The treatment effects of pensions on the labor supply of older workers*

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Abstract

In the mid 1980's, the labor force participation of older workers began to rise after many decades in decline. One explanation for this reversal is the shift in pensions from defined benefit plans (DB) to defined contribution plans (DC). This study estimates a causal model of the treatment effects of pension plans on the labor supply of older workers, using data from the Health and Retirement Study. Econometrically, we use a propensity score matching estimator to estimate the population average treatment effect, the population average treatment effect on the treated and the population average treated effect on the non treated; where treatment in our analysis refers to having a defined benefit plan and having a defined contribution plan. We find no difference between the labor market behavior of older workers with DC pensions and older workers with only social security. Because older workers with DC plans essentially follow the same retirement path as if they only had Social Security, we expect the increase in the retirement age of older workers to continue. Our approach avoids having to make strong assumptions about the functional form of the utility function, and makes the identifying variation from pension incentives clearer, while addressing endogeneity and self-selection in pensions and retirement.

Keywords: Labor supply; Retirement; Pensions.

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*Preliminary and incomplete.

1 Introduction

The aging of the population in the US and around the world makes understanding the behavior of older workers, including retirement choices, a critical component of labor markets. The labor force participation choices of older workers impact a number of policy issues, such as the sustainability of public institutions like Social Security, private retirement and health insurance systems.

The labor force participation of older workers, especially men, declined for most of the twentieth century.[1] The labor force participation rate of males 65 years and older decreased from 47.8 percent in 1947 to 20 percent in 1979.[2] This trend then began to level off in early 1980s. The labor force participation rate of 65 year old males stayed around 15 percent from 1984 to 1999, then gradually started increasing to 22 percent by 2010 (see Figure 1). One possible explanation for this reversal is the shift in pensions from defined benefit plans (DB) to defined contribution plans (DC).[3]

While the literature on the effect of pensions on retirement is vast (Lazear, 1986; Lumsdaine and Mitchell, 1999), most of these studies ignore endogeneity issues in pensions and retirement. Pension eligibility and actual retirement age are determined by both the productivity and marginal disutility of work, factors that are influenced by worker and job characteristics (Filer and Honig, 2005). Previous studies have acknowledged that pensions and retirement may be endogenously determined (Coile and Gruber, 2000; Friedberg and Webb, 2005), yet empirical studies of pension and retirement tend to treat pensions as exogenous determinants of the retirement decision. Furthermore, most of the existing literature assumes specific types of individuals do not self-select into different kinds of plans. To the extent this kind of self-selection does indeed take place, the estimated coefficients in these

[1]This trend may have begun as early as the late nineteenth century (Lazear, 1986).

[2]For women, the general tendency toward earlier retirement has been offset by the increase in labor force participation at all ages (Friedberg, 2007).

[3]In addition to the change in pension type, Friedberg (2007) summarizes other possible explanations for the reversal in retirement trends, such as changes to social security, health insurance and healthcare policy, and the job market environment.

models will be picking up differences in the types of individuals, rather than differences in plan characteristics (Munnell, Cahill and Jivan, 2003).

In this study, we estimate a causal model of the treatment effects of pension plans on the labor supply of older workers. More specifically, this study uses a causal inference approach (Rubin, 1974) to compare age at retirement for workers with pension plans (either DB or DC) to the age at retirement for workers without pension plans (other than Social Security). Econometrically, we use a propensity score matching estimator to estimate the population average treatment effect, the population average treatment effect on the treated and the population average treated effect on the non treated; where treatment in our analysis refers to having a defined benefit plan and having a defined contribution plan. Our approach makes the identifying variation from pension incentives clearer, while addressing the endogeneity and self-selection in pensions and retirement ignored by most structural models. In addition our approach avoids having to make strong assumptions about the functional form of the utility function, which could lead to misspecification errors.

Using 10 waves of data from the Health and Retirement Study (HRS), we find no difference between the labor market behavior of older workers with DC pensions and older workers with only social security. Because older workers with DC plans follow the same retirement path as if they only had Social Security, we expect the increase in the retirement age of older workers to continue.

The remainder of this paper is organized as follows. In the second section below, we analyze the existence for pensions, discuss how differences between defined benefit and defined contribution pensions can impact the retirement choice, and review previous literature on pensions and retirement. In section three we motivate our analysis by looking at endogeneity and self-selection issues in pensions in more detail. The fourth section provides a discussion of the data and methodology used to estimate treatment effect of DB and DC pension plans on retirement. The results are reported in the fifth section, and the final section concludes.

2 Pensions and retirement

In the early 80s, almost half of all workers were covered by a pension. The predominant pension plan offered by employers was a defined benefit (DB) type. Under DB plans, workers accrue benefits over their work life and receive an annuity for as long as they live after retirement. This benefit is usually calculated based on number of years of service, or a percentage of final salary, or a combination of the two. Following Friedberg and Owyang (2002), we can describe the present value flow of a DB pension. Let P_t be the real value of a worker's expected future benefits if the job ends at time t. Then, pension wealth accrual is the real change in pension wealth if the employee works one more year before retiring:

$$\frac{1}{1+\delta}P_{t+1} - P_t, \tag{1}$$

where $0 < \delta < 1$ is the discount rate.

One feature of DB plans is that P_t accrues at a very slow rate in the early years of a career, faster after roughly 10-20 years, to encourage workers to stay in a job during their most productive years; but after 20 years, pension accruals decrease and become negative, to encourage workers to retire when their productivity declines. Samwick (1998) estimated the effects of both Social Security and DB pensions on retirement and found stronger effects on the probability of retirement from DB pensions than Social Security.

Since the early 1980s, the nature of pension coverage began to shift noticeably. While the percentage of workers covered by a pension did not change, most workers were covered not by DB plans but by defined contribution (DC) plans. DC are very different from DB plans. DC plans are like savings accounts, where the employer and employee both contribute to the account over the employee's work life. Employees in DC plans control the allocation and risk structure of the plan.

DC plans are also portable, which means workers can take their pensions from job to job. However, the employee bears the investment risk of the plan. Following Friedberg and

Owyang (2002), after vesting, pension wealth in a DC plan is:

$$P_t^{DC} = P_{t-1}^{DC}(1 + r_t) + c_t, \tag{2}$$

where r_t is the investment rate of return, and c_t are the employee's contributions in period t.

Because DB and DC plans differ in the financial incentives, benefit accrual and investment risk, they impact the retirement decision differently (Munnell, Cahill and Jivan, 2003). In terms of financial incentives, DB plans offer a substantial subsidy for early retirement. This subsidy is the result of companies offering benefits at an early retirement age (ERA). These benefits are not actuarially fair, because the benefit amount is not sufficiently reduced to take into account the worker will receive benefits for a longer period of time. DC plans do not have such a subsidy. In fact, wealth accrual in a DC plan is not a function of the workers retirement decision, because pension wealth can continue to increase even if employee contributions are zero (assuming positive investment returns). Thus, DC plans do not provide a financial incentive to retire at a particular age, while DB plans offer a strong financial incentive to retire before the normal retirement age (NRA).

