The Effect of Pensions on Job Mobility: Empirical Evidence for the UK

Rodrigo Lluberas[‡]
Watson Wyatt Worldwide

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Abstract:
In this paper we study the effect of pension provision on employee turnover in the UK. In Great Britain, there are three forms of pension coverage: the public social security system, occupational pension plans and personal pensions. We focus on the effect of occupational pension plans on job mobility by studying the different patterns formed by workers in Defined Contributions vs. workers in Defined Benefit pension schemes. Using two distinct empirical approaches we find that workers in DB pension schemes are less likely to move jobs than those in DC schemes.

Keywords: job mobility, occupational pension plans, matching, treatment evaluation, selection models.

JEL Classification: *C21, C25, H55, J32, J63*

[‡] **Correspondence Address**: Watson Wyatt Global Research Services, Montevideo.
Edificio Biotec Plaza, Office 006-008,
Ruta 8, Km. 17.500,
Zonamerica Business Park,
Montevideo, Uruguay.
Tel: (005982) 5182329, ext. 25.
Fax: (005982) 5182329, ext. 19.
E-Mail: rodrigo.lluberas@watsonwyatt.com

1. Introduction

This paper analyzes the effect of pensions on job mobility in the UK. From an empirical perspective, the current UK social security system allows us to evaluate the effect of pension choice on employee turnover. Indeed, workers in Britain may have access to three different types of pension coverage: the public social security system, occupational pension plans and personal pension plans.

We aim to study the effect that different occupational pension plan types have on employee turnover. Broadly speaking, workers in occupational pension plans belong to either a Defined Benefit (DB) pension scheme or to a Defined Contribution (DC) pension scheme. Under a typical DB scheme, an employee is entitled to a pension that depends on the number of years of service and his salary over the last years of work. By contrast, under a DC scheme, pension amount depends on the contributions made to the fund over the entire work history, the rate of return of the fund, and the annuity rate at retirement. One feature that differentiates these plans is pension portability. In theory, DC pension plans carry lower leaving costs due to their more transparent transferability of pension rights. If pension capital loss associated with job mobility is lower for DC members than DB ones, we may expect lower turnover rates among the latter.

The paper is organized as follows. Section 2 presents early literature on the topic focusing on the empirical evidence for the UK. Section 3 provides two empirical approaches to study the effect of pension provision on job mobility using recent household survey data. Section 4 concludes.

2. Literature Review

While the effect of pension type on employee turnover has been widely analyzed for the U.S.[1] it has received less attention in the empirical literature for the U.K. For the U.K., the phenomenon has been broadly studied in terms of comparing turnover rates of those workers participating in occupational pension plans vis a vis those not participating. But there are not empirical works that directly study the different pattern of job mobility between workers in DB pension schemes and workers in DC schemes

The first attempt to analyze the effect of occupational pension provision on job mobility in the UK is McCormick and Hughes (1984). First, they present a theoretical analysis of the costs associated with leaving a pensionable job. The authors assume that workers leave their current jobs to move to another pensionable job and that the type of pension provision is identical between jobs. For a worker who is allowed to choose among three different types of compensations – deferred pension, cash refund and pensions transfer – they conclude that, under certain assumptions, the optimality of the different options depends on the length of tenure. A deferred pension would be the minimum cost alternative if the number of years of tenure is close to normal retirement age while cash refund would be preferred early in a worker's career; pensions transfer would be preferable if the employee is in the middle of his career.

Secondly, the authors empirically analyze the effect of pension provision on job mobility by using the 1974 General Household Survey and following two approaches: estimating the

[1] See: Schiller and Weiss (1979), Mitchell (1982), Ippolito (1987, 2002), Allen, et. al. (1993), Gustman and Steinmeier (1993), Dorsey (1995), Munnel et. al. (2006), among others.

probability of employer change in the last year and the likelihood that a worker is looking for another job; controlling in both cases for job satisfaction, occupational pension membership, level of education, age, occupation, house tenure, sex and marital status. McCormick and Hughes (1984) found that workers in pensionable jobs are less likely to change job than non-pensionable workers and that the effect of pension membership is greater on job mobility than on job search. Indeed, results are robust both for younger employees and for different types of workers[2].

