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DISABILITY INSURANCE INCENTIVES AND THE RETIREMENT DECISION: EVIDENCE FROM THE U.S.

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ABSTRACT

A rising share of older workers in the U.S. make use of the Disability Insurance (DI) program in their transition to retirement, with about one in seven men and one in nine women ages 60 to 64 now enrolled in the program. This study explores how financial incentives from Social Security and DI affect retirement decisions, using an option value approach. We find that financial incentives have a significant effect on retirement, particularly for those in poor health or with low education, who may be more actively considering retirement at younger ages. Simulations suggest that increasing the stringency of the screening process for DI would increase the expected working life of DI applicants.

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1. Introduction

The rolls of the U.S. Disability Insurance (DI) program have risen dramatically since the program's inception in 1956. Over the past two decades, the share of the population age 25 to 64 receiving DI benefits more than doubled, from 2.3 percent in 1989 to 5.1 percent in 2012 (Figure 1). The growth of the program is likely to continue, stabilizing at 7 percent of the non-elderly population, according to one projection (Autor and Duggan, 2006). The rising number of DI beneficiaries has jeopardized the program's ability to pay benefits, with annual benefit expenditures reaching $140 Billion in 2012 and the DI Trust Fund projected to be depleted by 2016. As the Trustees of the program recently warned, "lawmakers need to act soon to avoid reduced payments to DI beneficiaries three years from now" (OASDI Trustees, 2013).

Concerns about the DI program have been amplified by the observation that the program's growth does not appear to be driven by worsening population health. Over the period that DI participation doubled, the fraction of people reporting themselves to be in poor health or suffering from a work-limiting health problem was unchanged if not declining (Milligan, 2012; Duggan and Imberman, 2008). These trends have led to renewed interest in understanding the causes of the rise in the DI rolls, as well as its consequences. The effect of DI on labor supply has been a subject of interest since Bound (1989, 1991) and Parsons (1991) reached different conclusions from comparisons of the earnings of accepted and rejected DI applicants. More recent work by Maestas et. al. (2013), French and Song (2012), and Chen and van der Klaauw (2008) has made use of plausibly exogenous variation in DI receipt coming from random assignment of DI applicants to medical examiners or similar sources.

This study takes a different approach to exploring the effect of the DI program on labor supply, specifically labor force withdrawal or retirement. The methodology employed here builds on Coile and Gruber (2004, 2007), who construct several measures of the financial incentives for additional work arising from the structure of the Social Security (SS) program. One measure is the "option value", which captures the gain in utility resulting from retiring at the optimal future date, over and above the utility available by retiring today. Those studies find that having a larger financial incentive for continued work is associated with a reduced probability of retirement. However, these studies ignore the DI program, treating Social Security (and private pensions) as the only possible pathway to retirement.

In the current study, I construct an "inclusive" option value measure that incorporates the financial incentives arising from both SS and DI, and estimate models that relate this new measure to the retirement transitions of workers aged 50 to 69, using data from the Health and Retirement Study (HRS). To explore the effect of incentives on retirement conditional on health, I control for health using an index developed in Poterba et. al. (2013). I explore whether the effect of incentives on retirement varies by health and education, both of which are strongly related to the probability of DI receipt. Finally, to put the magnitude of the findings into context and gauge the relevance of DI to retirement decisions, I use the regression estimates to simulate the effect of reducing access to DI.

I have several key findings. First, the probability of DI receipt is strongly linked to education, even conditional on health. Second, the inclusive OV measure has a negative and significant effect on the probability of retirement; the effect is robust to choice of specification and varies by education and health. Finally, the simulations suggest that reducing access to DI would have large effects on the labor force participation of DI applicants.

The remainder of the paper is structured as follows. In the next section, I provide background on the U.S. DI program and the past literature on DI and labor supply. Next, I describe the empirical strategy, notably how the inclusive OV measure is constructed, as well as the data used. I present descriptive statistics on the probability of DI receipt, and then present the main regression results. I conclude with a simulation of the effect of reducing access to DI and a discussion of the implications of the findings.

2. Background

2.1 Institutional Features of Social Security and Disability Insurance

Disability Insurance in the U.S. is part of the Social Security program. Eligibility for DI and the calculation of DI benefits is similar to that for SS, with a few key differences.

Workers become eligible for Social Security retired worker benefits after 10 years (40 quarters) of covered employment, which now encompasses most sectors of the economy. Benefits are determined by first calculating the Average Indexed Monthly Earnings (AIME), an average of the individual's highest 35 years of earnings, indexed by a national wage index. Next, a progressive linear formula is applied to the AIME to get the Primary Insurance Amount (PIA), where 90 cents of the first dollar of earnings is converted to benefits but only 15 cents of the last dollar. Finally, the PIA is multiplied by an adjustment factor for claiming before or after the Normal Retirement Age (currently 66, but rising slowly to 67 for those born in 1960 or later) to obtain the monthly benefit amount. Benefits are first available at age 62 but may be claimed as late as age 70, and the adjustment factor for early or delayed claiming is considered to be roughly actuarially fair.[1] Before the NRA, workers face an earnings test if their earnings exceed a threshold amount, $15,480 in 2014. Benefits are available for spouses and survivors of retired workers, though a spouse who is also qualified for retired worker benefits receives only the larger of the benefits to which she (or he) is entitled. For the median earner, the Social Security replacement rate is 47 percent of average lifetime earnings (Biggs and Springstead, 2008).

While receipt of retired worker benefits upon claiming is automatic for an insured worker, the DI application process is more complex. First, in order to be disability insured, a worker must meet both "recent work" and "duration of work" tests, working in at least 5 of the last 10 quarters (less if disabled by age 30) and for up to 40 quarters over the worker's lifetime (depending on age at disability). An insured worker applying for DI must be determined to have a disability, defined as the "inability to engage in substantial gainful activity (SGA) by reason of any medically determinable physical or mental impairment(s) which can be expected to result in death or which has lasted or can be expected to last for a continuous period of not less than 12 months." The review of a DI application can be a lengthy, multi-step process – the initial decision is made by an examiner at a state Disability Determination (DDS) office, but denied applicants have up to four levels of appeal available to them. One recent study found that although only one-third of applicants were allowed in the initial determination, nearly two-thirds were ultimately awarded benefits (Maestas et. al., 2013). Successful DI applicants begin receiving benefits five

[1] Shoven and Slavov (2013) estimate that returns to delayed claiming have increased over time, particularly since 2000, while Munnell and Sass (2012) argue that the actuarial fairness of the Social Security adjustment factor has changed little over time. Coile et. al. (2002) show there is a financial and utility gain from claiming delay for many individuals.

months after disability onset, and are eligible for Medicare after two years. Beneficiaries who earn more the SGA threshold, $1,070 per month in 2014, lose DI eligibility.

The disability screening process has been subject to changes over time. In the late 1970s, DDS offices tightened medical eligibility criteria in response to growing DI enrollments, resulting in a sharp increase in initial denial rates (Gruber and Kubik, 1997). A 1980 law increased the number of "continuing disability reviews" (CDRs), leading to the termination of benefits for 380,000 individuals over the next three years (Rupp and Scott, 1998). These actions generated a public backlash that led Congress to enact new legislation in 1984. While the new law did not change the statutory definition of disability, it shifted the focus of screening from medical to functional criteria, instructing examiners "to place significant weight on applicants' reported pain and discomfort, to relax its strict screening of mental illness and to consider multiple nonsevere ailments ("impairments") as constituting a disability during the initial determination decision, even if none of these impairments was by itself disabling" (Autor and Duggan, 2006). The 1984 law also put more weight on medical evidence provided by applicants' own health care provider and less on that from the Social Security Administration's medical examination.

Several differences between SS retired worker and DI benefits are relevant for the discussion of financial incentives below. First and foremost, DI benefits are available (to a successful applicant) from the age of disability onset, while retired worker benefits are available only starting at age 62. Second, DI benefits are not subject to reduction for early claiming; thus, a worker claiming retired worker benefits at age 62 would receive 75% of their PIA (based on current rules), while a worker who was awarded DI benefits at age 62 (or any other age) would receive 100% of their PIA.[2] Finally, there are some small technical differences in the calculation of the two benefits, such as a lower number of years of earnings and different indexing year (both due to the shorter career) used in the calculation of the AIME and PIA for DI benefits.

2.2 Relevant Past Literature

This paper, like nearly any study of the U.S. DI program, is motivated at least in part by the growth over time in DI enrollments, and thus the literature exploring the reasons for this trend is of interest. Changes in the stringency of medical screening are clearly one important factor. As Figure 1 illustrates, fluctuations in DI enrollment over time match up with the dates of screening changes, with the DI participation rate falling by 20 percent between 1977 and 1984 (from 2.8% of the non-elderly population to 2.2%) following the initial tightening of eligibility criteria and increase in CDRs and rising again sharply following the 1984 law. The composition of the DI population has also shifted dramatically in the past two decades, with the number of beneficiaries with musculoskeletal and mental disorders growing by over 300 percent while the number with cancer and heart disease grew by only 30 percent; the explosive growth in the former group is consistent with the 1984 law's relaxed screening of mental illness and greater emphasis on pain and workplace function (Autor and Duggan, 2006).

Economic and demographic factors have also been put forward as possible explanations for the time-series trend. Autor and Duggan (2003) point out that the value of

[2] The rise in the NRA makes it more attractive for early retirees to apply for DI when they retire, since the actuarial reduction for claiming retired worker benefits at age 62 is rising over time from 20% (for those born before 1938) to 30% (for those born starting in 1960). Li and Maestas (2008) find that the increase in the NRA has led to an increase in DI applications, particularly among those in poor health.

DI relative to potential labor market earnings has risen since the late 1970s because of the interaction between the DI benefit formula and rising income inequality, whereby DI benefits become relatively more generous if an individual's earnings growth lags behind the average growth of earnings in the economy. Over the past two decades, the increase in DI enrollment has been largest for those without a high school degree, consistent with their weakening position in the economy (Katz and Autor, 1999). Another potential explanation is rising women's labor force participation, which has made more women eligible for DI. As illustrated below, women's DI participation rates rose more rapidly over this period than did men's, lending some credence to this theory; however, Autor and Duggan (2006) estimate that increased attachment to the labor force explains only one-sixth of the increase in women's DI participation over time, suggesting that other factors may matter more. Finally, as mentioned above, changes in health do not appear to be a major driver of the growth in DI enrollment, since mortality rates have fallen over time while other health measures have generally been either flat or improving.

A second strand of the literature that is highly relevant for the present analysis concerns the effect of the DI program on labor supply. The long-term decline in the labor force participation of older men that began after the end of World War II (before stabilizing and ultimately reversing starting in the early 1990s) coincided with the rapid growth of the DI program in its first two decades of existence, prompting analysts to explore the effect of DI on men's labor force participation as far back as Parsons (1980). Estimating the effect of the DI program on labor supply is difficult because the counterfactual – how much DI recipients would have worked in the absence of the DI program – is unobservable. Comparing the labor force participation of DI recipients with that of the population at large is fraught because DI recipients are in worse health and may differ in other unobservable ways, introducing bias in the estimation.

Bound (1989) offers a novel solution, using the post-decision earnings of rejected DI applicants as an upper bound estimate of the work capacity of successful applicants, the former group presumably being in better health than the latter. Finding that rejected DI applicants had labor force participation rates of less than 50 percent, Bound concludes that the work capacity of successful applicants is low. Subsequent papers (Parsons, 1991; Bound, 1991) have raised and debated potential problems with this approach. Rejected applicants may need to remain out of the labor force for years to avoid jeopardizing their appeals and may also suffer depreciation of human capital due to the interruption in their work career (which would not occur in the absence of a DI program). Lahiri et. al. (2008) found that rejected DI applicants also tend to have intermittent work histories, further calling into question their use as a comparison group.

More recent contributions to this literature have surmounted the usual endogeneity problem by identifying plausibly exogenous sources of variation in DI receipt. Maestas et. al. (2013) exploit variation in the allowance rates of DI examiners at the initial stage in the DI determination process. They find that among the roughly one-quarter of applicants on the margin of program entry, employment would have been nearly 30 percentage points higher in the absence of DI benefits. These effects are heterogeneous, ranging from no effect for the most impaired to a 50 percentage point effect for the least impaired. French and Song (2012) employ a similar methodology, using variation that arises from random assignment of DI cases to administrative law judges, a later stage in the DI determination process. Chen and van der Klaauw (2008) employ a regression discontinuity approach based on discrete changes in eligibility standards at various ages (e.g., age 55) that are codified in the "Medical-Vocational Guidelines" and used for applicants when a disability determination cannot be made on medical grounds alone. The latter two papers obtain estimates roughly similar to those of Maestas et. al. (2013). Gruber (2000) differs slightly from the other papers in this group in that he focuses on the generosity of DI benefits. Making use of a differential increase in benefits in Quebec vs. the rest of Canada in the 1980s to estimate a differences-in-differences model, he finds an elasticity of labor force non-participation with respect to DI benefits in the range of 0.3.

The approach employed in this paper takes a different tack, building on the analysis in Coile and Gruber (2001, 2004, 2007). As explained in more detail below, this approach involves calculating the financial incentive to continued work through the SS and DI programs ("option value") and estimating its effect on retirement decisions. Rather than comparing labor supply outcomes of DI recipients and non-recipients, as most of the above-referenced papers do, the approach taken here compares the labor supply outcomes of those with more and less to gain from continued work. As explained at greater length in the Coile and Gruber papers, there is substantial heterogeneity in the option value measure.[3] While some of this heterogeneity arises from differences in characteristics such as age, marital status, and earnings (which may influence retirement decisions but can be included as control variables), much of it also arises from factors such as non-linearities in the Social Security benefit formula and how they interact with the particulars of an individual's earnings history. As we argue in those earlier papers, this is a fruitful source of

[3] This is also true of the purely financial-based incentive measures that play a bigger role in these earlier studies, namely the "accrual," or increase in lifetime present discounted value (PDV) of Social Security benefits arising from an additional year of work, and "peak value," or change in PDV associated with working from the present age to the age at which PDV is maximized.

variation for estimating the effect of Social Security on retirement. The innovation in this paper, relative to those earlier studies, is to incorporate DI incentives in to the option value measure through the construction of the "inclusive option value" measure.