A second difference between DB and DC plans affecting the retirement decision is the benefit payout. DB plans pay an annuity, while DC plans usually pay a lump sum. Employees may react differently to an expected lifetime flow of income than a lump sum of equal value. That is, even if the present value of equations (1) and (2) are the same, individuals may want a higher amount of wealth under a lump sum payment than under an annuity payment (i.e., $P_t^{DC} > P_t$) to ensure they have sufficient assets to maintain an equal level of consumption (Munnell, Cahill and Jivan, 2003).

Another difference between DB and DC plans is employees bear the investment risk of a DC plan, which means a higher level of uncertainty about the adequacy of pension wealth at retirement than under a DB plan. One way to decrease this uncertainty is to remain on the workforce longer. Delaying retirement reduces uncertainty by increasing the amount of contributions into the plan and reducing the horizon over which pension assets need to be amortized. These differences in financial incentives, benefit payouts and investment risk, suggest workers covered by DC plans should be expected to exit the labor force at an older age than workers covered by DB plans.

2.1 Empirical Studies of the Effect of Pensions on Retirement

Clark and Quinn (1999) describe the empirical evidence regarding the effect of pensions on retirement as falling into two categories. One category is based on simple comparisons of retirement patterns with pension incentives by age, and the second category is based on econometric methods to estimate how retirement depends on various factors.

The first category includes work by Ippolito (1987), Kotlikoff and Wise (1989) and Ruhm (1996). These studies show the presence of financial incentives (like those in DB plans) can strongly influence behavior. However, these studies do not reach a consensus on whether this influence is to encourage or discourage retirement. Studies falling under the second category include research by Stock and Wise (1990) Lumsdaine, Stock and Wise (1997), Samwick (1998), Munnell, Cahill and Jivan (2003), Friedberg and Webb (2005) and Hurd and Rohwedder (2011). Both strands of research have found evidence of an increase in the labor force participation of workers with DC plans, compared to workers covered by DB plans. The studies found DC workers will postpone retirement anywhere in the range between 1.2 to 4.9 percentage points.

Most of the econometric studies of the effect of pensions on retirement use structural models, such as the life-cycle model used by Heiland and Li (2012). In a life cycle model, the consumer maximizes lifetime utility subject to a budget constraint, which includes pension wealth. Lazear (1986) reviews various early static life cycle models looking at the effect of pensions on retirement. A simple lifetime retirement model uses the standard demand for leisure framework. In this framework leisure is defined as number of year of life (T) - years of work (L), and the individual's annual salary is defined by the wage rate W. Then, the worker's lifetime utility maximization problem is:

$$max[U = (leisure, consumption)] \tag{3}$$

subject to the budget constraint

$$consumption = LW = (T - leisure)W \tag{4}$$

Spataro (2002) points out a number of drawbacks for static retirement structural models. For instance, they ignore the effect of institutional features such as mandatory retirement and eligibility rules. Also, the linear approach fails to capture the discrete nature of the retirement choice. In addition, these models are not able to incorporate heterogeneity and uncertainty, which are important in understanding the impact of changes in incentives on short run labor supply decisions.

Technological advances in computing and new data sets allowed researchers to develop dynamic models of retirement that tried to solve some of the issues of static models. As Lumsdaine and Mitchell (1999) explain, these dynamic life cycle models allowed researchers to model heterogenous behavior under uncertainty. These dynamic life-cycle models assume the individuals behavior is the solution to a controlled discrete stochastic process. The study by Gustman and Steinmeier (1986) was one of the earliest works applying a dynamic life-cycle model to study the retirement decision problem. In this model, the individual maximizes lifetime utility:

$$U = \int_0^T u[C(t), L(t), t] \, \mathrm{d}t \tag{5}$$

where $C(t)$ is consumption and $L(t)$ is leisure, respectively at time t, and T is the maximization horizon. The lifetime budget constraint is:

$$A_0 + \int_0^T e^{-rt}\{y[L(t), t] - C(t)\}dt = 0 \tag{6}$$

where A_0 is assets at time $t = 0$, $y[L(t), t]$ relates income to leisure and r is the real interest rate. Tractability in this model requires specifying the utility form. Gustman and Steinmeier (1986) use a CES utility. One strength of this model is it allows a gradual transition from full-time work to part-time work and then to retirement.

Stock and Wise (1990) developed a dynamic option value model of retirement. According to this model, the individual will compare the value of retiring in any given year, with the maximum value of retiring in any of the subsequent years. The difference between these two years is the option value of postponing retirement. So the decision rule in this model is continue working as long as the option value is positive. Lumsdaine, Stock and Wise (1992) use a stochastic dynamic programming model instead. This approach assumes the individual's behavior is the solution of a controlled discrete stochastic process.

$$E\Big\{\sum_{t=0}^{T} \beta^t u(d_t, s_t)/s_0 = s\Big\} \tag{7}$$

where E is the expectation operator, $u()$ is the instantaneous utility function, d and s are sets of control and state variables respectively, and β is the intertemporal discount rate. The problem is solved by finding an optimal decision rule $d_t = \theta(s_t)$ that is a solution to:

$$V_0^T(s) \equiv E_\theta\Big\{\sum_{t=0}^{T} \beta^t u(d_t, s_t)/s_0 = s\Big\} \tag{8}$$

where E_θ is the expectation with respect to the controlled stochastic process (d_t, s_t).

Whereas the option value model is based on the maximum of the expected present values of future utilities, the stochastic dynamic programming model is based on the expected value of the maximum of current versus future options. This implies the option value model will underestimate the value of postponing retirement relative to the stochastic dynamic programming model.[4]

Because dynamic programming decision rules look at the maximum of future disturbance terms, these models depend heavily on the type of error structure assumed, making it difficult to compare results across models. Whether static or dynamic, life-cycle models require the researcher to assume a functional form for the utility function. This opens the door to misspecification problems, and the results too dependent on the chosen assumptions.

While model misspecification is an important concern with the existing literature on pension and retirement, a bigger concern is the treatment of pensions as an exogenous determinant of retirement decisions, but pension eligibility and actual retirement age are determined by the productivity and marginal disutility of work, factors that are influenced by worker and job characteristics (Filer and Honig, 2005). Ignoring the endogeneity of pensions in the retirement decision would result in biased estimates of the ability of pension changes to impact retirement behavior. The next section below models the endogeneity and self selection in pensions, and motivates our analysis that follows in the remaining sections.

3 Endogeneity in pensions

Our estimation of the effect of pension type on the retirement decision can be motivated using the simple model of pension plans and retirement used by Filer and Honig (2005). The model is based on three assumptions:

1. The marginal disutility from work (reservation wage) will increase and the marginal productivity will fall for each worker as they age.

2. Workers and firms will want retirement to occur when the reservation wage for working one more period is greater than the marginal productivity of working that extra period.

[4]The expected value of a maximum of a series of random variables is greater than the maximum of the expected values.