Shah (1985) studies the determinants of job tenure in general, including among covariates: individual characteristics, trade unionism, structure of the housing market and pension wealth. Using the 1968-69 Survey of Household Resources and Standards of Living in the UK, the author estimates a structural probit model including as covariate the estimated wage differential of the expected wage between "movers" and "stayers" workers. In terms of the effect of pension on job mobility, results confirm earlier evidence in McCormick and Hughes (1984). Indeed, estimations suggest job tenure is lengthened by pension coverage and that this effect increases with the amount of pension wealth.

In a different setting, Henley et. al. (1994) analyze the effect of housing wealth and occupational pension on job tenure in the UK. They treat pension rights as another asset held by families and estimate job tenure by a Cox regression separately for head of household men and head of household women using 1985 General Household Survey data. The authors find that being a member of an occupational pension scheme increases expected job tenure and that the effect is stronger for men than for women. Conversely, even though they do not differentiate between DB and DC pension scheme effects, they find that the increased transferability of pension rights reduces expected job duration.

More recently, Disney and Emmerson (2002) estimate the probability of job mobility by a probit model corrected for sample selection for those not working[3] using British Household Panel Study data from 1992 to 1998. The authors include as covariates not only individual, industry and corporate characteristics, but also a variable reflecting the gap between predicted and actual wage as well as the pension status of the employee. In particular, they classified workers in the following pension status categories:

- Not offered an occupational pension, with state earnings-related pension
- Not offered an occupational pension, with personal pension
- Offered an occupational pension, without personal pension
- Offered an occupational pension, joined a personal pension
- Offered and joined an occupational pension
- Offered and joined an occupational pension and with personal pension

Results suggest that those workers who are offered to join an occupational pension scheme – regardless of whether they join the scheme or not– have lower rates of job mobility than those who are not offered. The difference in turnover rates is even higher when comparing those who do actually join with those who do not. On average, according to the econometric estimations,

[2] McCormick and Hughes (1984) show predicted job search and job turnover rates for five types of male workers according to age, marital status, level of education, occupation and house tenure.
[3] A similar approach is followed in the first part of the empirical section of this paper.

non-members switch jobs in 16.7% of cases while the figure is just 5.8% for occupational pension plan members.

The above studies do not consider the fact that pension status and job tenure may be determined simultaneously. Workers who are more mobile may choose not to join an occupational pension scheme or prefer more flexible plan in terms of pension capital transferability. The first attempt to tackle this issue is Mealli and Pudney (1996). They estimate job mobility between different employment states[4] using data from the 1988-1989 UK Retirement Survey by a competing risk model allowing the existence of unobservable random effects. Their results confirm early evidence that workers in pensionable jobs tend to have longer job tenure than workers in non-pensionable jobs. The issue of pension choice endogeneity is addressed indirectly by allowing the presence of random effects in both the state of origin and the state of destination in job transitions. Simulation results suggest that the potential unobserved heterogeneity does not play a key role in explaining the positive relationship between job duration and pension coverage and thus weakens the hypothesis that less mobile workers tend to choose pensionable jobs.

A second study that considers the endogeneity of pension choice is Andrietti (2004). Using data from the first twelve waves of the British Household Panel Survey, the author estimates the probability of quitting jobs between two waves of the survey controlling for demographic and occupational characteristics of respondents; including among the latter, dummy variables reflecting respondents' pension status. In a first setting, Andrietti estimates job mobility without taking into account the potential endogeneity of pension choice and finds that job mobility is less likely among workers in occupational pension plans. However, using the "occupational pension offer rate by region of residence" as an instrument for occupational pension coverage in order to address the issue of pension choice endogeneity, he finds that the effect of occupational pension coverage on job mobility is not statistically significant. The author argues that this result implies, contrary to Meally and Pudney (1996), that the unobserved heterogeneity is what explains the positive relationship between occupational pension coverage and job duration.

This paper presents evidence not only that occupational pension coverage implies a lower employee turnover rate but also, in line with Meally and Pudney (1996), that the selection of unobservables is not likely to affect this pattern. Moreover, we go into detail and present evidence of the different effect that DB occupational pension schemes have on job mobility relative to DC schemes. In particular, we find that workers in DB pension schemes are less likely to move jobs than those in DC schemes.