3. Empirical Approach

3.1 Data

The data for the analysis comes from the Health and Retirement Study (HRS). The HRS began in 1992 as a survey of individuals then aged 51-61 (born in 1931-1941) and their spouses, with re-interviews of these individuals every two years. Over time, new cohorts have been added to the survey, to maintain a national panel of individuals over age 50 and their spouses.[4] To date, 11 waves of data (1992-2012) have been collected; as the 2012 data has only recently been made available, this paper uses the 1992-2010 data. The paper uses the RAND HRS data file, a cleaned data set that links information over time and across family members and defines variables consistently over time.

A key feature of the HRS is that it includes Social Security earnings histories for most respondents.[5] This allows for the calculation of SS and DI benefit entitlements, which depend on the entire history of earnings. The HRS also contains richly detailed health information that is used in constructing the health index, as detailed below.

The size of the HRS – over 30,000 individuals have appeared in one or more survey wave over the years – as well as the fact that it is a panel allows for the construction of a

[4] The AHEAD cohort (born before 1924) was added to the survey in 1998, when the previously separate AHEAD survey was merged with the HRS. The War Babies (1942-1947) and Children of the Depression (1924-1930) cohorts were also added in 1998. The Early Baby Boomer cohort (1948-1953) joined the survey in 2004 and the Mid Baby Boomer cohort (1954-1959) in 2010.

[5] These data are restricted and available by application only.

large sample of person-year observations. Specifically, the estimation sample includes observations for all men and women in any year from 1992 to 2009 in which they met three criteria: 1) they were ages 50 to 69 during the year; 2) they were in the labor force at the beginning of the year; 3) they were observed in the subsequent survey wave, in order to be able to determine whether or not they retired that year. Thus an individual who was, for example, age 50 when first observed in the HRS in 1998 and retired in 2008 at age 60 would contribute 11 person-year observations to the sample, so long as he remained in the survey until 2010 (to determine whether he retired in 2008). The final sample includes 70,675 observations from 10,570 individuals.

The labor supply outcome of interest in the paper is retirement. Retirement is defined based on the labor force status reported at each wave, an individual being classified as retired when he or she has transitioned from working or unemployed at the previous wave to out of the labor force in the current wave, with the year of retirement assigned based on the date the individual reports at the current wave. Retirement is treated as an absorbing state, so that once an individual reports himself as out of the labor force after age 50, any subsequent employment spells are not used in the analysis.

3.2 Pathways to retirement

While in some other developed countries, early retirement or unemployment insurance benefits offer a viable means of income support from the time a worker leaves his or her job until he or she becomes eligible for social security benefits, in the U.S. there are only two relevant pathways from employment to retirement: the traditional Social Security (SS, meaning retired worker) path and the Disability Insurance (DI) path.[6][7]

As noted above, SS benefits are available starting at age 62. In the construction of the incentive measures, described in more detail below, SS benefits are treated as being claimed at the later of age 62 or when the individual retires. Although claiming is a separate decision from retirement and an individual could theoretically claim benefits either before retirement (once he or she has reached age 62) or after, this assumption seems reasonable given that the SS earnings test, which is still in place for workers until they reach the NRA, depresses pre-retirement benefit claiming (Gruber and Orszag, 2003) and that it is relatively rare for individuals to delay SS benefit receipt after retirement (Coile et. al., 2002).

DI benefits are treated as being claimed at the time of labor force withdrawal, since there is no advantage to (or even mechanism for) delayed claiming.[8] While this may be a reasonable assumption, it is clearly not realistic to assume that everyone can be a successful DI applicant. There is a medical screening process, and though it may be imperfect (as evidenced by the large number of denied applicants who are successful upon

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[6] Unemployment Insurance (UI) benefits are typically available for only 6 months and only to insured workers who are laid off, limiting their value as a source of early retirement income. Coile and Levine (2007) suggests that UI benefits are not empirically important for the retirement decision, finding that workers who reach age 62 in a period of high unemployment are more likely to retire but that the generosity of UI benefits has no effect on retirement transitions. They conclude that SS may be more relevant than UI in protecting older workers from the impact of a late-career employment shock.

[7] In theory, private pensions should be incorporated in the analysis as well, not as a distinct path to retirement but as an income source available to those individuals in the sample who are eligible for defined benefit (DB) pensions, whether they retire along the SS or DI path. Coile and Gruber (2007) calculate incentive measures using SS income only and using both SS and pension income and obtain very similar regression estimates from the two sets of measures, providing some justification for their omission here.

[8] Successful applicants are eligible for benefits after a 5-month waiting period from the onset of disability, as discussed earlier, but this detail is ignored in the analysis. DI applicants often spend more than 5 months waiting for their final disability determination, but benefits are paid retroactively.

appeal, for example), some individuals – those in worse health, also potentially those who are older or in certain occupations due to the use of vocational guidelines in some cases – would be expected to have a higher probability of a success. A discussion of how the uncertainty in access to DI benefits is incorporated into the empirical analysis is deferred to the following section.

3.3 Option Value Calculations

To review, the goal of the analysis is to develop a retirement incentive measure that will reflect the financial incentives for continued work arising from both the SS and DI programs and to estimate its effect on retirement. To explain the paper's approach, in this section I first describe the standard, SS-only option value measure used in prior analyses (Coile and Gruber, 2004, 2007). I then explain how this will be expanded to an "inclusive OV" measure that incorporates DI benefits, including how the uncertainty about an individual's ability to access DI is addressed. Finally, I explain other details relevant to the calculation of the inclusive OV measure.

The option value (OV) approach was pioneered by Stock and Wise (1990) in order to model retirement incentives for workers with defined benefit (DB) pensions. Because DB pensions can have non-monotonic accrual patterns, for example very large returns to work in the year that pension vesting occurs or that the individual reaches the pension plan's normal retirement age, the one-year change in the present discounted value (PDV) of pension wealth resulting from an additional year of work (the "accrual") fails to capture the fact that by working this year, the employee is effectively purchasing an option to work in a future year with a larger accrual. Although non-monotonicities in the accrual of SS benefits do not tend to be as large or frequent as those found for DB pensions, Coile and Gruber (2001) nonetheless show that they exist for SS as well.

OV is a forward-looking measure of the utility gain arising from working to the optimal future retirement date, in excess of the utility available by retiring today. Traditionally, OV has included only SS (and sometimes pension) benefits, but since the present analysis analyzes DI incentives as well, I use the notation *OVSS* to indicate the traditional measure that only includes SS. The *OVSS* calculation begins as follows:

$$OVSS(R)_i = \left[\sum_{t=0}^{R} \frac{1}{(1+\delta)^t} probalive_{it}(wage_{it})^\gamma + \sum_{t=R}^{T} \frac{1}{(1+\delta)^t} probalive_{it}(k * SSben(R)_i)^\gamma\right] - OVSS(R_0) \qquad (1)$$

where R refers to a future retirement date, R_0 refers to today, and T is the final period in which the individual could be alive. *OVSS(R)* is essentially the sum of earnings until time R and of SS benefits (which are a function of R) from time R to time T, discounted for time preference and survival probability, where δ reflects the discount rate, γ reflects the curvature of the utility function, and k reflects the greater utility individuals receive from retirement income due to the utility of leisure. Unlike Stock and Wise (1990), who obtain values for the utility parameters by a structural estimation of their model, we assume that these three parameters take on the values of 0.03, 0.75, and 1.5, respectively.[9]

Equation (1) reflects the utility gain associated with retiring at some future date R, so the individual must repeat this calculation for all possible values of R and estimate:

$$OVSS_i = \max_R\{OVSS(R_1)_i, OVSS(R_2)_i, \dots, OVSS(R_{max})_i\} \qquad (2)$$

[9] An informal grid search over a range of possible values for the three parameters suggests that the likelihood function is relatively flat with respect to parameter choice.

where *OVSS* is the gain in utility arising from delaying retirement and receipt of SS benefits from the present time until the optimal date, the date at which utility is maximized. In our analysis, age 69 is treated as the last possible retirement age considered by the worker.

Having made this calculation for *OVSS*, it is straightforward to calculate *OVDI* in the same manner, temporarily ignoring the possibility that the DI path may be difficult to access for many individuals. In essence the *OVDI* calculation tells us, if one is going to retire via the DI program, what the optimal date (age) at which to do so is and how large the utility gain is from waiting until that optimal date.

Having calculated *OVSS* and *OVDI* brings us to two related questions. First, how can we construct a single incentive measure that incorporates both?[10] Second, what is the appropriate way to account for the fact that not everyone who might want to will be able to choose to retire down the DI path? It turns out that both questions have the same answer, which is to construct an "inclusive OV" measure that is a weighted average of the two individual measures, as follows:

$$OVInclusive_i = (DIprobability_i * OVDI_i) + \big((1 - DIprobability_i) * OVSS_i\big) \qquad (3)$$

OVInclusive is the key regressor in our retirement regressions. The obvious question that arises in its calculation is what value to use for *DIprobability*. In theory, this measure should reflect the probability that the DI path is a realistic option for a given individual. Our approach is to calculate the probability that people age 55 to 64 are receiving DI by year, sex, and education cell, and use these cell probabilities. This approach has the

[10] One very relevant reason for preferring a single measure in the current context is that the results presented here will be combined with those from the other countries participating in the NBER International Social Security project, and the number of pathways may differ across countries. One of the important benefits of having analysts in a large number of countries undertake the same analysis (as nearly as possible) is the insights that can be derived when results are combined.

practical advantage that it requires relatively little data, making it feasible to apply in contexts where rich data such as the HRS is not available. While it would be possible, using the HRS, to go beyond this approach to estimate a predicted probability that any given individual would go on DI, incorporating health information that is surely relevant to DI application and receipt, an advantage of using cell averages is that it avoids the use of these potentially endogenous covariates. Additionally, since some regression specifications interact our incentive measure with health, it is awkward to also have health embedded in the construction of the incentive measure. In essence, one can think of this as similar to an instrumental variables approach, where we limit ourselves to the variation that is more plausibly exogenous to retirement to obtain a cleaner, if less precise, estimate of *DIprobability*. The actual values used for *DIprobability* are reported below.

Finally, I briefly discuss a few salient technical details relevant to the calculation of *OVInclusive*; more information about these calculations can be found in the appendix to Coile and Gruber (2001). The worker's potential future earnings must be projected to age 69 in order to calculate *OVSS* and *OVDI*, as earnings enter directly in the OV measures. Following Coile and Gruber (2004), I grow real earnings by 1% per year from the last observed value. I estimate PIAs for all possible future retirement dates using a program that incorporates the Social Security benefits rules and has been cross-checked against the Social Security Administration's ANYPIA model. The appropriate actuarial adjustment factor is applied in the calculation of *SSBen(R)*. For married workers, *OVSS* and *OVDI* incorporate dependent spouse and survivor benefits, allowing for the probability that at any given age, either or both spouses may be surviving. The inclusion of spousal benefits is complicated by the fact that a spouse who is qualified for retired worker benefits is entitled to the greater of this or her dependent benefit, which will depend on her retirement date. A full modeling of joint retirement decisions is beyond the scope of this paper, so I assume that any working wives (or husbands) retire at age 62 for the purpose of incorporating dependent benefits on the spouse's record, a seemingly reasonable assumption, given that the median retirement age is 62 for married women who were working at age 50.

3.4 Health Quintiles

An important goal of the larger project of which this paper forms a part is to ask: given health status, to what extent are differences in labor force participation within and across countries determined by the provisions of DI programs? To be able to answer this, it is necessary to control for health in the analysis, preferably in way that incorporates as much information as possible and can be replicated across countries.

The approach adopted here, which builds on Poterba et. al. (2013) and is described at more length elsewhere in this volume, is to construct a health index based on 27 questions, including self-reported health diagnoses, functional limitations, medical care usage, and other health indicators. To do so, one first obtains the first principal component of these indicators, which is the "weighted average of indicators where weights are chosen to maximize the proportion of the variance of the individual health indicators that can be explained by this weighted average." The estimated coefficients from the analysis are then used to predict a percentile score for each respondent, referred to as the health index. An individual's health index value typically will vary by HRS survey wave, as updated health information points is incorporated. As Poterba et. al. (2013) demonstrate, the health index is strongly related to mortality and to future health events such as stroke and diabetes onset, though not to new cancer diagnosis. In the analysis below, respondents are divided into health quintiles based on their health index scores.

4. Results

4.1 Descriptive Analysis: DI Participation Rates

Before turning to the regression results, I present some figures on DI participation. Figures 2a and 2b show participation rates for men and women ages 50 to 64 since 1982, using data on DI beneficiaries from the Social Security Administration and population data from the U.S. Census Bureau. Trends over time for older workers mirror those seen in Figure 1 for the population at large. By 2012, one in seven men ages 60 to 64 (14.2%) is on DI, as is one in ten men at ages 55 to 59 (10.6%) and one in fourteen at ages 50 to 54 (7.1%). DI participation rates for older women have risen even more dramatically than for older men in the last three decades, doubling for the age 60-64 group, from 5.6% in 1982 to 11.4% in 2012, and tripling for women age 50 to 54, from 2.0% in 1982 to 6.4% in 2012.

Figures 3a through 3d show rates of DI receipt by education and health for men and women ages 55 to 64. These and subsequent figures use data from the HRS;[11] representative years from 1992 through 2008 are shown on the graph, though calculations are made for all years. The first thing to note is that the values shown on Figures 3a and 3b are the *DIprobability* values used in the construction of *OVInclusive*, as they are year-sex-education cell average participation rates.

Figure 3a shows a substantial DI participation gradient by education, with the lowest education group, high school dropouts, being 5 to 6 times more likely to be on DI

[11] The data in these figures reflect all HRS respondents in the relevant age group, and are not limited to workers.

than the highest education group, college graduates; in 2008, the rates were 22% for the former group and 4% for the latter. The rise in DI rates over time that was evident in earlier figures is present here as well for all education groups; the DI participation rate for high school graduates, for example, rises by 41% from 1992 to 2008, from 7.1% to 10.0%. Figure 3b shows that the DI participation gradient by education is, if anything, steeper for women; the rise in DI over time is also more pronounced, consistent with earlier figures.