3. Given the second assumption, pension plan provisions will include incentives to encourage retirement at the optimal age. This implies that, given the costs of information, age eligibility provisions in pension plans are better indicators of optimal retirement age for workers than pension wealth calculations.

In a world without uncertainty and with worker-specific labor contracts, the retirement eligibility age will equal the actual retirement age. However, the world is uncertain, and labor contracts are written for workers with heterogeneity in productivity, marginal disutility of work, occupation and industry. Therefore, the retirement eligibility age and the actual retirement age are not the same, but they are related.

Let X be a vector containing job characteristics and worker attributes (e.g., age, race, health, etc.) at the time of initial employment, determining worker productivity and disutility from work. These characteristics determine both the age of retirement and the age of pension eligibility for benefits. If we let A_e be the age at which a worker is eligible to receive benefits and we let A_r be the actual retirement age, then we can define the following two relationships:

$$A_e = f(X, Y) \tag{9}$$

$$A_r = g(X, Y, A_e) \tag{10}$$

where Y is a vector of variables specific to the determination of age of benefit eligibility, and X is a vector of variables that determines actual retirement age only.

From equations (9) and (10) we can see estimation of A_r under the assumption that A_e is exogenous, will lead to biased estimates of equation (10), because A_e is correlated with the error term in equation (10). But this is precisely what the structural models discussed in section 2 do. They estimate equation (10) only, treating A_e as exogenous.

Notice also that equation (9) implies the $cov(X, A_e) \neq 0$. Therefore, estimating equation (10) results in an omitted variable problem as well, by not including worker and job characteristics in the estimation of equation (10). This additional source of bias will result in estimates that overstate the true impact of exogenous changes in A_e on retirement behavior (Filer and Honig, 2005).

Given the relationships defined in equations (9) and (10), we want to analyze the effects of DC and DB plans on the retirement age, using an approach that considers the role of worker and job characteristics on the retirement decision, avoiding endogeneity and omitted variable bias. For identical workers, in terms of worker and job market characteristics, who differ only on whether or not they have a pension, we can view having a pension as a "treatment effect" (τ). This treatment will bring about a change in the the retirement age. The difference in the retirement age between those with a pension and those without will measure the causal effect on the retirement age from the treatment. That is

$$\mathbb{E}[A_r \mid P = 1] - \mathbb{E}[A_r \mid P = 0] = \tau \tag{11}$$

where $P = 1$ and $P = 0$ refers to workers with and without a pension, respectively.

4 Data and Methodology

Our data is the Health and Retirement Study (HRS) (Juster and Suzman, 1995). The HRS is a biennial longitudinal study funded by the National Institute of Aging and the Social Security Administration. The first wave of the study was in 1992 and it interviewed 12,600 people born between 1931 and 1941 (51-61 years old), and their spouses (regardless of age). It is a representative sample of the US population, with certain oversamples, which requires the use of weights to calculate population averages. The HRS asks respondents questions on health economic status, labor market activity, financial information and many other topics. Respondents provide information on various aspects of their labor force and employment status, including information about whether they participate in a pension on their job. Pension information includes plan type (DB, DC, or both), benefits and benefit age eligibility. The HRS is the dominant data source for economists researching economic issues on retirement, including pensions (Venti, 2011).

We use ten waves of the HRS, spanning the years 1992-2010. We select our sample as follows. Beginning with 12,652 individuals in the first HRS wave, we drop anyone not in the labor force in 1992. We also drop anyone with a zero sample weight, anyone not providing financial data in 1992, and anyone not providing pension information. Finally, we drop .17% and .23% of the low end in age ($<$ 50 years old) and the high end in age ($>$ 61 years old), respectively. This leaves us with a sample of 6,068.

We define the retirement year as the year when their labor force status changed from working either full or part time, to retired or partially retired. We drop anyone with a retirement year earlier than 1992. We then define pension type as the pension type reported the final working year. We drop 162 respondents reporting both a DB and a DC pension their last year of work. This brings our final sample to 5,695. Of the 2,881 with pensions, 1,744 (60.53%) have a DB pension and 1,137 (39.47%) have a DC plan.

To obtain the treatment effect of pensions on the retirement age of workers in the HRS, we use the potential outcomes approach developed by Rubin (1974). This approach views causal effects as comparisons of potential outcomes defined on the same unit.

We observe N units (in our case workers/retirees), indexed by $i = 1, ..., N$, viewed as randomly from a large population. Each unit is characterized by a pair of potential outcomes $Y_i(0)$ for the outcome under the control treatment and $Y_i(1)$ for the outcome under the active treatment. In addition, each unit has a vector of covariates, X, consisting of worker and job characteristics. Each unit is exposed to a single treatment; $W_i = 0$ if unit i receives the control treatment and $W_i = 1$ if unit i receives the active treatment. We thus, observe for each unit the triple (W_i, Y_i, X_i), where Y_I is the realized outcome:

$$Y_i \equiv Y_i(W_i) = \begin{cases} Y_i(0) & \text{if } W_i = 0 \\ Y_i(1) & \text{if } W_i = 1 \end{cases} \tag{12}$$

To estimate the treatment effect of pensions, we utilize a propensity score matching estimator. The propensity score is the probability of receiving treatment, conditional on the vector of covariates, X,

$$p(X) \equiv Pr(W = 1 \mid X) = \mathbb{E}[W \mid X] \tag{13}$$

Matching estimators impute the missing potential outcomes, using only the outcomes of the nearest neighbors of the opposite treatment group. Matching estimators have been thoroughly analyzed both practically and theoretically (Heckman, Ichimura and Todd, 1998; Abadie and Imbens, 2002). These estimators have the attractive feature that given the matching metric, the researcher only has to choose the number of matches (Imbens, 2012). Another advantage of matching estimators is they do not require arbitrary functional form assumptions, which decrease the likelihood of misspecification bias (Price, Spriggs and Swinton, 2011).

Formally, given a sample, $\{(Y_i, X_i, W_i)\}_{i=1}^{N}$, let $\ell_m(i)$ be the index l that satisfies $W_l \neq W_i$ and

$\sum_{j|W_j \neq W_i} 1\{\|X_j - X_i\| \leq \|X_l - X_i\|\} = m$, where $1(\cdot)$ is the indicator function, equal to one if the expression in brackets is true and zero otherwise (Imbens, 2012). In general, the index $\ell_m(i)$ chooses an observation in the opposite treatment group that is the mth closest to unit i in terms of the distance measure based on the norm $\|\cdot\|$. If we let $\jmath_M(i)$ denote the set of indices for the first M matches for unit i, we can define the imputed potential outcomes as:

$$\hat{Y}_i(0) = \begin{cases} Y_i & \text{if } W_i = 0 \\ \frac{1}{M}\sum_{j \in \jmath_M(i)} Y_j & \text{if } W_i = 1 \end{cases} \tag{14}$$

and

$$\hat{Y}_i(1) = \begin{cases} \frac{1}{M}\sum_{j \in \jmath_M(i)} Y_j & \text{if } W_i = 0 \\ Y_i & \text{if } W_i = 1 \end{cases} \tag{15}$$

Given a sample of N observations, the matching estimator for the population average treatment effect (Imbens, 2012) is:

$$\tau^P = \frac{1}{N}\sum_{i=1}^{N}\left[\hat{Y}_i(1) - \hat{Y}_i(0)\right] \tag{16}$$

Because we view treatments as policy interventions targeting particular subpopulations, where some individuals self-select into treatment while others do not, we are also interested on an estimate of the average treatment effect on the treated:

$$\tau^T = \frac{1}{N_1}\sum_{i:W_i=1}\left[\hat{Y}_i(1) - \hat{Y}_i(0)\right] \tag{17}$$

where N_1 is the number of treated units.