3. Empirical Evidence

The available empirical evidence on job mobility and occupational pension provision in the UK suggests that workers in occupational pension plans, either DC or DB, are less likely to change job relative to non-covered workers[5]. In this section we confirm this finding and go a bit farther. Indeed, using data from the two available waves of the English Longitudinal Study of Ageing (ELSA) we study not only the effect of pension provision on employee turnover, but also the different behaviour of workers in DB and workers in DC occupational pension schemes. The

[4] They estimate transitions between the following states: pensionable full-time job, non-pensionable full-time job, unemployment, other employment, and out of the labour market.
[5] Andrietti (2004) is the only exception when considering instrumental variables technique.

ELSA is a multidisciplinary survey which aim is to allow the study of older people in terms of health, retirement, work, wealth, income, pensions and many other aspects of ageing in the UK. Two waves of the ELSA have already been collected, the first between March 2002 and March 2003 and the second wave between June 2004 and July 2005.

Across both waves, of the 2,502 of individuals that answered the question of whether they have changed employer in the last year, 2,076 (83%) stated that they are working with the same employer while 426 (17%) stated they are not. Table 1 summarizes job mobility rates for different characteristics of respondents. In particular, turnover rate is higher for men than for women, for unmarried individuals and for lower income earners.

TABLE 1

Turnover Rate for Individual Characteristics

	Turnover Rate	**Number Of Observations**
Gender		
Male	19.1%	1,118
Female	15.4%	1,384
Marital Status		
Married	16.2%	1,893
Not Married	19.5%	609
Employment[6]		
Full-Time	18.6%	935
Part-Time	15.9%	1,537
Firm Size		
2-99 Employees	19.5%	691
100-499 Employees	17.8%	275
500-999 Employees	23.6%	161
More than 1,000	13.9%	1,299
Weekly Income		
Less than £300	18.9%	967
£300 - £550	16.7%	939
More than £550	14.4%	596

Source: English Longitudinal Study of Ageing, Wave 1 and Wave 2.

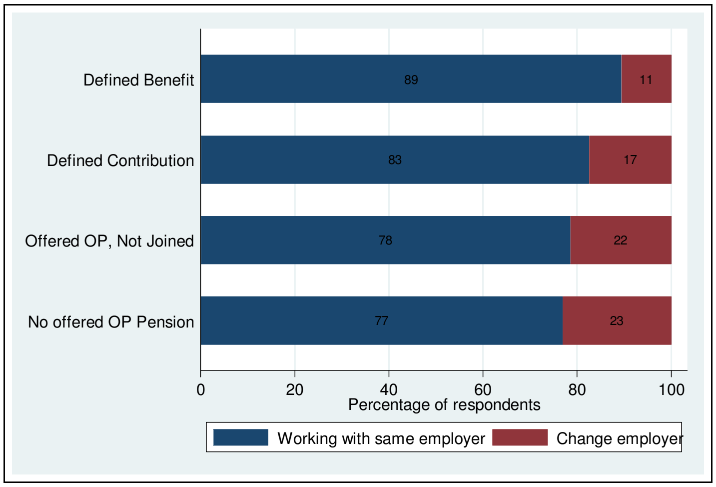
Our main interest is in the effect of occupational pension coverage on employee turnover. We consider four types of pension status: workers with DB occupational pension coverage, workers with DC occupational pension coverage, workers that were offered membership of their employer scheme but refused and those who were not invited to join any occupational pension scheme. Turnover rates for each category of worker are shown in Figure 1.

[6] We consider as full-time workers those respondents that state they work 40 hours or more per week.

Clearly, workers in DB pension schemes are the least mobile whereas those not covered – either because they were not invited to join a scheme or refused to do so – are the ones with higher turnover rates. Moreover, according to our results DC members switch jobs in 17% of cases while the figure is 11% for DB members.

FIGURE 1

Job mobility and Occupational Pension (OP) Provision



Source: English Longitudinal Study of Ageing, Wave 1 and Wave 2.