Figures 3c and 3d repeat the exercise, stratifying by health quintile (as defined above) rather than by education group. The DI participation gradient with respect to health is much steeper than that for education. This is not terribly surprising, in that there is a medical screening process for DI, so those in worse health (measured using data from the current survey wave) should be more likely to be on DI. Among men ages 55 to 64 in 2008, 46% of those in the lowest health quintile were on DI, versus 9% for the second quintile, 3% for the third, and essentially no one in the top two quintiles. The strong relationship between DI receipt and the health index would seem to provide some reassurance both that the health index we construct is a useful summary statistic for health status and that the DI medical screening process is at least somewhat successful in identifying the least healthy. The graph for women is very similar, though the probability of being on DI for those in the lowest health quintile is somewhat lower, only 37% in 2008.

One question raised by these figures is whether the correlation between education and DI receipt seen in Figures 3a and 3b primarily reflects the effect of health, since low socioeconomic status is known to be correlated with poor health (Smith, 1999), or whether there is a relationship between education and DI receipt even conditional on health. This question is answered in Figures 3e and 3f, which show the probability of DI receipt by education and health, averaged across all years. The education gradient is substantially smaller, but remains non-trivial, with male high school dropouts in the lowest health quintile being 46% more likely to be on DI than college graduates in the same health quintile (50% vs. 34%), while female high school dropouts are 66% more likely to be on DI (38% vs. 23%). The education gradient is equally strong if not stronger in higher health quintiles, though the absolute rates of DI participation are quite small in the top two quintiles. Thus, we can conclude that education has a robust relationship with DI receipt. This is consistent with rising income inequality being one of the explanations for the rise in the DI rolls, as mentioned above. It is also consistent with finding that DI applications and awards tend to rise with the unemployment rate (Autor and Duggan, 2003), since less educated workers experience higher rates of unemployment.

4.2 Descriptive Analysis: Incentive Measures

Before examining the regression results, it is useful to take a closer look at the incentive measures that are the key regressors in those models. Figures 4a and 4b show the mean values of the OV measures by age for men and women. These figures are constructed by taking a sample of workers at age 50 and computing their incentive measures at all future ages through age 69; there is no concern of sample selection (e.g., higher income workers being less likely to retire) as the sample ages, as mean OV is calculated using data for all workers, regardless of their ultimate retirement decision.

Starting with Figure 4a, the first thing to note is that the mean for all of the OV measures (*OVSS, OVDI,* and *OVInclusive*) is positive, indicating that on average there is some utility gain associated with remaining in the labor force until the optimal future retirement date, whether the individual is contemplating retirement along the SS or DI path. For all measures, the mean value is declining with age, reflecting the fact that the closer one gets to the optimal retirement date, the smaller the utility gain associated with waiting until that date to retire.[12] As far as the magnitudes, the OV measures are in utility units rather than in currency units, so the values do not have an easy interpretation, though higher values reflect a larger gain from retirement delay. The values of OVDI are lower than those for OVSS, for reasons I explain below, but have the same pattern of declining with age. The values for *OVInclusive* are much closer to those of *OVSS* than *OVDI*; this is expected, given that *OVInclusive* is a weighted average of the two and the average *DIprobability* in the sample is approximately 10%, putting more emphasis on *OVSS* in the calculation. The values for women, shown in Figure 4d, are lower than for men, as women's lower average earnings mean that they have less to gain from retirement delays (recall that the OV measures incorporate the value of earnings through retirement as well as the value of SS or DI benefits after retirement). However, the decline with age and relative magnitudes of the different measures display the same patterns observed for men.

Some additional insight into these measures, and particularly into the relationship between *OVSS* and *OVDI*, can be gleaned from Figures 4c and 4d. These report a simpler measure, the PDV of lifetime SS or DI benefits associated with each possible retirement date. The PDV measures reflect the financial (not utility) gain from additional work if one retires along either the SS or DI path, and include only changes in the value of benefits and not the additional wages that may result from additional work.

[12] By construction, OV cannot be negative, but it will be 0 once the individual has passed his or her optimal retirement date.

As Figure 4c indicates, *PDVSS* rises moderately with additional work through age 62, the age of SS eligibility, as additional years of earnings may replace zeroes or low-earnings years in the SS benefit calculation. After age 62, the *PDVSS* grows more slowly, as an additional year of work is accompanied by a delay in SS benefit claim that results in the loss of one year of SS benefits (lowering the PDV) but also in a higher actuarial adjustment and permanently higher SS benefits once receipt commences (raising the PDV); at the mean, the net of these two effects is positive, but modestly so.[13] With a 3% discount rate, the series essentially peaks at or near the NRA. Here, the values (reported in 2011 Euros, for consistency with other studies in this volume) do have a concrete meaning – working from ages 50 to 62 raises the PDV of SS benefits by about 27,000 Euros.

The evolution of *PDVDI* with the age of retirement is much different – *PDVDI* starts at a much higher value than *PDVSS* but declines much more sharply with age thereafter. The reasons for this relate to the differences between SS and DI benefits highlighted above. While additional years in the workforce can raise DI benefits by replacing a zero or low earnings year with a higher earnings year, as for SS, this effect is relatively less important for DI because DI uses a shorter averaging period.[14] More importantly, DI benefits are available immediately upon DI award (after a 5-month waiting period) and are not subject to actuarial adjustment. Therefore delaying onset of DI benefit receipt means a loss of benefits today, with no compensating increase in future benefits. For men, mean *PDVDI*

[13] These results will be sensitive to the choice of the discount rate, since the cost of remaining in the labor force for an additional year is borne now and the benefit is received in the future.

[14] To elaborate on this, a 50-year-old considering retiring now through the SS path would likely have zeroes in the calculation of his PIA for SS benefits, as he is unlikely to have 35 years of covered earnings by this point. By contrast, for a 50-year-old considering retiring now through the DI path, the PIA would be calculated based on only the highest 23 years of earnings, so it is less likely that this calculation would include zeroes.

falls from 270,000 Euros if retirement occurs at age 50 to 151,000 Euros if it occurs at age 66. As expected *PDVSS* and *PDVDI* for women have lower values but display the same patterns as for men.

Returning to Figures 4a and 4b, *OVDI* can be positive (and declining with age) even when *PDVDI* peaks at a retirement age of 50 because the OV measures include earnings as well as SS or DI benefits. The replacement rates from SS and DI are fairly low, both in absolute terms and by international standards, and so even though the OV calculation puts a greater value on a dollar of retirement income than a dollar of earnings because of the utility of leisure, it may still be optimal to delay retirement along the DI path even if DI benefits are immediately available in order to accumulate additional years of earnings. Nonetheless, the key point is that the sharply different profiles of *PDVSS and PDVDI* explain the much lower values of *OVDI* relative to *OVSS* in Figures 4a and 4b – there is simply much less to be gained by remaining in the labor force for those retiring along the DI path, relative to the gains available from delaying retirement for those retiring along the SS path.

4.3 Regression Results

Finally, we turn our attention to the regression models and results. These models generally take the form:

$$R_{it}= \beta_0+\beta_1 OV_{it}+\beta_2 AGE_{it}+\beta_3 Health_{it}+\beta_4 X_{it}+\upsilon_{it} \qquad (4)$$

where retirement (R_{it}) is a dummy variable equal to 1 if the individual retires during the year (reports being out of the labor force at the following survey year and specifies this year as the year of retirement). OV_{it} is the inclusive option value described above. We also use a 'percent change' version of this variable by dividing the option value by the level of utility available by retiring today. *AGE* represents either a set of age dummies or a linear variable for the individual's age. *Health* represents either a set of quintile dummies or the continuous health index. Finally, we include as a set of other controls (X_{it}) the individual's marital status, citizenship status, education, occupation, industry and the spouse's employment status.

The main regression results are presented in Table 1a. The first key finding is that *OVInclusive* has a negative and statistically significant effect on earnings. An increase of 10,000 units (which is somewhat smaller than the mean value of OV, which is 14,526) would reduce the probability of retirement by 3.3 percentage points, or about 40% relative to the baseline retirement rate of 7.9%. The estimates also suggest that a one-standard deviation change in the OV (a 14,770-unit change) would lower the probability by 5.6 percentage points. This result is quite consistent across specifications – using age dummies versus linear age or health quintiles versus the continuous health index has little effect on the results.

The other coefficients on Table 1a are much as expected. Health is an important determinant of retirement. In the models using health quintiles, relative to the poorest health group (omitted), those in higher health quintiles are 2.8 to 3.9 percentage points less likely to retire in any given year. The pattern of the four health quintile dummies suggests that the healthiest group has the lowest probability of retirement, though the difference between the lowest quintile and all others is more important than the differences between any of the other quintiles. The linear health index similarly suggests that better health (which is indicated with a larger index value) makes one less likely to retire, though the implied retirement gradient with respect to health is flatter using this continuous measure than that found using the quintiles. The probability of retirement rises with age, and the age dummies (not shown) exhibit the expected spikes at ages 62 and 65.

In Table 1b, the standard *OVInclusive* measure is replaced with the percent change version of this measure. The results suggest that a 100% increase in *OVInclusive* would reduce the probability of retirement by 5.9 percentage points. A 100% increase in *OVInclusive,* evaluated at the mean, would represent something like a 14,000-unit increase. Thus it seems about right that this effect (5.9 percentage points), is roughly similar to the one-standard-deviation change effect (5.6 percentage points), since that simulates a similar change in *OVInclusive*.

The next set of tables explore whether the effects seen in Tables 1a and 1b vary by health. In theory, it is not clear whether the impact of a given change in *OVInclusive* should have a bigger or smaller effect for someone in poor health. On the one hand, poor health may make individuals less likely to respond to economic incentives, as health becomes the most important factor in the retirement decision. On the other hand, the incentives may be more important for individuals in poorer health because they are more actively considering retirement, while those in good health may just plan to continue working until they reach some critical age, such as 62. The results presented in Table 2a through Table 2c support the second hypothesis, as the responsiveness to the incentives is higher for those in poor health. For example, in Table 2a (specification 1), the impact of a 10,000 unit increase in the option value would be to lower retirement probability by 6.2 percentage points for those in the lowest health quintile, but only by 2.0 percentage points for those in the top quintile. This pattern of results is similar across specifications and for both the option value and percentage gain in option value formulations.

In Tables 3a and 3b, the effect of *OVInclusive* is allowed to vary by education group. Workers with lower education will have lower lifetime earnings, and thus can expect to receive a higher replacement rate (though lower benefits in absolute terms) from DI and SS relative to that experienced by higher-income workers, due to the progressive nature of the benefit calculation. This, along with the increased likelihood that less-educated workers are in poor health (which has already been found to increase the responsiveness to incentives) may make less-educated workers more responsive to financial incentives .

Tables 3a and 3b confirm this hypothesis. More highly educated individuals are less responsive than lower educated individuals to the same incentive. For example, in Table 3a (specification 1), the impact of a 10,000 unit increase in the option value would be to lower retirement probability by 6.3 percentage points for high school dropouts, but only by 2.0 percentage points for college graduates. The results are generally robust across specifications, though in Table 3b, where the incentive measure is defined in terms of a percentage change, the coefficients for high school dropouts are small and statistically insignificant.

Overall, our regression results confirm the findings of Coile and Gruber (2004, 2007) that the financial incentives for continued work arising from the structure of the Social Security system – now construed broadly to include both SS retired worker benefits and DI benefits – have a significant effect on retirement decisions. The effect is in the expected direction, in that workers with a larger financial incentive to delay retirement are more likely to do so, and its magnitude suggests that a large change in financial incentives will have a large impact on the probability of retirement. In addition, I find that the impact of financial incentives on retirement is strongest for those in poor health and those with less education, potentially reflecting a greater salience of financial incentives for groups that may tend to begin to consider retirement at relatively younger ages.

5. Simulations and Discussion

One of the benefits of constructing an inclusive measure that incorporates the financial incentives from both SS and DI is that it can be used to simulate the effect of changes to the DI program. Such simulations are also another way to gauge whether the magnitude of the estimated effects seems sensible. Note that the simulations discussed below are not intended to reflect likely real-world changes to the DI program, but rather to give some sense of the program's importance for labor supply decisions.

I undertake several simulations, all of which essentially amount to reducing the likelihood that workers are able to access the DI path. The results of the simulations are shown in Figures 5a and 5b. The first set of bars on Figure 5a show the predicted work life expectancy if individuals may only consider retiring along the SS path vs. along the DI path. To elaborate on how this calculation is made, I first use the regression estimates from Table 1a, specification 4 to predict each individual's probability of retirement using *OVDI* (or equivalently, setting *DIprobability* to 1 and recomputing *OVInclusive*) and using OVSS (setting *DIprobability* to 0). I then sum the predicted probability of retirement by age for the whole sample under each scenario and retain the mean value, using this to generate a survival function and using the survival function to estimate the average expected remaining work life.

This calculation yields the prediction that on average, age-50 individuals would work for an additional 11.9 years if SS were the only pathway to retirement versus 10.2

years if DI were the only path. Relative to the expected work life (after age 49) when DI is the only path, workers work 17.3% longer when they must retire through SS – this figure is reported on Figure 5b.

The second set of bars repeats this calculation using only those individuals who ever apply for DI. In general, they are in worse health, so their projected remaining work life is smaller than that for the full sample, whether contemplating retiring via SS or DI. But the increase in work life when access to the DI path is turned from off to on is fairly similar to that for the whole sample, 15.7%. The remaining two calculations are similar but reflect the fact that it is unlikely that the DI program would be eliminated entirely in the real world. Rather, it is more likely that the medical screening might be tightened, as it was in the late 1970s. Thus I estimate the effect if access to DI were lost for two-thirds of DI applicants (3rd set of columns) or for one-third of DI applicants (last set of columns). Naturally, the projected effects of these program changes are smaller than that of eliminating DI entirely – they are projected to increase the labor supply of the DI applicant pool by 10.1% and 5.0%, respectively. Since DI applicants make up only a fraction of the total population, the effect on aggregate labor supply (not estimated here) would be smaller.