And, an estimate of the average treatment effect on the untreated:

$$\tau^{NT} = \frac{1}{N_0}\sum_{i:W_i=0}\left[\hat{Y}_i(1) - \hat{Y}_i(0)\right] \tag{18}$$

where N_0 is the number of untreated units.

5 Results

The first step in our analysis is to estimate the propensity score, $p(X)$–the probability of having a pension–conditional on worker and job market characteristics. In order to get some guidance on which covariates to select in our estimation of $p(X)$, we followed the approach of Taubman (1981). Taubman used probit equations of the form:

$$Pr(Y = 1) = \phi(X'\beta) \tag{19}$$

where X is the set of worker and job market characteristics, to estimate the probability of having a pension. We estimate equations like (19) for the probability of having a pension, the probability of having a DB pension, and the probability of having a DC plan. We estimate separate equations for men and women. Table 1 presents definitions and summary statistics for our dependent variables.

Table 2 reports mean and standard deviation information of the various variables we considered in our probit estimations. The variable *stopwork* takes a value of 1 if the respondent answered in 1992 that he expected to retire by age 65. It can be considered a proxy for respondents' own life expectancy and health. However, the HRS includes a question asking respondents for their self assessment of health status. We constructed the variable *health* based on this question, and it takes the value 1 if the respondent answered his health was as good or better than other people his age; however, it was insignificant in all the estimations. Taubman (1981) explains people with different risk preferences will sort themselves by occupation, observed wages partly reflect differences in preferences for risk, and therefore, wage rates and earnings should not be include in the estimations. However, we do include a variable for the total value of assets.

Table 3 reports the results for the probability of having a pension. Years of education and working in public administration and manufacturing industries have significant positive effects for both men and women, while self-employment has significant and substantial negative effects. Men are 64% less likely to have a pension if self-employed, and women are 66% less likely to have a pension if self-employed. Total assets had a positive effect on both men and women, but the effect for women was not significant.

Table 4 reports the results for the probability of having a defined benefit plan. Like in the estimation for the probability of having a pension, education, working in public administration and manufacturing have significant positive impact for both men and women, but working in the utility and service sectors also positively impact the probability of having a defined benefit pension. While self-employment again had significant negative impact on the probability of having a defined benefit pension for both men and women, the effect was bigger for men. The expectation of retiring by age 65 had significant positive effects on both the probability of having a pension and the probability of having a defined benefit plan for both genders.

Table 5 reports the results for probability of having a defined contribution plan. Unlike the case for pensions and defined benefit plans, working in manufacturing is the only industry to have a positive and significant effect on the probability of having a defined contribution plan, and this result is only for men. For women, the only positive and significant effects come from education and the expectation of retiring by age 65. The expectation of retirement was also positive and significant for men. Marital status was significant in all of the estimations, with the exception of women with defined contribution plans. Like in tables 3 and 4, self-employment decreased the probability of having a defined contribution plan, but the magnitude was much lower. The only job type to have a significant effect was professional jobs, and only for men. In terms of demographics, being a hispanic male significantly decreased the probability of having a pension of any type.

We estimated another set of equations for each dependent variable, in which we added the square of assets and the interaction of education with assets and with the square of assets. Only the square of assets had a positive and significant effect on the probability of having a pension and a defined contribution pension for men. We also tried binary outcome variables for different levels of education, and a binary outcome variable for health, but their effects were not significant.

Having the results in tables 3, 4 and 5 to guide us, we select the covariates to use in our estimation of the propensity score as a function of worker and job market characteristics. Use of a propensity score to estimate causal effects requires the commons support condition be satisfied (Imbens, 2004) That is, it requires sufficient overlap between treated and control units. Figures 3, 4 and 5 show histograms of the density/distribution of the propensity score for having a pension, having a defined benefit plan, and having a defined contribution plan, respectively. These histograms show satisfaction of the common support condition. For the propensity score of pension, there is sufficient overlap throughout almost all of the distribution. For defined benefit plan, there is sufficient overlap for values of the propensity score between 0.1 and 0.9. For defined contribution plan, there is sufficient overlap between 0 and 0.95.

Table 6 reports estimates of the population average treatment effect (τ^P), the population average treatment effect on the treated (τ^T), and the population average treatment effect of the non treated (τ^{NT}) of having a pension, having a defined benefit plan and having a defined contribution plan. The parameter estimates in Table 6 show that the population average treatment effect of having a pension of any type is significant and negative on the retirement age. For those actually receiving the treatment, the results suggest that having a pension decreases their labor supply about .9 years on average. For those not receiving the treatment, the results suggest that not having a pension increases their labor supply about 0.5 years. For defined benefit plans, the results in Table 2 indicate a significantly more negative impact. Having a DB plan decreases the labor supply of older workers by about 1.3 years; 49% more than the effect of having a pension of any type. Workers not treated would have retired on average about 1 year earlier with a defined benefit pension plan.

In contrast, the treatment effects of a DC plan are slightly positive but insignificant. This suggests that the labor supply of workers with a defined contribution plan is not different than the labor supply of workers with only Social Security. This in turn suggests that changes to Social Security may do a better job explaining the increasing labor force participation of older workers. As the proportion of workers with defined contribution plans increases, while the proportion of workers with defined benefit plan decreases, workers will react more to incentives from changes in Social Security benefits and eligibility than to incentives from their defined contribution plan. Recent changes to Social Security have been designed to incentivize eligible workers to delay retirement. Our estimates in table 6 suggest these changes are not only affecting the behavior of those with Social Security only, but also those with defined contribution pensions. Our results are in contrast with studies like Munnell, Cahill and Jivan (2003) and Hurd and Rohwedder (2011) which find pension changes account for a considerable part of the increase.

6 Conclusion

This paper considered the role of pension types in explaining increases in the labor supply of older workers since the mid 1980s. Our approach departed from previous models that have neglected the endogeneity between pensions and retirement. Econometrically, we used a propensity score matching estimator to estimate the population average treatment effect, the population average treatment effect on the treated and the population average treated effect on the non treated; where treatment in our analysis refers to having pensions in general, having a defined benefit plan and having a defined contribution plan. In addition, our approach avoids having to make strong assumptions about the functional form of the utility function which could lead to misspecification errors.

Our results suggest the labor supply of workers with defined contribution plans is not different from the labor supply of workers with Social Security. Because older workers with DC plans essentially follow the same retirement path as if they only had Social Security, we expect the increase in the retirement age of older workers to continue. Furthermore, our results suggest to the extent more and more workers are covered by DC plans, changes to Social Security will be important to our understanding of the future labor supply of older workers with and without pensions.