In order to study more deeply the effect of pension provision on employee turnover we follow two different empirical approaches: estimating a probit model of the chance of employee turnover corrected for sample selection and using a matching technique for treatment evaluation. Sample bias accounts for the fact that retirees or unemployed respondents may have different turnover rates than employed individuals. Even though both approaches allow us to overcome the issue of sample bias, due to lack of efficient instruments we are unable to solve the problem of the endogeneity of occupational pension choice[7]. However, in the case of matching methods, we will be able to test the robustness of our results to unobserved heterogeneity by following the bounding approach suggested by Rosenbaum (2002).

3.1 Probit model with sample selection

Our first approach is based on the estimation of a probit model for the likelihood of changing job corrected for sample selection[8]. In case of a dichotomous dependent variable, maximum likelihood estimation should be performed. This procedure implies the estimation of the chance of employee turnover between Wave 1 and Wave 2 corrected for the sample bias that may arise due to the impossibility of considering those respondents that were not working at the time of the survey's Wave 1 or even though there were working during Wave 1 but no Wave 2. Then, the model structure is a probit with sample selection.

[7] As stated above, Andrietti (2004) uses as instrument for occupational pension coverage the "occupational pension offer rate by region of residence", not available in the database used in the present study.

[8] See Van de Ven and Van Praag (1981).

In general terms, we model the probability of employee turnover between t and $t+1$ as a function of several individual characteristics at time t. We are interested in the distribution of the dependent variable T conditional on a vector of independent variables X_1 but we observe the dependent variable only for a sub-sample of the total population; i.e. those working at the time of the interview. For individual i, we have the following regression equation for latent probability of turnover between t and $t+1$:

$$T_i^* = X_{1i}\beta_1 + \varepsilon_{1i} \qquad i = 1,\ldots,n$$

With:

$$\begin{cases} T_i = 0 \text{ if } T_i^* \leq 0 \\ T_i = 1 \text{ if } T_i^* > 0 \end{cases}$$

Where, X_{1i} is a vector of individual characteristics, β_1 is a vector of unknown parameters and ε_{1i} is a vector of error terms. Employee turnover is observed only if the respondent is in employment both in t and $t+1$. Defining the working equation as:

$$W_i^* = X_{2i}\beta_2 + \varepsilon_{2i}$$

With:

$$\begin{cases} W_i = 0 \text{ if } W_i^* \leq 0 \\ W_i = 1 \text{ if } W_i^* > 0 \end{cases}$$

Where, X_{2i} is a vector of independent variables, β_2 is a vector of unknown parameters and ε_{2i} is a vector of error terms. As sample selection arises because T_i is observed only when the respondent is working, i.e. $W_i = 1$, then:

$$\begin{cases} T_i = T_i^* \text{ if } W_i = 1 \\ T_i \text{ is not observed if } W_i = 0 \end{cases}$$

In order to be able to estimate the model we need to assume that the correlated error terms follow a bivariate Normal distribution[9]:

$$\varepsilon_{1i}, \varepsilon_{2i} \approx N(0,\Sigma) \text{ with } \Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2 \\ \sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$$

[9] The normalization $\sigma_1^2 = 1$ is needed for identification purposes.

Our results confirm the idea of a lower turnover rate among workers in DB occupational pension schemes than those in DC schemes. Indeed, even after controlling for several individual characteristics, workers in DC schemes are 8% more likely to have changed employer over the last two years than those in DB schemes.

This pattern is even more pronounced when comparing workers without occupational pension coverage to both workers in DB and DC occupational plans. The ELSA questionnaire allows us to split workers without occupational pension coverage into two categories: those who have been invited to join the scheme but refused, and those who have not been offered membership of their employer pension scheme[10]. As expected, both groups of workers have higher turnover rates not only relative to workers in DB pension schemes, but also relative to those in DC. Certainly, employees who were invited to join an occupational pension scheme but refused are 12% more likely to have changed job than workers in DB schemes, while the figure is almost 15% for workers who have not been offered participation[11] (See Table 2 below and Table A.2 in the appendix).