In conclusion, this study revisits the question of how retirement incentives arising from the structure of Social Security affect retirement decisions, expanding on earlier work that focused on Social Security retired worker benefits to incorporate the incentives from the Disability Insurance program, which previously had been ignored. The paper uses a new "inclusive option value" measure to explore this question, in which the incentives from

Social Security (SS) and Disability Insurance (DI) are combined into a single incentive measure.

The paper has several key findings. First, descriptive statistics on DI participation reveal that there is a strong link between education and DI takeup, even once one controls for health. This is consistent with past work suggesting that rising income inequality and unemployment influence DI application decisions. Second, the inclusive OV measure has a negative and significant effect on retirement. Effects are robust to specification choice and are stronger for those in poor health or with low education, perhaps reflecting that they are more actively considering retirement. Finally, the simulations suggest that a large change in the probability that the DI path is available would have a sizeable effect on the expected work life of the DI applicant pool. An important implication of these findings is that if the U.S. were to tighten eligibility for DI, as was done in the late 1970s, individuals still in the labor force at age 50 would be expected to respond to by working longer, though there would almost certainly be heterogeneity in workers' ability to respond in this way and losses in lifetime income as a result.

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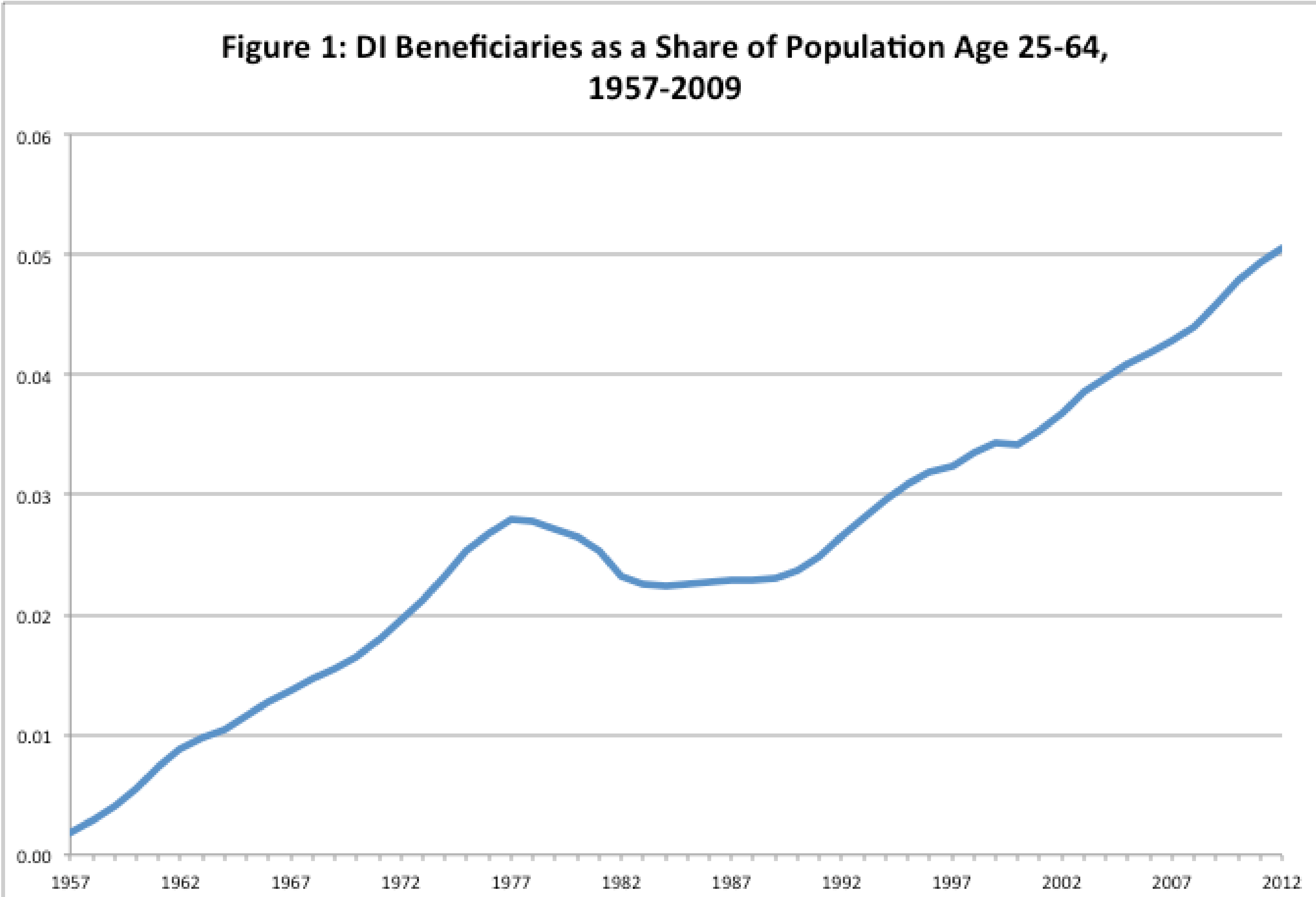
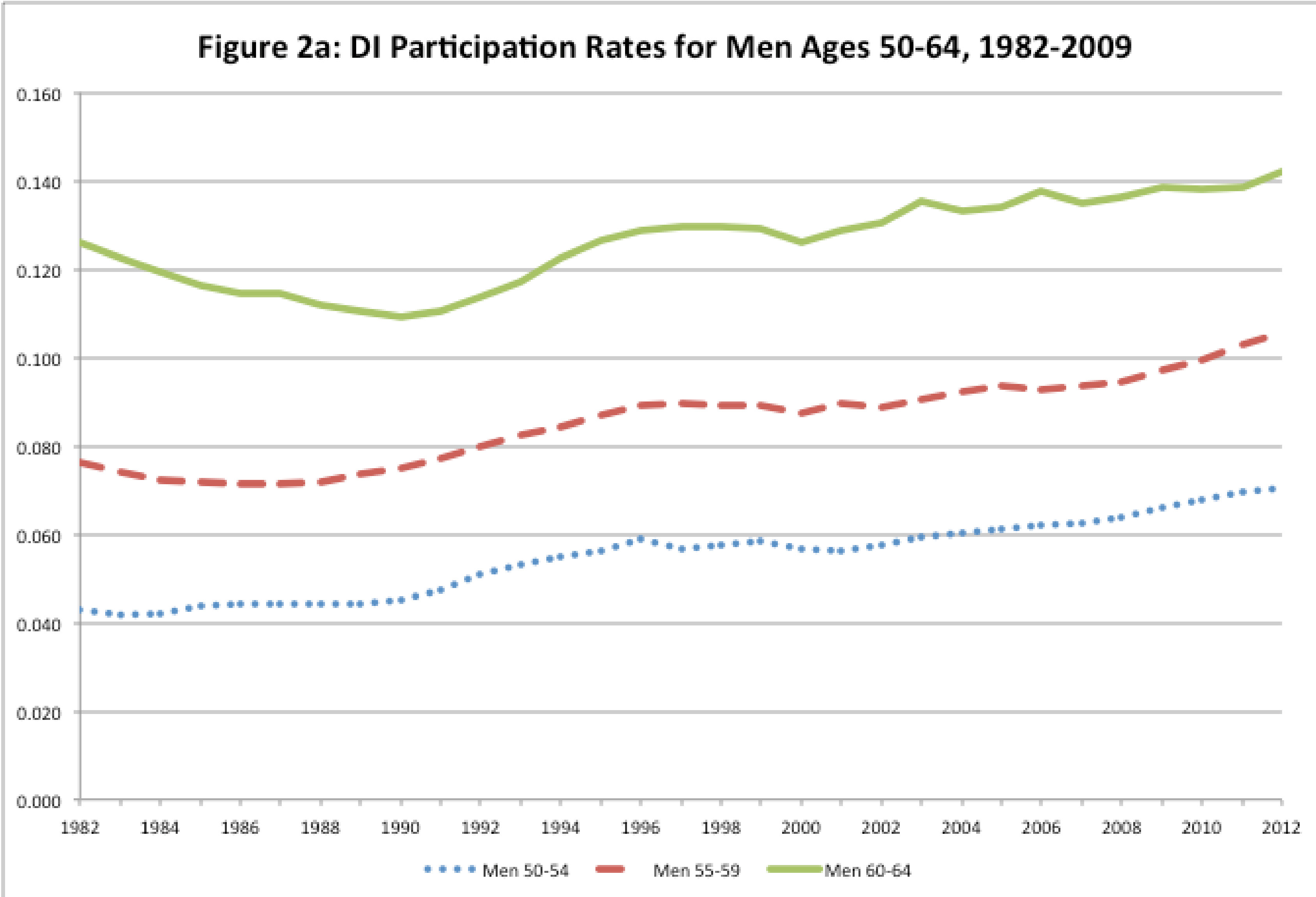


Source: authors' calculations based on Table 5.D3 from the Social Security Annual Statistical Supplement and population data from the U.S. Census (www.census.gov).



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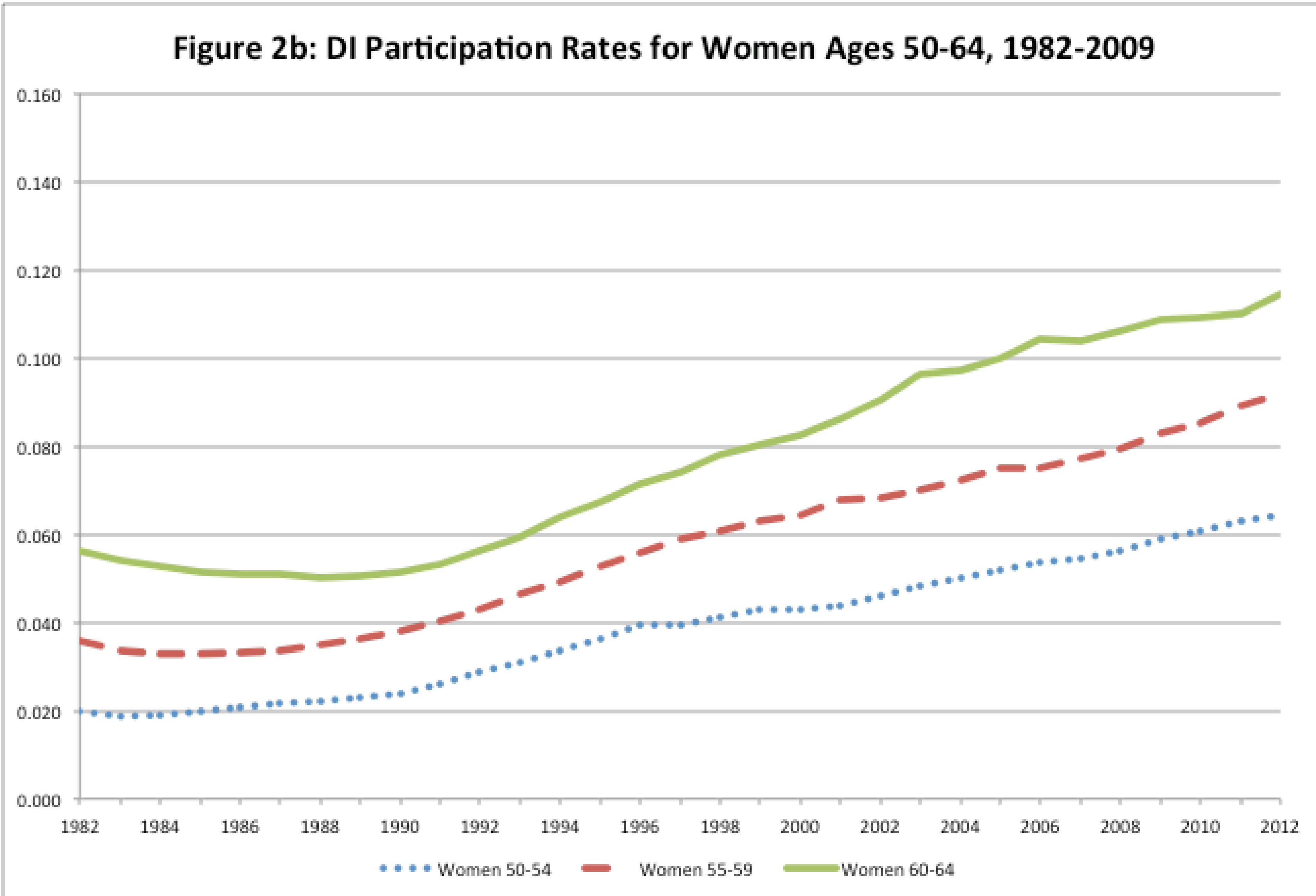

