52	2,327	0.4212	0.2269 *	11.44	350	-0.1023	0.0828	22.44	1,291	0.1712	0.3710	7.23	686
63-66	-0.0255	0.0545	19.25	4,689	0.3256	0.1370 **	20.71	726	-0.0872	0.0700	19.21	2,604	-0.0854	0.0902	17.13	1,359
62-67	-0.0278	0.0563	18.52	6,996	0.4379	0.1913 **	13.51	1,082	-0.1038	0.0772	16.45	3,887	-0.0445	0.0687	23.64	2,027
61-68	-0.0191	0.0388	32.01	9,287	0.3246	0.1254 **	23.66	1,454	-0.0589	0.0554	27.49	5,177	-0.0229	0.0525	36.04	2,656
60-69	-0.0158	0.0331	42.26	11,584	0.1914	0.0896 **	37.59	1,802	-0.0327	0.0420	45.18	6,469	-0.0212	0.0489	40.33	3,313
								B.2. Local Linear Regression								
64-65	-0.0244	0.0657	-..-	2,327	0.4580	0.1991 **	-..-	350	-0.1018	0.0829	-..-	1,291	-0.1283	0.0980	-..-	686
63-66	-0.0168	0.0410	-..-	4,689	0.2402	0.1111 **	-..-	726	-0.0454	0.0538	-..-	2,604	-0.0159	0.0588	-..-	1,359
62-67	-0.0119	0.0269	-..-	6,996	0.1364	0.0657 **	-..-	1,082	-0.0219	0.0362	-..-	3,887	-0.0186	0.0391	-..-	2,027
61-68	0.0037	0.0231	-..-	9,287	0.1540	0.0566 ***	-..-	1,454	-0.0248	0.0313	-..-	5,177	0.0114	0.0312	-..-	2,656
60-69	0.0216	0.0194	-..-	11,584	0.1195	0.0474 **	-..-	1,802	0.0109	0.0263	-..-	6,469	0.0110	0.0255	-..-	3,313

Notes: ***, **, * 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	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	0.8714	0.7745	0.6278	0.3416	0.7204	0.7407	0.5008	0.3031	0.7897	0.7601	0.4101	0.0121 **	0.5381	0.5636	0.2120	0.0121 **
63-66	0.8147	0.7955	0.6025	0.5072	0.4878	0.7056	0.5657	0.4347	0.4643	0.6957	0.4861	0.0233 **	0.1964	0.5817	0.2274	0.0233 **
62-67	0.9398	0.8260	0.8122	0.4680	0.3825	0.6225	0.1422	0.3500	0.3544	0.7451	0.0811 *	0.0053 ***	0.0992 *	0.6794	0.0047 ***	0.0053 ***
61-68	0.5561	0.3664	0.5992	0.5376	0.0435 **	0.1198	0.0309 **	0.1151	0.0421 **	0.1401	0.0207 **	0.0014 ***	0.0089 ***	0.1326	0.0015 ***	0.0014 ***
60-69	0.6336	0.2010	0.6329	0.7239	0.0572 *	0.0785 *	0.0396 **	0.2200	0.0563 *	0.0826 *	0.0197 **	0.0020 ***	0.0188 **	0.0645 *	0.0022 ***	0.0005 ***
Panel B. Stocks held in any form																
64-65	0.9314	0.4945	0.9345	0.1059	0.8619	0.1478	0.9539	0.0542 *	0.9069	0.1519	0.9852	0.0012 ***	0.8547	0.0361 **	0.9878	0.0000 ***
63-66	0.9243	0.5801	0.9519	0.2231	0.6547	0.3863	0.7376	0.1323	0.7557	0.3828	0.8431	0.0012 ***	0.2414	0.1348	0.7352	0.0000 ***
62-67	0.9908	0.7961	0.9796	0.2027	0.7826	0.4606	0.4482	0.0603 *	0.7734	0.5084	0.4769	0.0001 ***	0.1829	0.1972	0.2500	0.0000 ***
61-68	0.9934	0.9169	0.9768	0.2237	0.8701	0.6357	0.4765	0.0339 **	0.8076	0.6229	0.4756	0.0000 ***	0.1933	0.3187	0.2374	0.0000 ***
60-69	0.9959	0.9096	0.9908	0.4058	0.8440	0.5784	0.4414	0.0632 *	0.6923	0.6705	0.3503	0.0001 ***	0.1594	0.3416	0.1931	0.0000 ***

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