The chance of job mobility increases for full-time workers relative to part-time and for workers in firms of between 500 and 999 employees relative to those in firms of more than 1,000. On the other hand, the turnover rate seems to be lower among women and higher income workers. Indeed, a female worker is 4% less likely to change job than a male and an increase of £10,000 in weekly employment income implies a decrease of 3% in the probability of employee turnover. Finally, we found that an increase of £100,000 in workers' savings would suggest an increase of 5% in the probability of job change.

[10] See Table A.1 in the appendix.

[11] In order to confirm this result we perform the same regression but considering only whether the employee is member or not of his employer pension scheme instead of considering the 4 ranges of possible occupational pension status – i.e. DB, DC, offered OP-not joined and not offered –. As expected, workers without occupational pension coverage are more likely to change job than workers in occupational pension schemes. See Table A.3 in the appendix for full results.

TABLE 2

Probit Model with Sample Selection

Chance of Job Mobility

Regressor	Coefficient	Standard Error	Marginal Effect
Pension Coverage			
Defined Contribution	0.274*	0.102	0.082*
Offered OP, Not Joined	0.409*	0.095	0.123*
Not Offered	0.482*	0.111	0.145*
Individual Characteristics			
Female	-0.145***	0.081	-0.044***
Age	-0.034	0.050	-0.010
Age Squared	0.0003	0.0005	0.00008
Married	-0.075	0.079	-0.023
Employment			
Full Time	0.140***	0.079	0.042***
Employment Income	-0.009*	0.002	-0.003
2-99	0.023	0.091	0.007
100-499	0.038	0.110	0.011
500-999	0.299**	0.130	0.090**
Wealth			
Savings	0.017**	0.009	0.005**
House	0.0003	0.031	0.0007
Observations	Uncensored	Censored	Total
	2,080	6,099	8,179
Log-Likelihood	-3,616.88		
Wald	85.29		
Selection Correlation	-0.249	0.146	p-value 0.0889

Notes:

- * indicates significance at 1% confidence level
- ** indicates significance at 5% confidence level
- *** indicates significance at 10% confidence level
- Employment income is represented in £1,000s, Savings in £10,000s, and Housing wealth is represented in £100,000s.
- Standard Errors are robust to heteroskedasticity.
- The coefficients on DC, on Offered OP/not joined and not offered OP are with respect to DB. The coefficient on Female is with respect to Male. The coefficient on Married is with respect to the omitted category: Not Married. The coefficient on Full Time is with respect to Part Time. The omitted category for the number of employees is more than 1,000.

In sum, consistent with early studies, our results confirm that pension covered workers tend to have lower turnover rates than non-covered workers. However, we go farther and find not only coverage plays an important role in explaining job mobility but also the type of pension. Indeed, our findings confirm the hypothesis that DC members are more mobile than DB ones, suggesting that pension rights portability could facilitate job mobility. Although the results do not consider the potential simultaneity between pension choice and employee turnover, they suggest that firms offering DB pension schemes to their employees may expect lower turnover rates than those which offer DC pension plans or nothing at all. Whether this feature arises because more mobile workers may choose not to join an occupational pension scheme or join a more flexible plan in terms of pension capital transferability could not be concluded from these results. In the next section we follow an alternative empirical approach and offer evidence of the relatively robustness of our results in the presence of unobserved self-selection in pension choice.

3.2 Matching Methods

The second empirical approach pursued to address the issue of pension provision and employee turnover is the treatment evaluation econometric technique known as matching method. As already noted, even though this technique allows us to overcome the issue of sample selection or selection on observables, due to lack of efficient instruments we are unable to solve the problem of the endogeneity of the pension choice decision. However, as already noted, we will be able to check the sensitivity of our findings to the presence of unobserved heterogeneity.

Sample selection models estimation results are considered by some researchers to rely too heavily on their underlying assumptions and the specific characteristics of the data used in the analysis[12]. The assumption of bivariate normal distribution of selection and outcome equations disturbances, the correlation degree between both disturbances, the percentage of censored individuals – i.e. how many respondents in our sample are not working either on Wave 1 or Wave 2 – and the availability of exclusion restrictions, are aspects that alter sample selection models estimation results. Thus, in order to overcome this issue and to test our previous results we present in this section an alternative empirical strategy; treatment evaluation methods.