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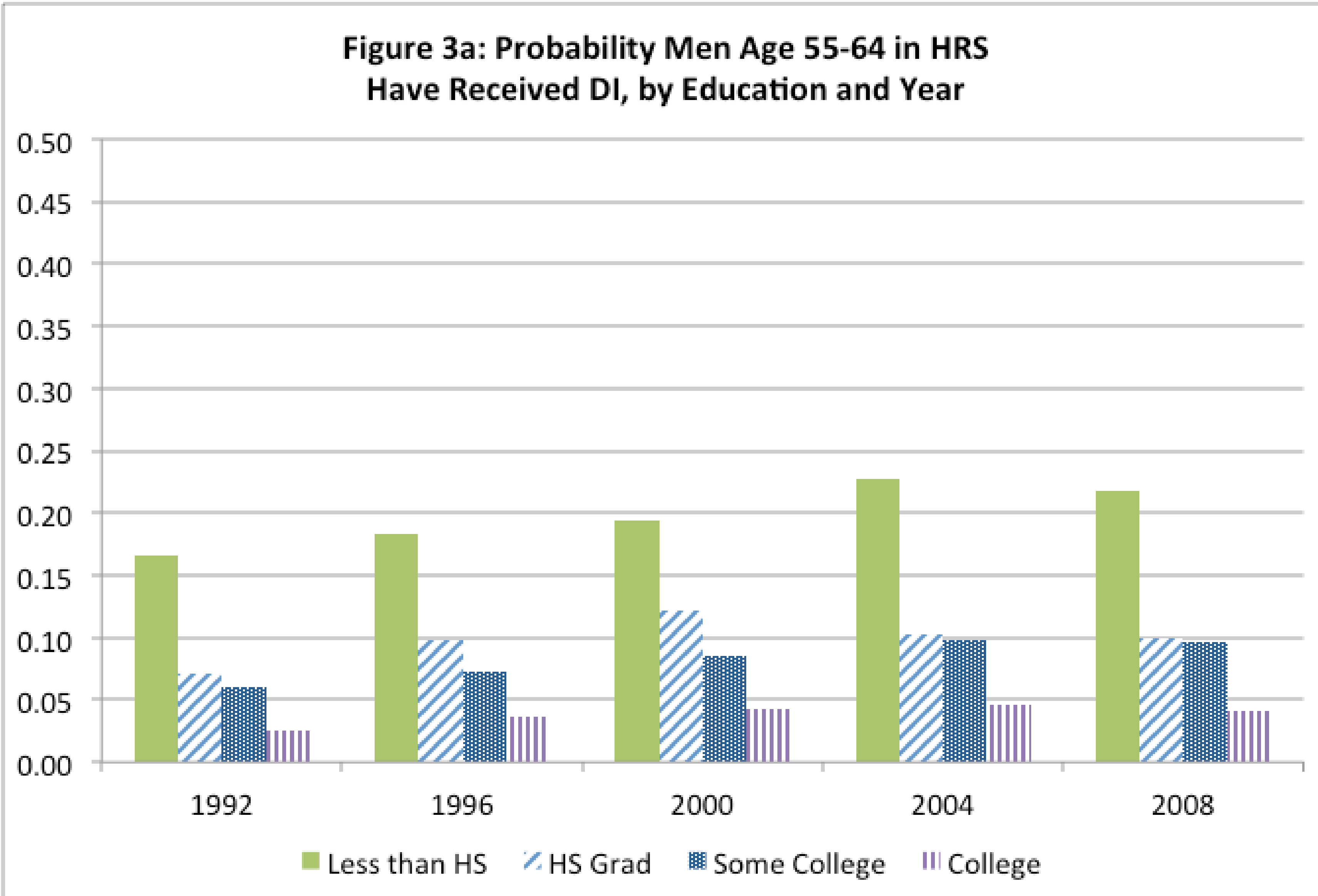

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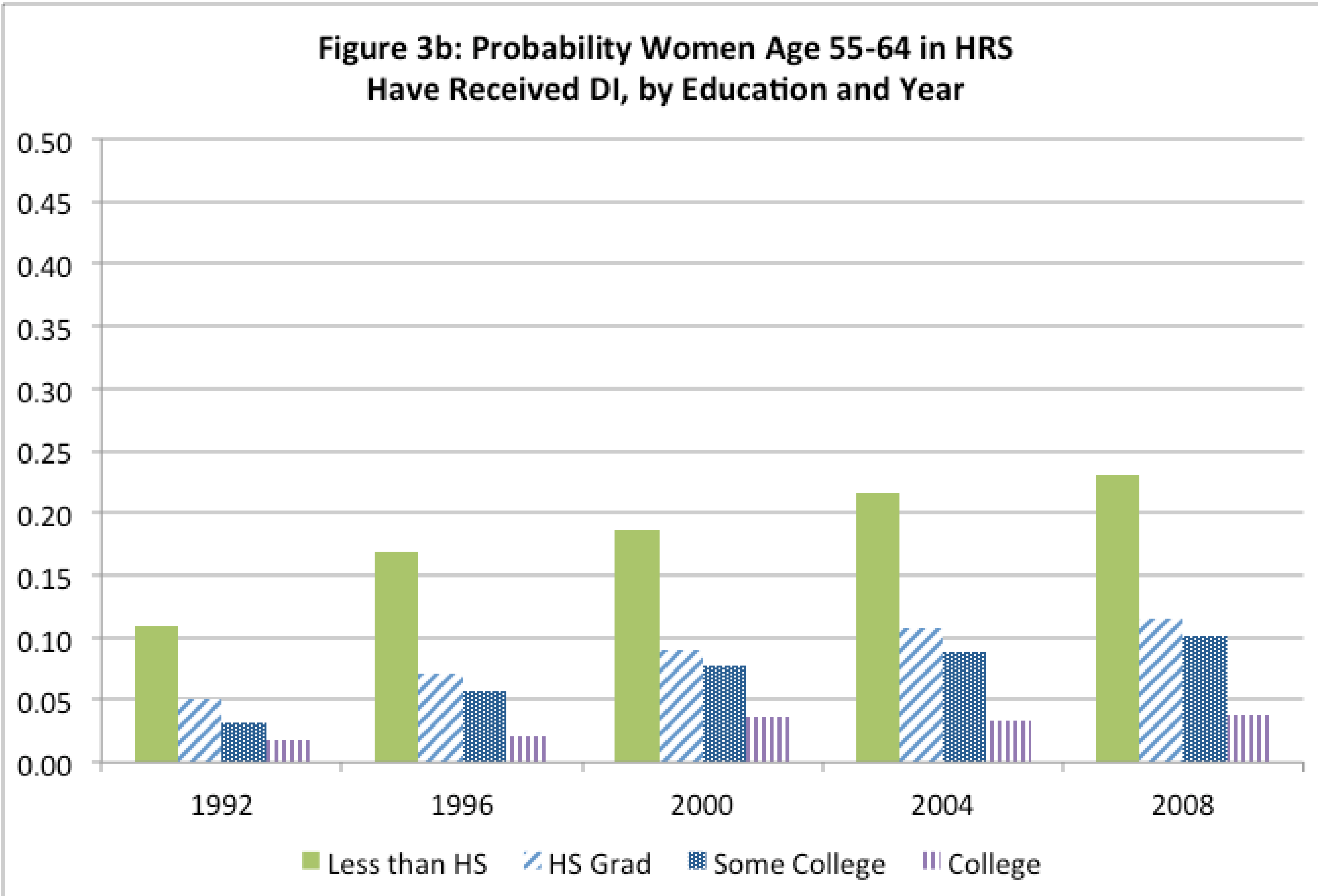

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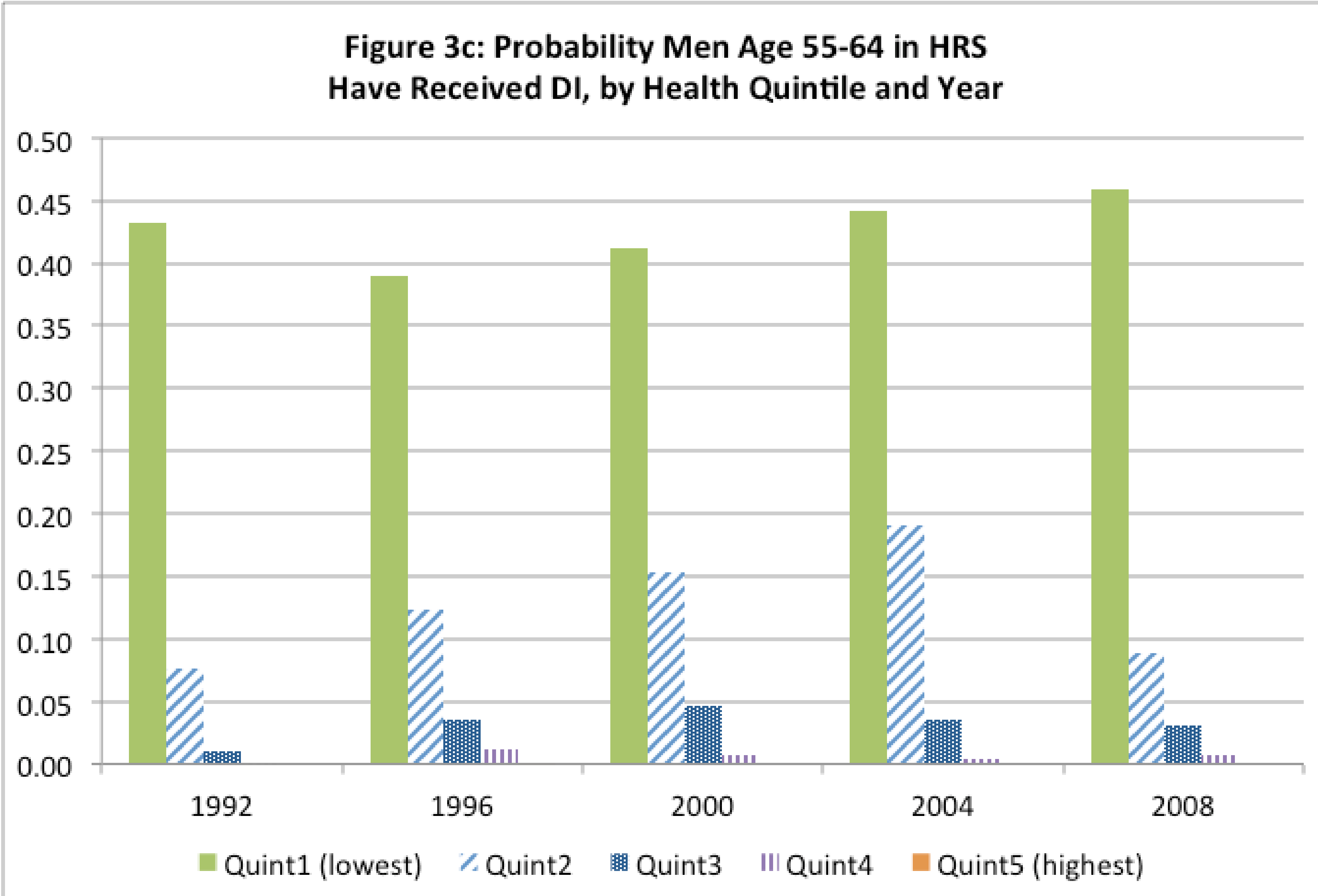

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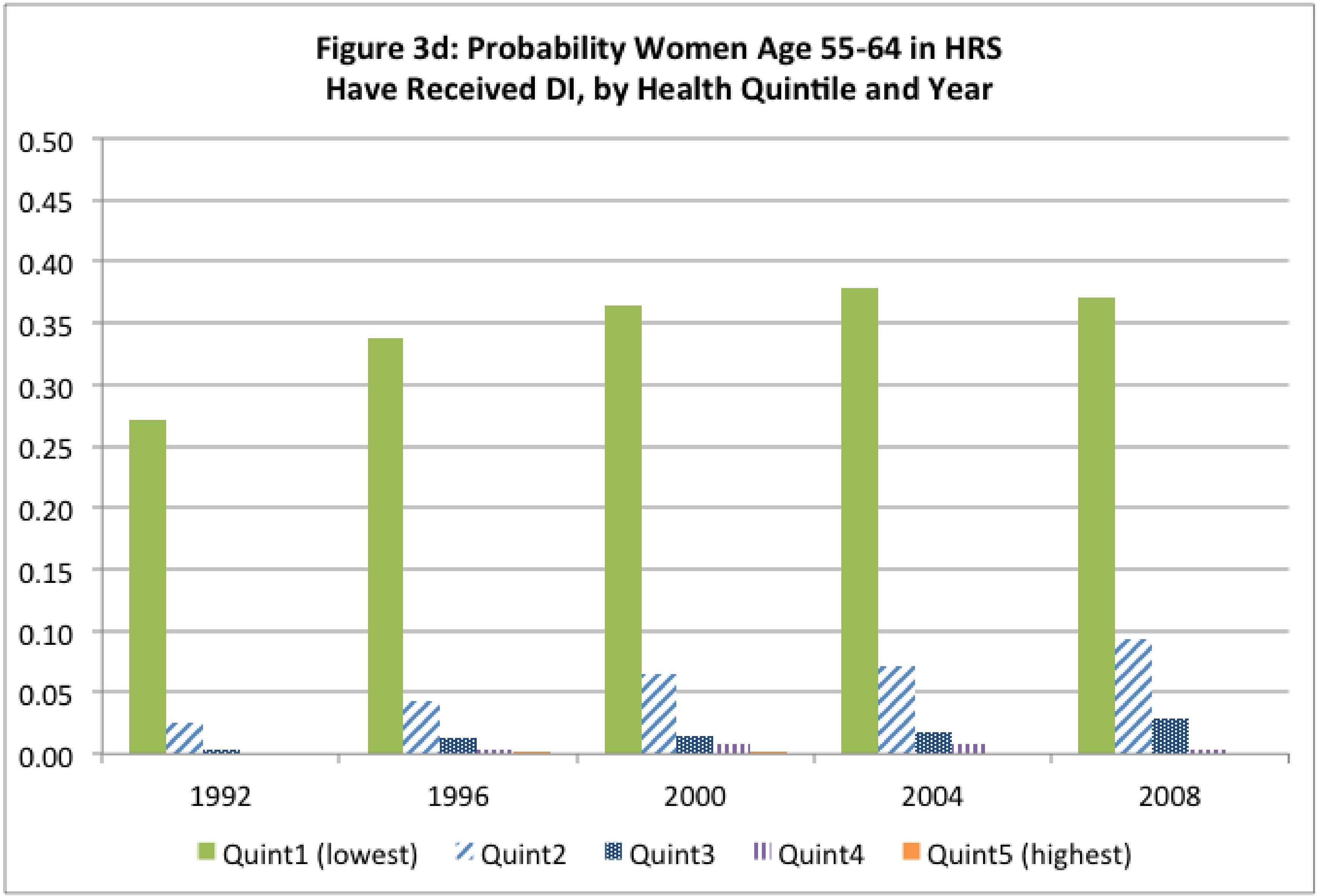