We are interested in conduction further research on this question using different econometric methodologies, such as regression discontinuity design and survival analysis. We are also interested in exploring this question using different definitions of labor supply, such as hours worked per week.

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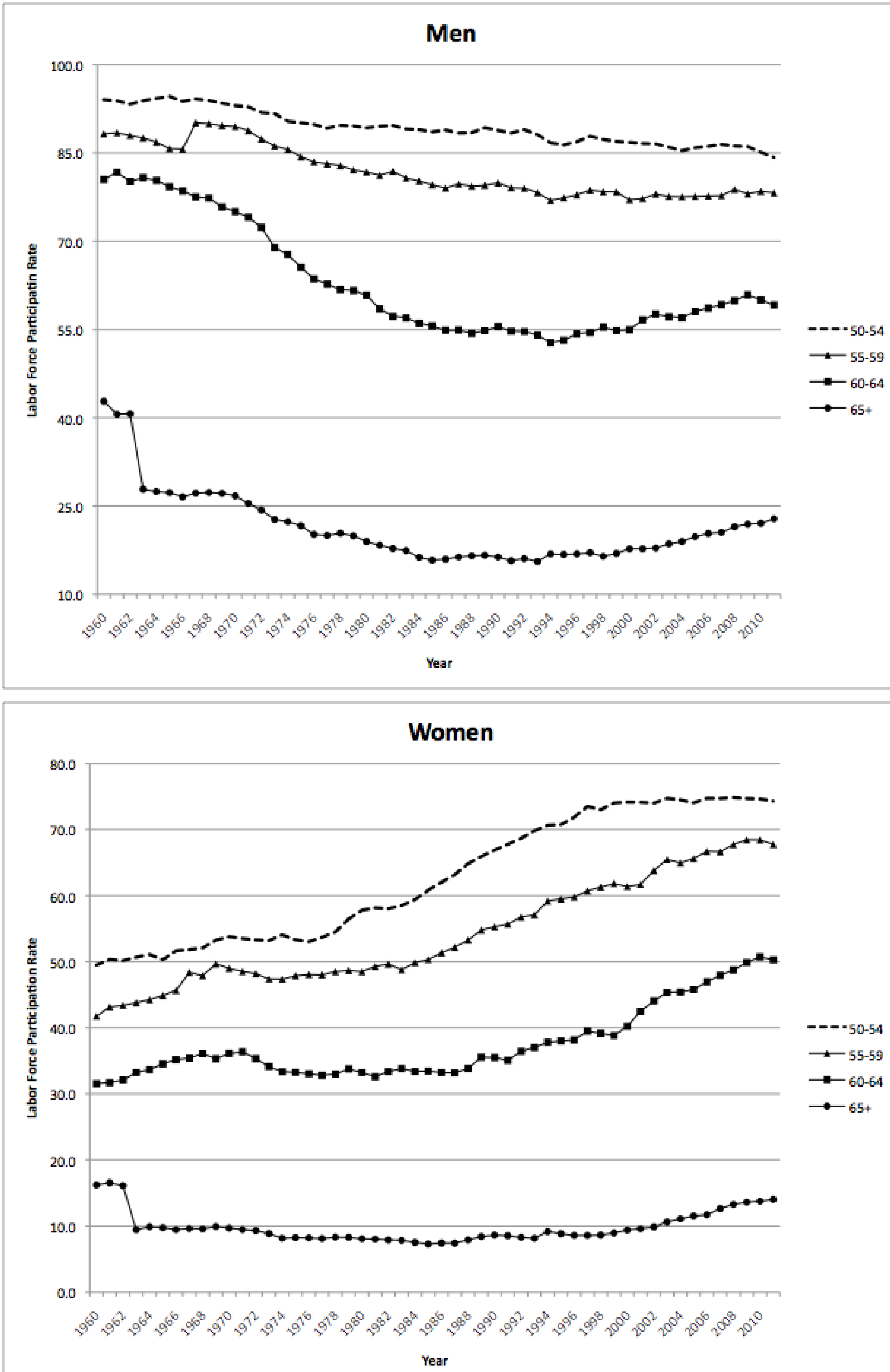
Figure 1: Labor Force Participation of Older Workers[5]



[5] *Source*: US Bureau of Labor Statistics, Current Population Survey.