Matching method pairs treated individuals with untreated members with similar observed characteristics and estimates the average treatment impact by considering the difference of mean outcome of both groups. In this case the treated group is a compound of workers in DC occupational pension schemes and the untreated group of workers in DB schemes. As always, the outcome of interest is whether the employee has changed job between the first and the second wave of the ELSA. The observed characteristics considered for matching both groups are: gender, age, employment income, marital status, number of employees in the firm, level of education, savings and whether the respondent is a full-time or part-time worker.

In general terms, we model employee turnover as a function of worker observables (X) and unobservables variables (ν_0, ν_1):

$$T_0 = \mu_0(X) + \nu_0$$

[12] See Stolzenberg and Relles (1990), Stolzenberg and Relles (1997), Leung and Yu (1996), among others.

$$T_1 = \mu_1(X) + \nu_1$$

T_0 being employee turnover if the person is in a DB occupational pension scheme and T_1 the employee turnover if the person is in a DC scheme. The difference in employee turnover due to type of pension provision is:

$$\Delta = T_1 - T_0 = \mu_1(X) - \mu_0(X) + \nu_1 - \nu_0 .$$

Where the first element, $\mu_1(X) - \mu_0(X)$, measures the gain of participation in the treatment for an individual with characteristics *X,* while the second term, $\nu_1 - \nu_0$, measures the individual specific gain and may be unobservable. As we can not see the same person in both types of occupational pension scheme the difference in employee turnover due to type of pension provision is not directly observable. To overcome this issue, we construct a potential control group for which its observed characteristics match, up to some extent, those of the treated group. Then, we compare the mean outcome of the constructed paired group of untreated individuals – members of DB occupational pension schemes – with the mean outcome of the treated group – members of DC occupational pension schemes – to obtain the difference in outcome due to the treatment effect; in this case, the type of pension provision.

Our main interest is in the mean effect of the treatment on the treated, in this case: the mean effect on employee turnover of being member of a DC pension scheme. This parameter is known as the average treatment effect on the treated (*ATET*) and is defined as:

$$E[T_1 - T_0 \mid X, DC = 1] = E[\Delta \mid X, DC = 1] = \mu_1(X) - \mu_0(X) + E[\nu_1 - \nu_0 \mid X, DC = 1]$$

Following Rosenbaum and Rubin (1983) we can pair both treated and untreated groups by a summary measure called propensity score and avoid matching in terms of multiple dimensions by using respondents' observed characteristics. Then, we define the propensity score as the probability of being assigned to the treated group conditional on individual observed characteristics:

$$p(X) = P(DC = 1 \mid X)$$

Being: *p(X)* the propensity score, *DC=1* if the respondent is in a DC occupational pension scheme and *X*, a vector of respondent observed characteristics. We estimate the propensity score of being in a DC occupational pension plan by using the following logit model specification:

$$\begin{aligned} P(DC = 1 \mid X) = \Lambda(&CONSTANT, GENDER, AGE, AGE^2, EARNINGS, EARNINGS^2, \\ &MARRIED, NOEMP, EDUCATION, SAVINGS, TIME, GENDER * TIME) \end{aligned}$$

The final model specification was the result of the implementation of the algorithm proposed by Dehejia and Wahba (2002) for estimating the propensity score. In general terms the aim of this procedure is to ensure the balance between the treated and control groups for a given set of propensity score strata. In this case we define 5 strata with boundary values of: 0.15, 0.35, 0.4, 0.6, and more than 0.6. Restricted to common support values, all covariate means are not significantly different from 0 – at 5% level – between control and treated groups for each stratum except for Gender in the last stratum. See Table A.4 in the Appendix for more details.

Table 3 shows a description of the variables included in the estimation and a summary statistics of both treated and control groups[13].