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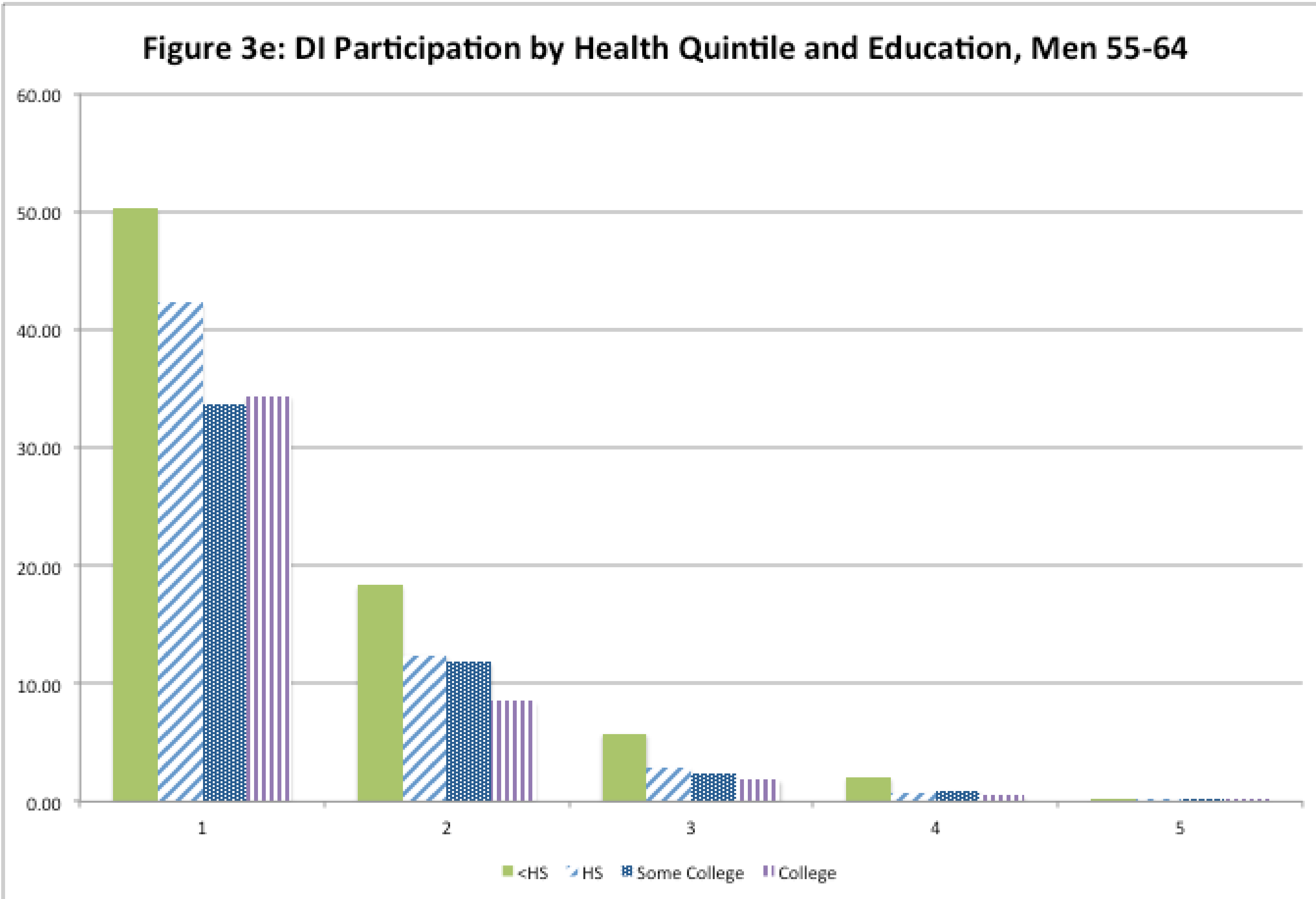

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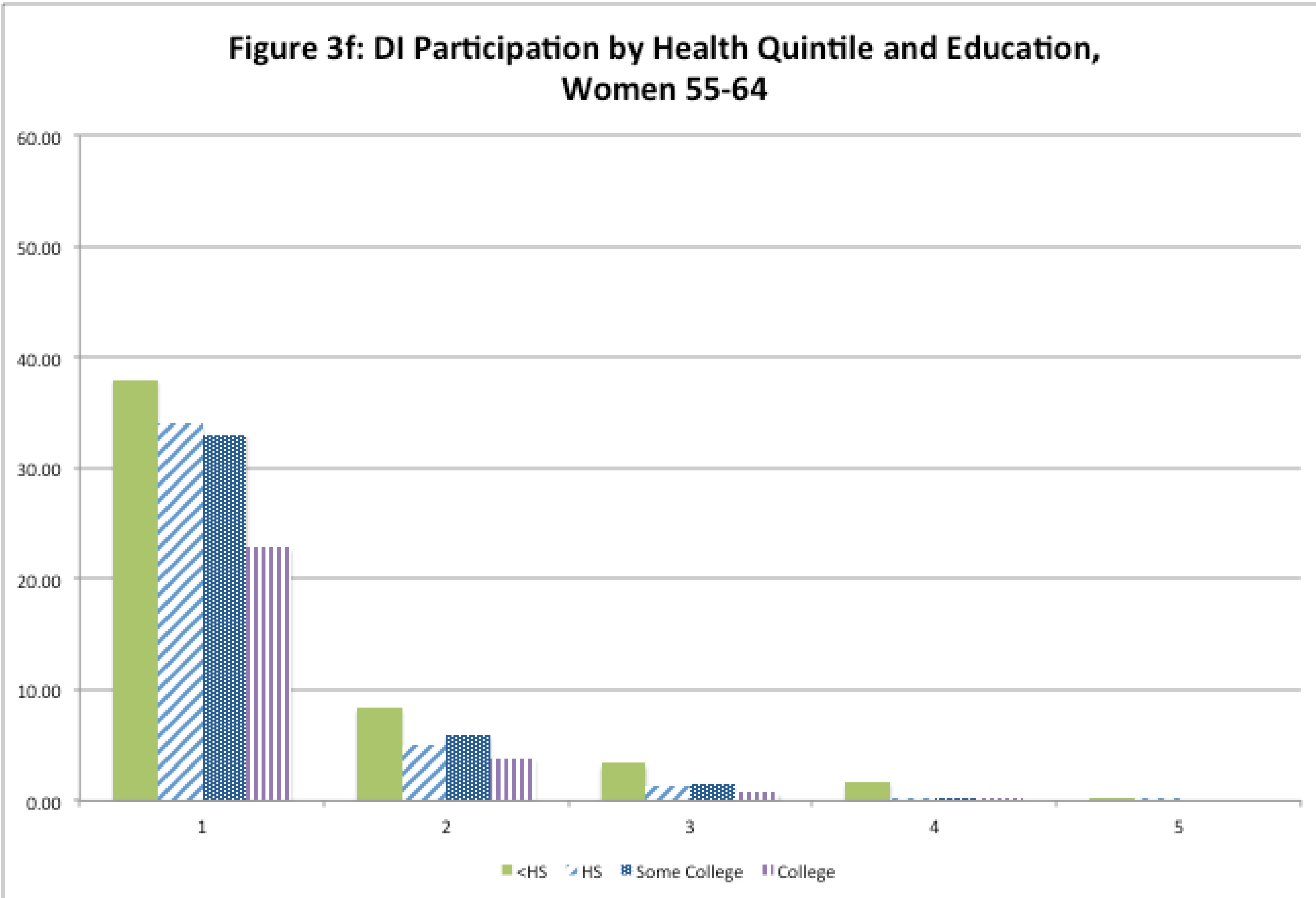

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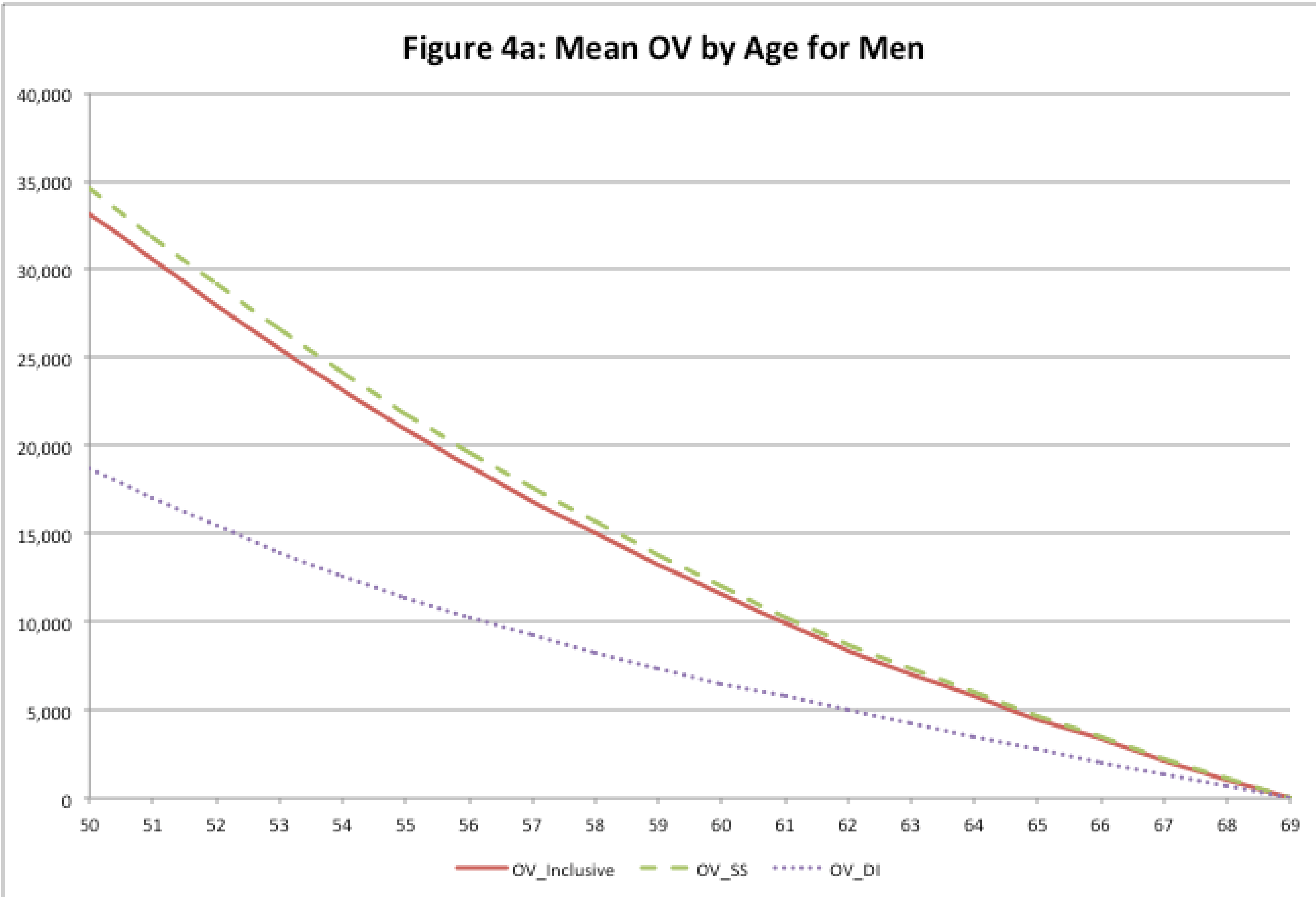
Figure 4a: Mean OV by Age for Men
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65
66
67
68
69
OV_Inclusive
OV_SS
OV_DI

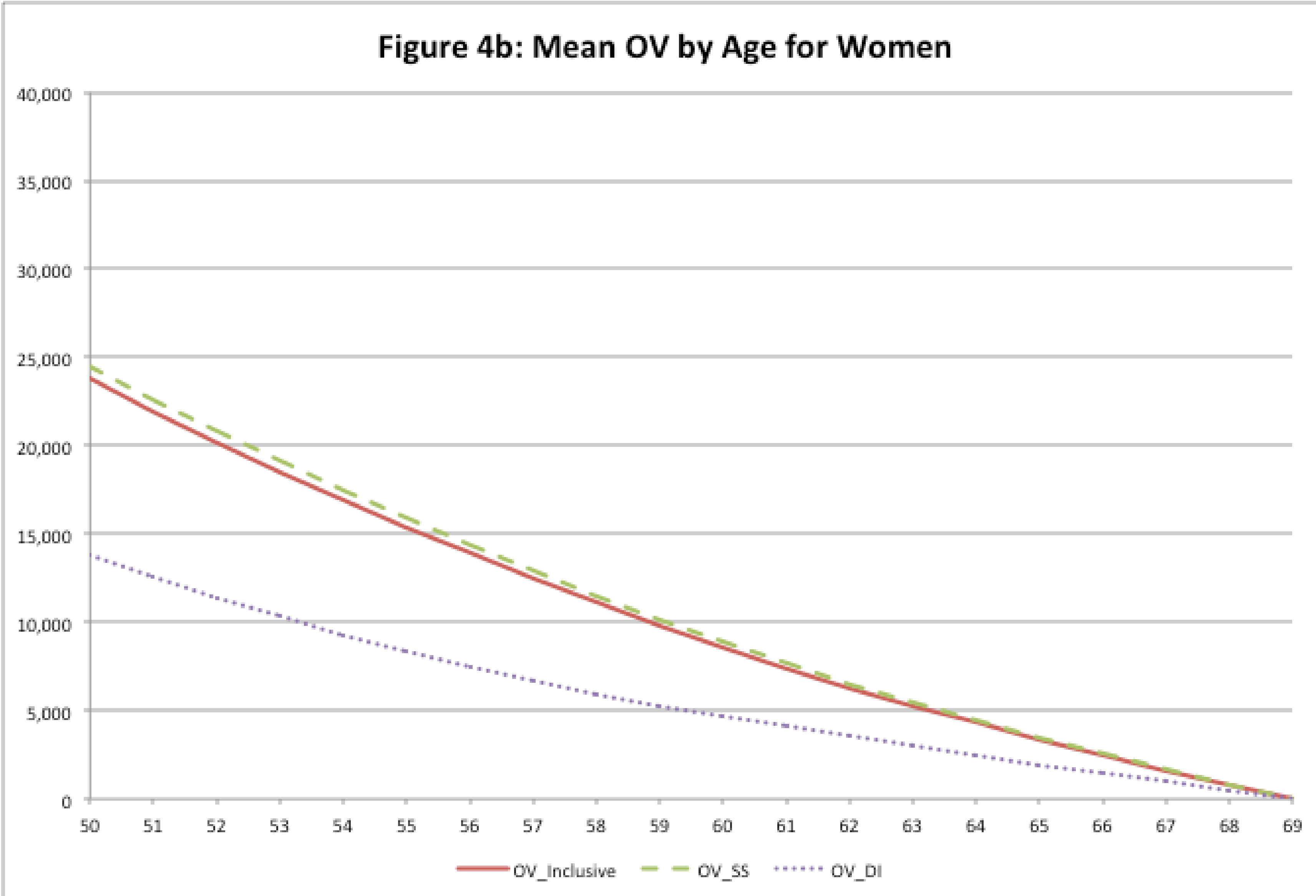
Figure 4b: Mean OV by Age for Women
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65
66
67
68
69
OV_Inclusive
OV_SS
OV_DI