Figure 2: Distributions of the Retirement Age

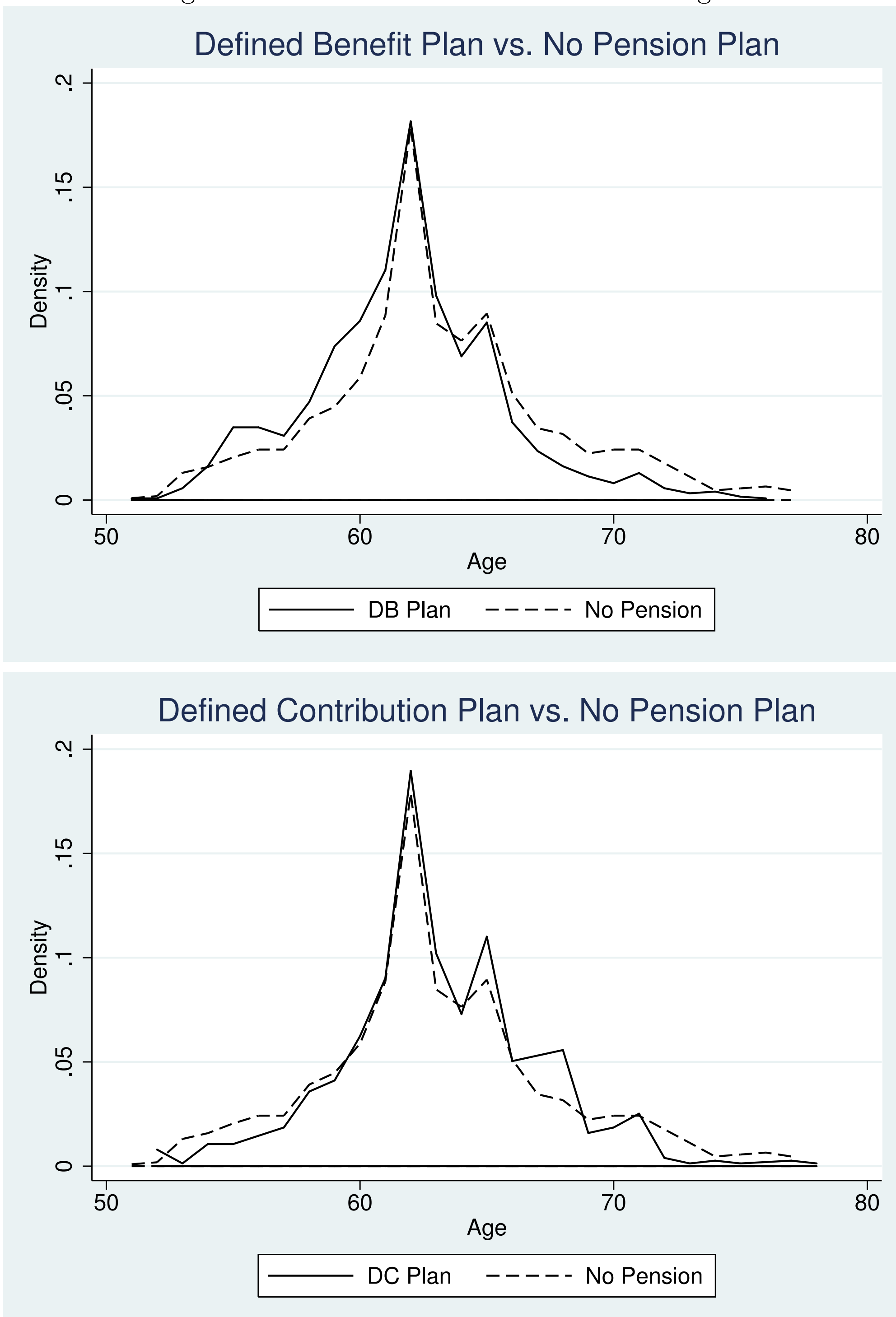


Figure 3: Propensity Score Distributions for Pensions

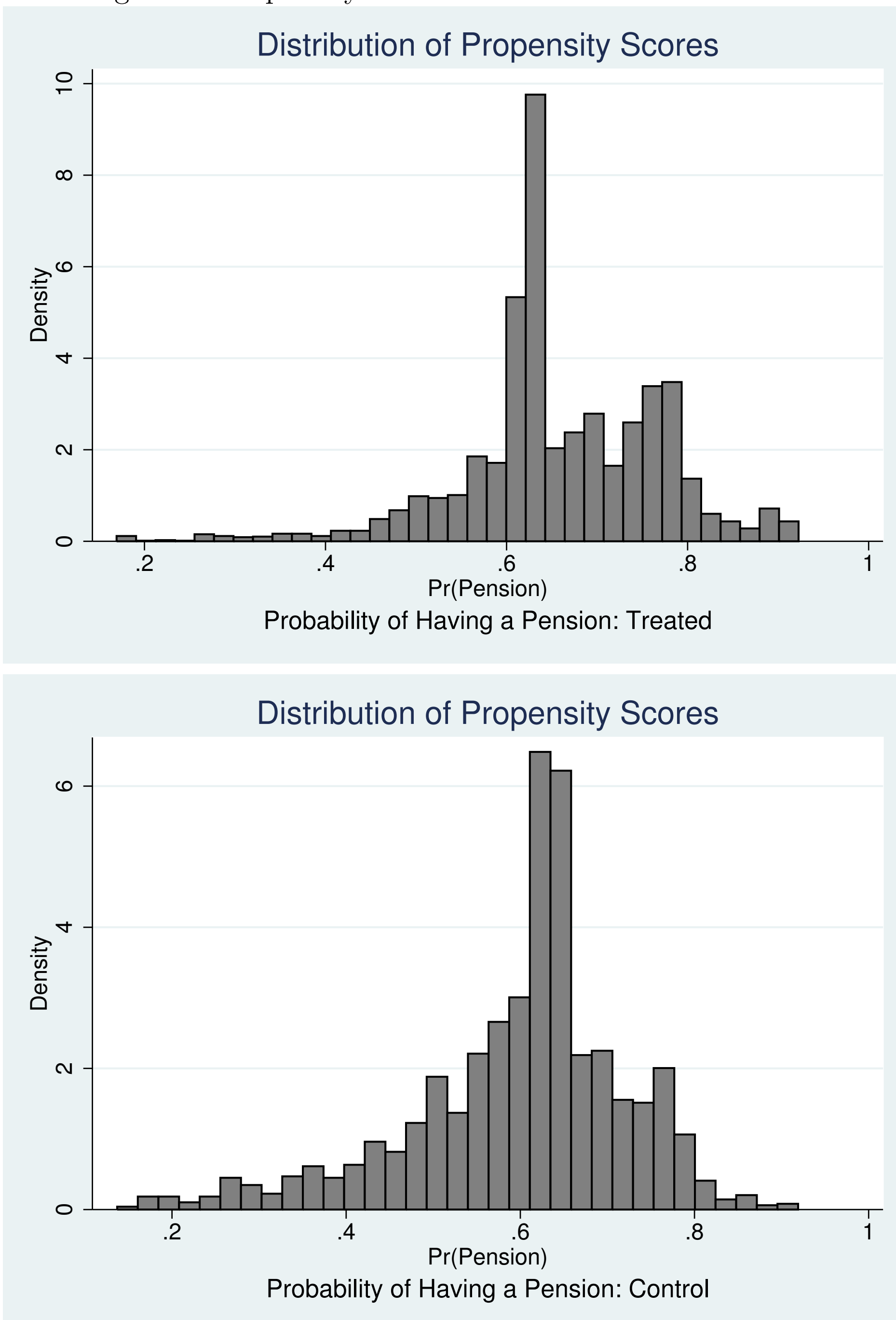


Figure 4: Propensity Score Distributions for Defined Benefit Plans

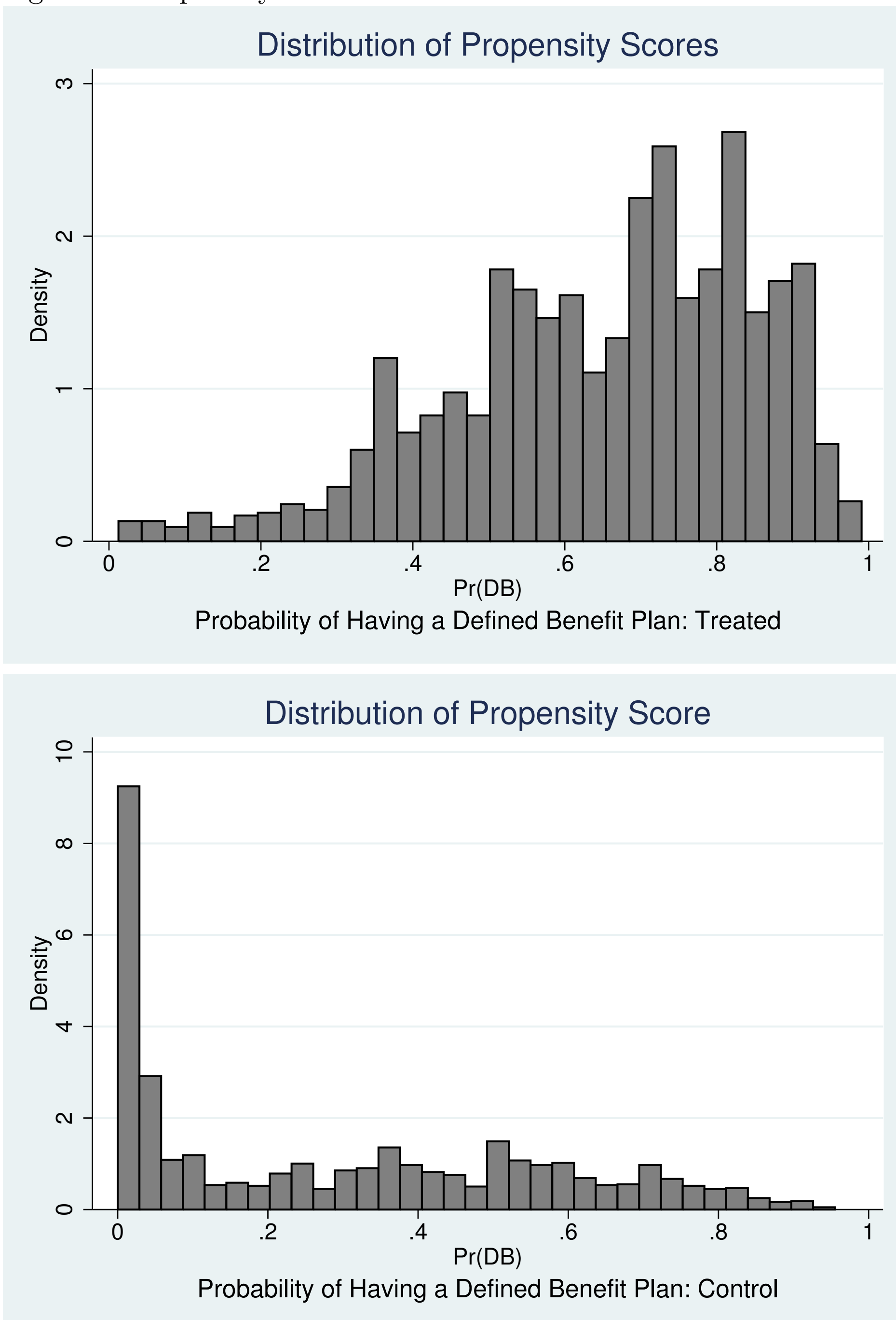
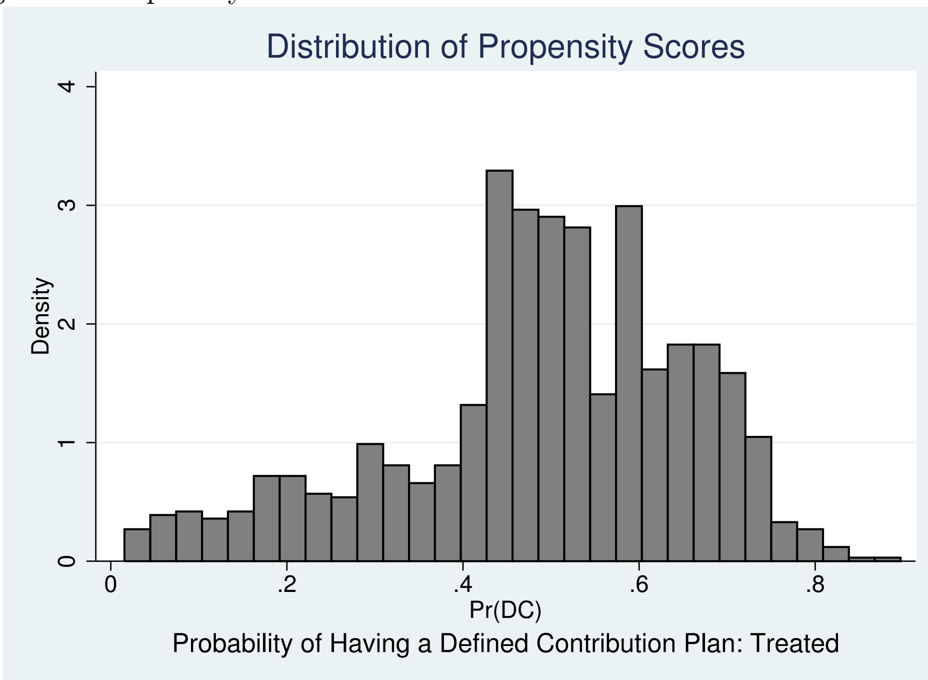


Figure 5: Propensity Score Distributions for Defined Contribution Plans



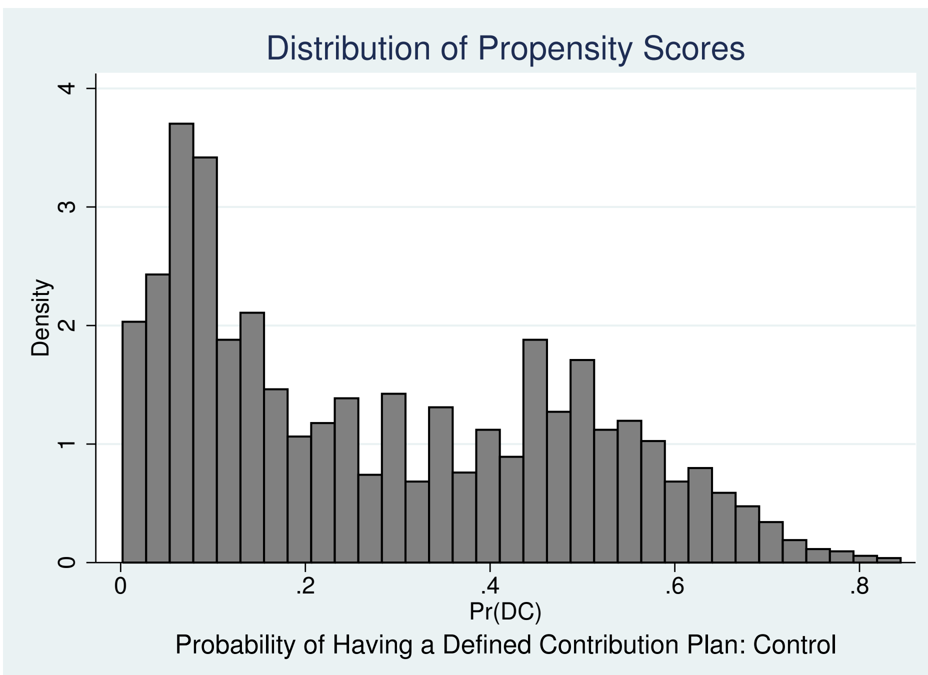


Table 1: Dependent Variable Definitions and Summary Statistics

Variable	Description	Full Sample	Male	Female
pension	1 if respondent has a pension	0.638 (0.481)	0.657 (0.475)	0.617 (0.486)
	Observations	5,695	2,988	2,707
db	1 if respondent has a defined benefit plan	0.458 (0.498)	0.478 (0.500)	0.437 (0.496)
	Observations	3,807	1,963	1,844
dc	1 if respondent has a defined contribution plan	0.355 (0.479)	0.370 (0.483)	0.340 (0.474)
	Observations	3,200	1,628	1,572