TABLE 3

Sample Summary Statistics: Means

Treated and Control Groups (Unmatched)

Variable	**Definition**	**Treated (DC)**	**Control (DB)**
GENDER	1 if female	41.1%	55.4%
AGE	Age in years	54.2	53.3
EARNINGS	Weekly Earnings in £1,000s	0.474	0.559
MARRIED	1 if married	74.7%	76.7%
NOEMP	Number of Employees		
	2-99	29.5%	6.9%
	100-499	16.2%	9.7%
	500-999	10.0%	5.9%
	1000+	44.3%	77.5%
EDUCATION	1 if Degree of above	17.7%	30.2%
SAVINGS	Total Savings in £10,000s	1.59	2.16
TIME	1 if full time worker	49.7%	40.1%
Sample Size		372	917

Under certain assumptions[14], the estimator of the average treatment effect on the treated is defined as a weighted sum:

$$MS(ATET) = \frac{1}{N_T} \sum_{i \in \{DC=1\}} [T_{1,i} - \sum_j W(i,j) T_{0,j}]$$

[13] Results of the logit model estimation are shown in Table A.5 in the Appendix.

[14] The main assumptions are: *i)* conditional independence: $T_0, T_1 \perp DC / X$, *ii)* matching: $0 < P(DC = 1 \mid X) < 1$ and, *iii)* conditional mean: $E[T_0 \mid DC=1, X] = E[T_0 \mid DC=0, X] = E[T_0 \mid X]$. For a full list of assumptions and a detailed description of the matching technique see: Cameron and Trivedi (2005), or Heckman, et al (1997), among others.

N_T being the number of treated individuals in the sample. There are different matching estimators depending on the choice of the weight $W(i, j)$ given to the j^{th} member of the control group when compared with the i^{th} member of the treated group[15]. In this study we estimate the ATET by considering three different matching methods: kernel matching, nearest-neighbour matching and radius matching.

The Kernel matching estimator defines the weight as:

$$W(i, j) = \frac{K\left[\frac{\hat{p}(X_j) - \hat{p}(X_i)}{h}\right]}{\sum_{k=1}^{N_{U(i)}} K\left[\frac{\hat{p}(X_k) - \hat{p}(X_i)}{h}\right]}$$

Where *K(.)* defines the Kernel function, *h* the band width and $N_{U(i)}$ is the number of control group members that are matched with the treated individual *i*. In this case we use the Epanechnikov Kernel function and four different band widths: 0.01, 0.03, 0.06 and 0.1.

The second matching method adopted is the nearest-neighbour on the propensity score. In this case we define the group of matched untreated individuals with the treated individual *i* as:

$$U(i) = \left\{\hat{p}(X_j) \mid \min_j \left\|\hat{p}(X_i) - \hat{p}(X_j)\right\|\right\}$$

Where $\| \;\|$ denotes the Euclidean distance. Defining as *NN* the number of individuals with the lowest values of the difference in propensity scores or the nearest-neighbours considered for matching purposes, the weight imputed for the estimation of the ATET under this method is:

$$W(i, j) = \begin{cases} \frac{1}{NN} & if \quad j \in U(i) \\ 0 & otherwise \end{cases}$$

Finally, we consider an alternative method that matches all the untreated individuals with an estimated propensity score within a predefined radius from the propensity score of the treated individual *i*. Then, the group of untreated individuals that are matched with the treated individual *i* is defined as:

$$U(i) = \left\{\hat{p}(X_j) \mid \left\|\hat{p}(X_i) - \hat{p}(X_j)\right\| < \delta\right\}$$

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[15] Note that: $0 < W(i, j) \leq 1$ and $\sum_j W(i, j) = 1$

δ being the radius assumed. The radius matching defines the weight to estimate the ATET as:

$$W(i,j)=\begin{cases}\dfrac{1}{N_i^{U(i)}} & if \quad j\in U(i)\\ 0 & otherwise\end{cases}$$

Where $N_i^{U(i)}$ is the number of untreated individuals matched with the treated individual *i*.

The aims of using the propensity score matching are to be able to compare the treated and untreated groups by using a summary measure, i.e. the probability of being assigned to the treated group conditional on individual observed characteristics, and avoid multidimensional comparisons. A critical aspect of this technique is the capability of the estimated propensity score to balance covariates between treated – DC members – and untreated – DB members – groups. In order to asses the quality of our matching and test for covariate imbalance, we use the standardized bias proposed by Rosenbaum and Rubin[16] (1985). The overall bias – considered as the unweighted average of covariates standardized bias – decreases from 23.6% before matching to between 4% and 7% after matching, depending on the matching algorithm considered. Then, we may state that our matching procedure allows us to substantially reduce the overall bias and assures us of the quality of our results in terms of covariates balance. Detailed results are shown in Table A.6 in the Appendix.