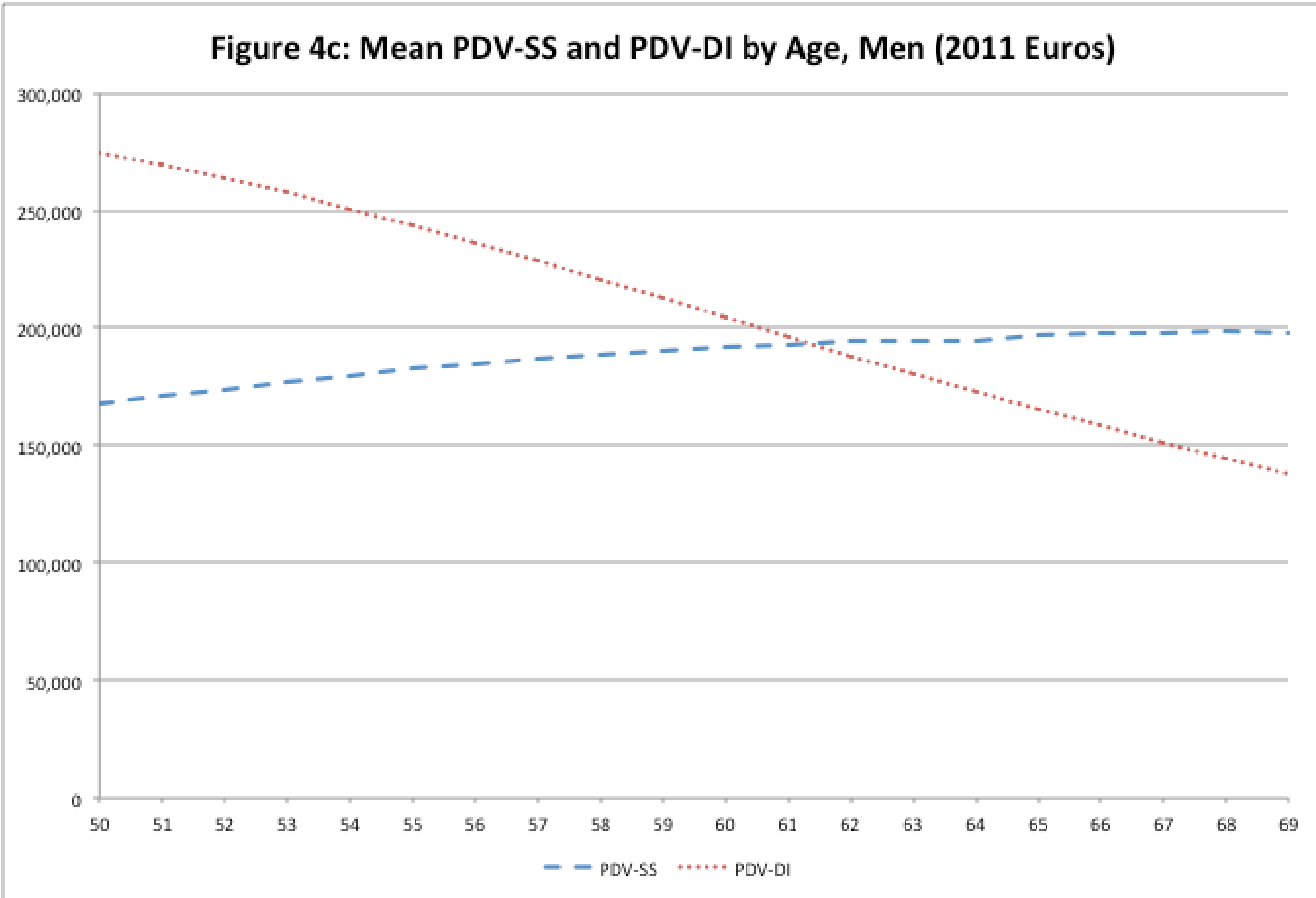

Figure 4c: Mean PDV-SS and PDV-DI by Age, Men (2011 Euros)
300,000
250,000
200,000
150,000
100,000
50,000
0
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65
66
67
68
69
PDV-SS
PDV-DI

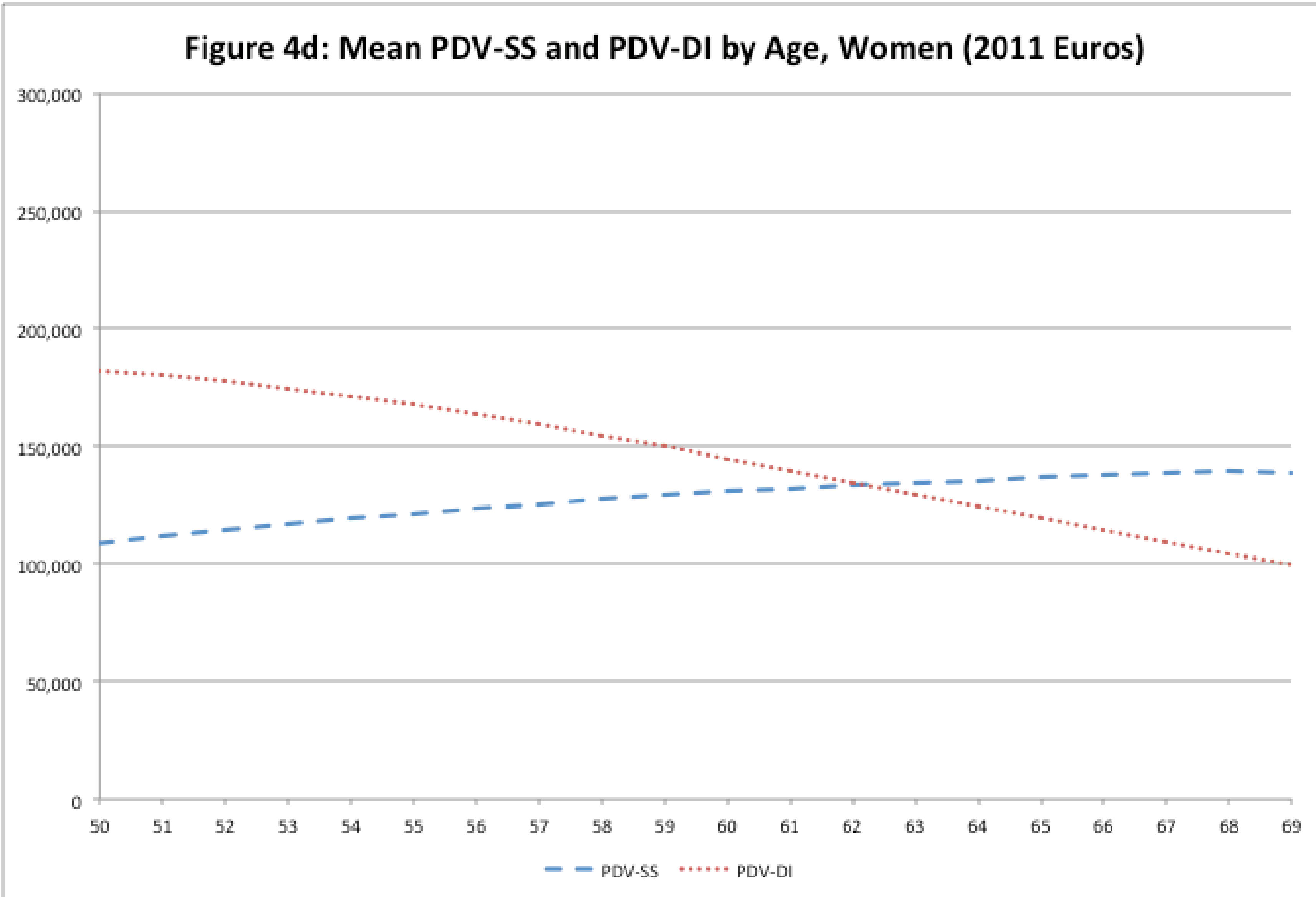
Figure 4d: Mean PDV-SS and PDV-DI by Age, Women (2011 Euros)
300,000
250,000
200,000
150,000
100,000
50,000
0
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65
66
67
68
69
PDV-SS
PDV-DI

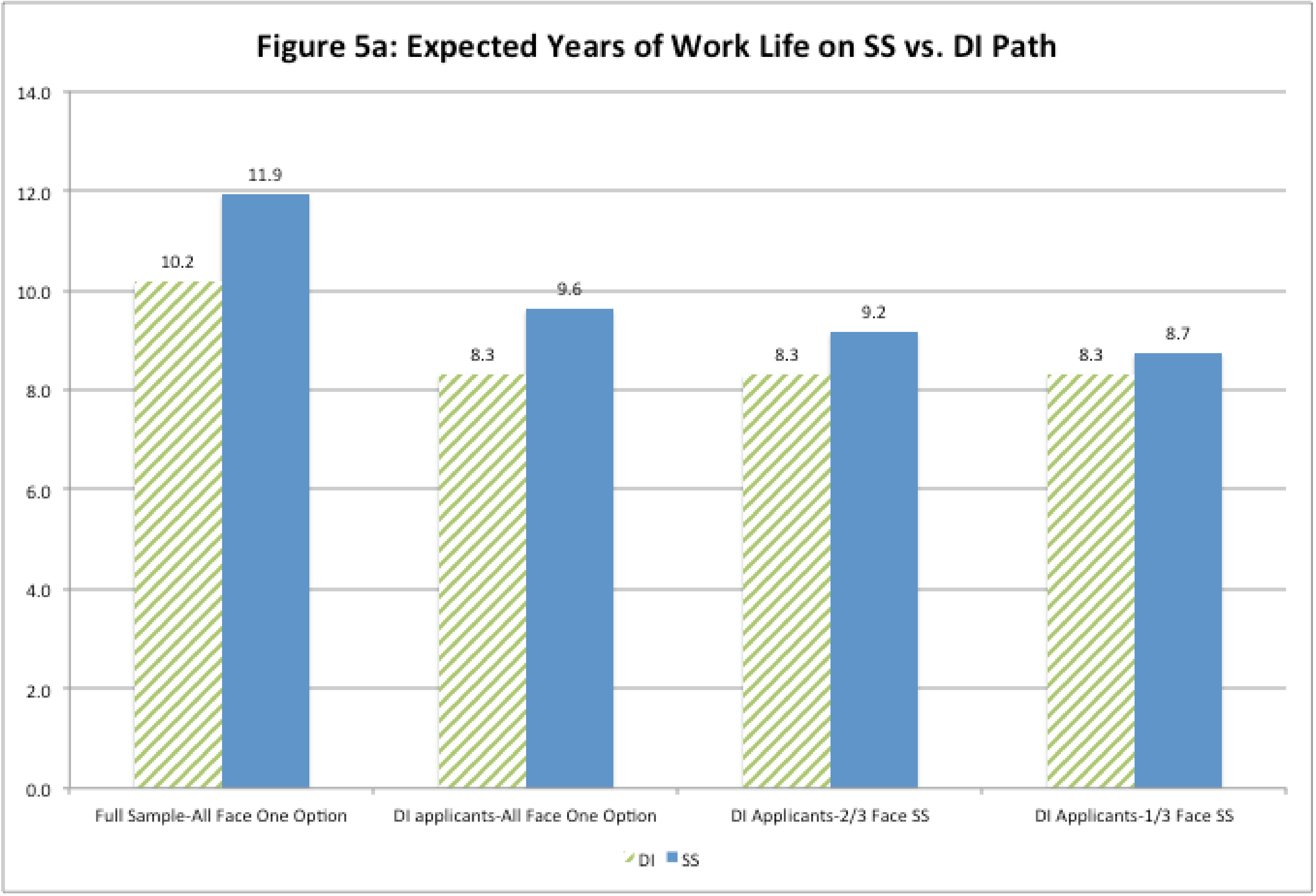
Figure 5a: Expected Years of Work Life on SS vs. DI Path
14.0
12.0
10.0
8.0
6.0
4.0
2.0
0.0
10.2
11.9
8.3
9.6
8.3
9.2
8.3
8.7
Full Sample-All Face One Option
DI applicants-All Face One Option
DI Applicants-2/3 Face SS
DI Applicants-1/3 Face SS
DI
SS