Table 2: Covariate Summary

Variable	DB Plan		DC Plan		No Pension	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Age	55.173	3.105	55.060	3.092	55.316	3.128
Sex	0.538	0.499	0.530	0.499	0.497	0.500
Married	0.739	0.440	0.760	0.428	0.733	0.442
Single	0.213	0.410	0.188	0.391	0.205	0.404
Widowed	0.048	0.214	0.053	0.224	0.062	0.240
Years of education	13.221	2.767	12.760	2.610	11.587	3.252
College	0.280	0.449	0.198	0.400	0.119	0.324
Some college	0.206	0.404	0.215	0.411	0.196	0.397
High School	0.366	0.482	0.422	0.494	0.371	0.483
Black	0.165	0.371	0.156	0.363	0.148	0.356
Hispanic	0.052	0.222	0.061	0.239	0.114	0.318
Professional	0.223	0.416	0.143	0.351	0.042	0.201
Blue collar	0.287	0.453	0.266	0.442	0.190	0.392
Managerial	0.148	0.355	0.156	0.363	0.063	0.243
Sales/Admin	0.224	0.417	0.2512	0.434	0.144	0.352
Service job	0.097	0.297	0.108	0.311	0.168	0.374
Self-employed	0.016	0.126	0.074	0.262	0.393	0.488
Stopwork at 65	0.222	0.416	0.151	0.358	0.077	0.266
Assets	170,327.00	337,326.90	196,980.60	424,028.90	210,056.60	441,888.50
Public Admin	0.092	0.290	0.0484	0.215	0.024	0.154
Retail	0.053	0.224	0.107	0.310	0.164	0.371
Manufacturing	0.255	0.437	0.230	0.421	0.143	0.350
Service industry	0.419	0.494	0.395	0.489	0.380	0.486
Utility industry	0.089	0.285	0.055	0.227	0.057	0.231
Farming	0.006	0.079	0.011	0.102	0.068	0.252
Good health	0.887	0.317	0.891	0.312	0.836	0.370
Observations	1,744		1,137		2,063	

Table 3: Probit for Probability of Having a Pension

Dependent Variable: *pension*		
Independent Variable	Coefficient for Male	Coefficient for Female
married	0.070**	-0.053**
	(0.030)	(0.024)
ed	0.027**	0.031**
	(0.004)	(0.006)
black	0.023	0.038
	(0.031)	(0.029)
hisp	-0.108**	0.014
	(0.043)	(0.043)
age	-0.006	-0.008**
	(0.003)	(0.004)
prof	0.104**	0.070
	(0.044)	(0.039)
bluecol	-0.021	0.044
	(0.038)	(0.043)
manager	-.066	0.056
	(0.045)	(0.041)
service	-0.080	-0.217**
	(0.054)	(0.034)
selfemp	-0.636**	–0.663**
	(0.033)	(0.019)
stopwork	0.114**	0.136**
	(0.027)	(0.030)
assets	1.35e-07**	3.08e-08
	(0.000)	(0.000)
govt	0.147**	0.235**
	(0.037)	(0.051)
retail	-0.086	-0.002
	(0.045)	(0.057)
mfg	0.114**	0.122**
	(0.026)	(0.054)
svcind	0.057	0.143**
	(0.031)	(0.052)
util	0.059	0.136**
	(0.035)	(0.064)
farm	-.273**	-0.225
	(0.067)	(0.138)
Number of observations	2,988	2,707
Log-likelihood value	-1339.108	-1362.228
Pseudo R-square	0.293	0.245
Standard errors in parentheses **Significant at the .05 level		

Table 4: Probit for Probability of Having a Defined Benefit Plan

Dependent Variable: *db*		
Independent Variable	Coefficient for Male	Coefficient for Female
married	0.092**	-0.060**
	(0.040)	(0.030)
ed	0.040**	0.043**
	(0.006)	(0.007)
black	0.004	0.047
	(0.047)	(0.038)
hisp	-0.137**	-0.003
	(0.053)	(0.054)
age	-0.008	-0.003
	(0.005)	(0.004)
prof	0.156**	0.082
	(0.071)	(0.048)
bluecol	0.030	0.060
	(0.052)	(0.055)
manager	-0.077	0.033
	(0.056)	(0.052)
service	-0.084	-0.182**
	(0.065)	(0.033)
selfemp	-0.635**	-0.516**
	(0.024)	(0.016)
stopwork	0.208**	0.194**
	(0.045)	(0.043)
assets	1.42e-07**	-2.84e-08
	(0.000)	(0.000)
govt	0.334**	0.458**
	(0.062)	(0.073)
retail	-0.143**	0.050
	(0.057)	(0.075)
mfg	0.225**	0.230**
	(0.042)	(0.077)
svcind	0.135**	0.238**
	(0.049)	(0.059)
util	0.210**	0.255**
	(0.052)	(0.098)
farm	-0.263**	-0.086
	(0.061)	(0.149)
Number of observations	1,963	1,844
Log-likelihood value	-834.192	-897.477
Pseudo R-square	0.387	0.289
Standard errors in parentheses **Significant at the .05 level		

Table 5: Probit for Probability of Having a Defined Contribution Plan

Dependent Variable: *dc*		
Independent Variable	Coefficient for Male	Coefficient for Female
married	0.073**	-0.034
	(0.037)	(0.029)
ed	0.026**	0.020**
	(0.005)	(0.006)
black	0.044	0.004
	(0.047)	(0.035)
hisp	-0.133**	-0.007
	(0.044)	(0.048)
age	-0.005	-0.008
	(0.005)	(0.004)
prof	0.173**	0.019
	(0.077)	(0.048)
bluecol	-0.027	0.012
	(0.052)	(0.050)
manager	-0.020	0.075
	(0.058)	(0.051)
service	-0.062	-0.162**
	(0.065)	(0.030)
selfemp	-0.440**	-0.404**
	(0.039)	(0.019)
stopwork	0.117**	0.131**
	(0.048)	(0.043)
assets	1.35e-07**	2.97e-08
	(0.000)	(0.000)
govt	0.081	0.069
	(0.073)	(0.104)
retail	-0.056	-0.016
	(0.050)	(0.058)
mfg	0.093**	0.087
	(0.042)	(0.067)
svcind	0.037	0.090
	(0.042)	(0.053)
util	-0.068	0.074
	(0.054)	(0.092)
farm	-0.232**	-0.158
	(0.049)	(0.097)
Number of observations	1,628	1,572
Log-likelihood value	-856.098	-821.731
Pseudo R-square	0.211	0.184
Standard errors in parentheses *Significant at the .05 level		

Table 6: Treatment Effects of Pension, DB Plan and DC Plan on the Retirement Age

	Pension	DB Plan	DC Plan
Treatment Effect			
τ^P:	-0.763*	-1.159*	0.272
	(0.188)	(0.206)	(0.256)
τ^T:	-0.886*	-1.322*	0.037
	(0.212)	(0.235)	(0.262)
τ^{NT}:	-0.482*	-0.972*	0.439
	(0.189)	(0.232)	(0.316)
Number of Observations:	3,519	2,306	1,827
Number of Matches:	4	4	4

Standard errors in parentheses
*Significant at the .01 level