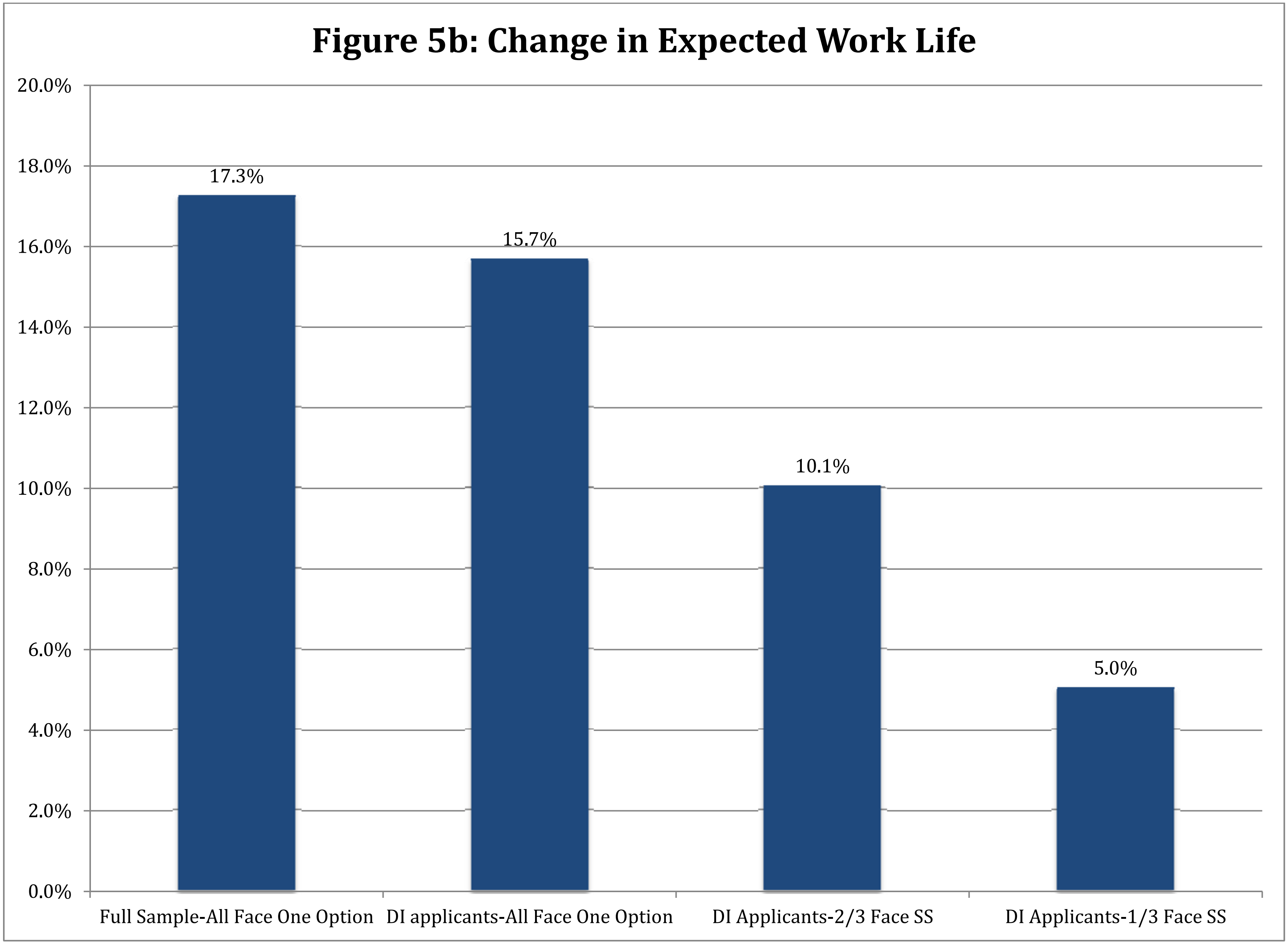
Figure 5b: Change in Expected Work Life
20.0%
18.0%
16.0%
14.0%
12.0%
10.0%
8.0%
6.0%
4.0%
2.0%
0.0%
17.3%
15.7%
10.1%
5.0%
Full Sample-All Face One Option
DI applicants-All Face One Option
DI Applicants-2/3 Face SS
DI Applicants-1/3 Face SS

Table 1a: Effect of Inclusive OV on Retirement

	Specification							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OV_Inclusive	-0.0333 (.0011) [-0.056]	-0.0325 (.0011) [-0.055]	-0.0338 (.0011) [-0.057]	-0.0331 (.0011) [-0.056]	-0.0332 (.0011) [-0.056]	-0.0325 (.0011) [-0.055]	-0.0338 (.0011) [-0.057]	-0.0331 (.0011) [-0.056]
Health Quint 2 (Second Lowest)	-0.0282 (.0022)	-0.0281 (.0021)	-0.0260 (.0022)	-0.0259 (.0021)				
Health Quint 3	-0.0302 (0.0022)	-0.0302 (0.0022)	-0.0283 (0.0022)	-0.0283 (0.0022)				
Health Quint 4	-0.0353 (.0022)	-0.0349 (.0021)	-0.0326 (.0022)	-0.0323 (.0022)				
Health Quint 5 (Highest)	-0.0388 (.0022)	-0.0385 (.0021)	-0.0362 (.0022)	-0.0360 (.0022)				
Health Index					-0.0007 (.00004)	-0.0007 (.00004)	-0.0006 (.00004)	-0.0006 (.00004)
Age	0.0017 (.0002)		0.0019 (.0002)		0.0015 (.0002)		0.0016 (.0002)	
Age Dummies		Included		Included		Included		Included
Female			-0.0031 (.0022)	-0.0031 (.0022)			-0.0037 (.0022)	-0.0037 (.0022)
Married			0.0044 (.0025)	0.0040 (.0025)			0.0040 (.0025)	0.0037 (.0025)
Spouse works			-0.0151 (.0022)	-0.0146 (.0021)			-0.0149 (.0022)	-0.0144 (.0021)
Total Assets (in millions of Euros)			0.0002 (.0013)	0.0000 (.0013)			0.0002 (.0013)	0.0000 (.0013)
Occup Dummies			Included	Included			Included	Included
Educ: <High School			0.0170 (.0040)	0.0157 (.0039)			0.0170 (.0040)	0.0159 (.0039)
Educ: High School			0.0100 (.0031)	0.0091 (.0031)			0.0100 (.0031)	0.0092 (.0031)
Educ: Some College			0.0023 (.0032)	0.0016 (.0031)			0.0021 (.0032)	0.0015 (.0031)
# of Observations	67,228	67,228	67,228	67,228	67,228	67,228	67,228	67,228
Mean Ret. Rate	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
Mean of OV	14,526	14,526	14,526	14,526	14,526	14,526	14,526	14,526
Std. Dev. of OV	14,770	14,770	14,770	14,770	14,770	14,770	14,770	14,770

Note:
1) Coefficients are marginal effects of a 10,000 unit change in OV from probit models. Standard errors are shown in parentheses. The effect of a one standard deviation change in OV is shown in brackets (this is estimated as the effect of increasing inclusive OV from the current value - 0.5 std. dev to the current value + 0.5 std dev).

Table 1b: Effect of % Gain in Inclusive OV on Retirement

	Specification			
	(1)	(2)	(3)	(4)
% Gain in OV	-0.0578	-0.0555	-0.0615	-0.0593
	(.0118)	(.0114)	(.0129)	(.0124)
Linear Age	X		X	
Age Dummies		X		X
Health Quintiles	X	X	X	X
Other Xs			X	X
# of Observations	63,564	63,564	63,564	63,564
Mean Ret. Rate	0.079	0.079	0.079	0.079
Mean of % Gain in OV	0.687	0.687	0.687	0.687
Std. Dev. of % Gain in OV	1.135	1.135	1.135	1.135

Notes:
1) Models are the same as models 1-4 on Table 1.
2) Coefficients are marginal effects. Standard errors are shown in parentheses.

Table 2a: Effect of Inclusive OV on Retirement by Health Quintile

	# of Obs	Mean Ret. Rate	Mean of OV	Std. Dev. of OV	Specification (1)	(2)	(3)	(4)
OV: Lowest Quintile (Worst Health)	13,701	0.132	10,632	11,818	-0.0617 (.0038) [-0.076]	-0.0608 (.0038) [-0.075]	-0.0604 (.0038) [-0.074]	-0.0594 (.0038) [-0.073]
OV: 2nd Quintile	13,525	0.081	12,702	13,232	-0.0347 (.0027) [-0.050]	-0.0338 (.0027) [-0.049]	-0.0363 (.0027) [-0.053]	-0.0353 (.0026) [-0.052]
OV: 3rd Quintile	13,398	0.074	14,205	14,149	-0.0339 (0.0024) [-0.055]	-0.0328 (0.0023) [-0.054]	-0.0346 (0.0023) [-0.057]	-0.0336 (0.0023) [-0.056]
OV: 4th Quintile	13,476	0.062	16,103	15,579	-0.0239 (.0019) [-0.043]	-0.0232 (.0019) [-0.042]	-0.0240 (.0019) [-0.044]	-0.0234 (.0018) [-0.044]
OV: Highest Quintile (Best Health)	13,128	0.054	17,192	15,847	-0.0197 (.0017) [-0.036]	-0.0192 (.0017) [-0.035]	-0.0202 (.0017) [-0.037]	-0.0197 (.0017) [-0.037]
Linear Age					X		X	
Age Dummies						X		X
Other Xs							X	X

Notes:
1) Models are the same as models 1-4 on Table 1, but are estimated separately by health quintile; each coefficient on the table is from a different regression.
2) Coefficients are marginal effects of a 10,000 unit change in OV from probit models. Standard errors are shown in parentheses. The effect of a one standard deviation change in OV is shown in brackets (this is estimated as the effect of increasing inclusive OV from the current value - 0.5 std. dev to the current value + 0.5 std dev).

Table 2b: Effect of % Gain in Inclusive OV on Retirement by Health Quintile

	# of Obs	Mean Ret. Rate	Mean of % OV	Std. Dev. of % OV	Specification (1)	(2)	(3)	(4)
OV: Lowest Quintile (Worst Health)	12,802	0.132	0.561	0.850	-0.0641	-0.0620	-0.0674	-0.0653
					(.0319)	(.0308)	(.0345)	(.0334)
OV: 2nd Quintile	12,739	0.081	0.607	1.050	-0.0598	-0.0566	-0.0631	-0.0599
					(.0185)	(.0172)	(.0201)	(.0187)
OV: 3rd Quintile	12,713	0.074	0.639	0.684	-0.0772	-0.0738	-0.0806	-0.0774
					(0.0060)	(0.0058)	(0.0059)	(0.0057)
OV: 4th Quintile	12,829	0.062	0.698	0.773	-0.0531	-0.0510	-0.0564	-0.0544
					(.0052)	(.0051)	(.0050)	(.0049)
OV: Highest Quintile (Best Health)	12,481	0.054	0.793	1.866	-0.0390	-0.0374	-0.0407	-0.0393
					(.0047)	(.0045)	(.0046)	(.0044)
Linear Age					X		X	
Age Dummies						X		X
Other Xs							X	X

Notes:
1) Models are the same as models 1-4 on Table 1, but are estimated separately by health quintile; each coefficient on the table is from a different regression.
2) Coefficients are marginal effects. Standard errors are shown in parentheses.

Table 2c: Effect of Inclusive OV on Retirement with Health Index Interaction

	Specification			
	(1)	(2)	(3)	(4)
OV	-0.0392 (.0034) [-0.065]	-0.0387 (.0034) [-0.065]	-0.0396 (.0033) [-0.067]	-0.0391 (.0033) [-0.066]
OV*Health Index	0.00009 (.00005)	0.00010 (.00005)	0.00009 (.00005)	0.00009 (.00005)
Health Index	-0.0008 (.00006)	-0.0008 (.00006)	-0.0007 (.00006)	-0.0007 (.00005)
Linear Age	X		X	
Age Dummies		X		X
Other Xs			X	X
# of Observations	67,228	67,228	67,228	67,228
Mean Ret. Rate	0.079	0.079	0.079	0.079
Mean of OV	14,526	14,526	14,526	14,526
Std. Dev. of OV	14,770	14,770	14,770	14,770

Notes:

1) Models are the same as models 5-8 on Table 1, with the addition of an OV*health index interaction.
2) Coefficients are marginal effects of a 10,000 unit change in OV from probit models. Standard errors are shown in parentheses. The effect of a one standard deviation change in OV is shown in brackets (this is estimated as the effect of increasing inclusive OV from the current value - 0.5 std. dev to the current value + 0.5 std dev).

Table 3a: Effect of Inclusive OV on Retirement
By Education Group

	# of Obs	Mean Ret. Rate	Mean of OV	Std. Dev. of OV	Specification (1)	(2)	(3)	(4)
OV: < High School	10,756	0.109	8,697	9,139	-0.0633	-0.0603	-0.0647	-0.0614
					(.0054)	(.0053)	(.0053)	(.0051)
					[-0.062]	[-0.059]	[-0.064]	[-0.061]
OV: High School	24,006	0.086	12,444	12,077	-0.0413	-0.0405	-0.0430	-0.0421
					(.0023)	(.0023)	(.0023)	(.0023)
					[-0.055]	[-0.054]	[-0.058]	[-0.057]
OV: Some College	15,541	0.070	16,033	14,893	-0.0293	-0.0285	-0.0305	-0.0297
					(0.0019)	(0.0019)	(0.0019)	(0.0019)
					[-0.050]	[-0.049]	[-0.053]	[-0.052]
OV: College	16,925	0.060	19,715	18,560	-0.0201	-0.0198	-0.0204	-0.0202
					(.0013)	(.0013)	(.0013)	(.0013)
					[-0.043]	[-0.043]	[-0.044]	[-0.044]
Linear Age					X		X	
Age Dummies						X		X
Health Quintiles					X	X	X	X
Other Xs							X	X

Notes:
1) Models are the same as models 1-4 on Table 1, but are estimated separately by education group; each coefficient on the table is from a different regression.
2) Coefficients are marginal effects of a 10,000 unit change in OV from probit models. Standard errors are shown in parentheses. The effect of a one standard deviation change in OV is shown in brackets (this is estimated as the effect of increasing inclusive OV from the current value - 0.5 std. dev to the current value + 0.5 std dev).

Table 3b: Effect of % Gain in Inclusive OV on Retirement By Education Group

	# of Obs	Mean Ret. Rate	Mean of % OV	Std. Dev. of % OV	Specification (1)	(2)	(3)	(4)
OV: < High School	9,864	0.109	0.550	2.171	-0.0229 (.0165)	-0.0213 (.0154)	-0.0242 (.0174)	-0.0224 (.0162)
OV: High School	22,875	0.086	0.602	0.668	-0.0785 (.0085)	-0.0756 (.0082)	-0.0858 (.0087)	-0.0829 (.0084)
OV: Some College	14,989	0.070	0.767	0.955	-0.0581 (0.0046)	-0.0564 (0.0044)	-0.0628 (0.0046)	-0.0611 (0.0044)
OV: College	15,836	0.060	0.819	0.840	-0.0487 (.0037)	-0.0475 (.0037)	-0.0515 (.0037)	-0.0504 (.0037)
Linear Age					X		X	
Age Dummies						X		X
Other Xs							X	X

Notes:
1) Models are the same as models 1-4 on Table 1, but are estimated separately by education group; each coefficient on the table is from a different regression.
2) Coefficients are marginal effects. Standard errors are shown in parentheses.