Average employee turnover rates both for the treated and the control group estimated under different matching methods[17] are shown in Table 4. Results confirm our findings using the probit model with sample selection: DC occupational pension scheme members are more likely to have moved job than DB ones. Indeed, results are robust to different matching assumptions. The treatment effect, i.e. the difference in employee turnover between DC and DB pension scheme members, ranges from 6.4% for the case of nearest neighbour matching with *NN*=10 to 5.3% for radius matching with δ=0.01 (See Table A.7 in the appendix for full set of results).

The difference in the employee turnover pattern of workers in DB vis-a-vis workers in DC pension schemes could be explained by backward-loading incentives. In the case of a DB pension scheme, if the worker leaves the firm before the scheme's early retirement age, he will be entitled to a lower pension income relative to a worker who stays in the firm until retirement age. As ELSA aims to represent the population aged 50 and over, this effect could be of particularly importance in our sample. Indeed, being a member of a DB pension scheme and changing job at an age close to retirement would imply a substantial pension capital loss, deterring job mobility. A second effect that our DB vs. DC measure captures is the fact that DB pensions schemes are typically more generous than DC ones. An increasing number of employers shifting from DB to pure DC pension schemes together with the fact that an important number of DB schemes are closed to new members imply that once you leave a DB scheme it will be difficult to join another one. Thus, those DB covered workers wanting to retire in a DB pension scheme will be less willing to change job and more likely to stay in their DB-covered post. Finally, it should be noted

[16] Standardized bias reduction due to matching is estimated using *pstest* STATA code developed by Leuven and Sianesi (2003).
[17] Average employee turnover for both DC and DB pension scheme members are estimated using *psmatch2* STATA code developed by Leuven and Sianesi (2003).

that as our analysis is based only on two waves of the ELSA survey, results should be considered as static and representing a particularly frame of time.

TABLE 4

Summary of Results:

Pension Type Effect on Employee Turnover Rates

Sample/ Method	Observations	Treated (DC)	Control (DB)	Treatment Effect $^{\zeta}$	Std. Error	p-value‡
Unmatched	1,289	17.47%	10.58%	6.90%	0.02030	0.000
Kernel h=0.1	1,262	17.44%	12.06%	5.38%	0.02395†	0.025
Nearest Neighbour NN=10	1,262	17.44%	11.03%	6.40%	0.02650†	0.016
Radius δ=0.01	1,230	17.15%	11.82%	5.33%	0.02820†	0.059

Notes:

- ζ Difference in employee turnover between DC and DB pension scheme members
- † Bootstrapped standard errors with 50 replications.
- Note that average treatment effect over treated differs in some cases due to the fact some observations for the untreated and the treated are off common support.
- ‡ Estimated p-value for the treatment effect – difference in means –.

So far we have assumed that treated (DC) and untreated (DB) individuals differ only in their observables characteristics. However, if DC and DB pension scheme members differ in unobservable characteristics the treatment effect would not necessary constitute a causal effect. To test the sensitivity of our results to the unobserved heterogeneity, we follow the bounding approach suggested by Rosenbaum (2002). According to this methodology, if two individuals with similar observed characteristics do not differ in terms of unobserved measures then the odds ratio between two matched individuals is equal to 1, i.e. both individuals have the same probability of belonging to the treated group. In that case, there is no room for unobserved self-selection and hence for the presence of a "hidden bias" in the estimation of the treatment effect[18]. Table 5 shows the Mantel-Haenszel statistic for the case of absence of unobserved heterogeneity and the odds ratio critical value for which the treatment effect becomes statistically not significant[19] (See Table A.8 in the appendix for full set of results).

If case of a positive hidden selection – i.e. more mobile workers choose to belong to a DC occupational pension scheme – the treatment effect would be overestimated. Then, the Mantel-Hanenszel statistic for the case of absence of hidden bias should be corrected downward. According to our findings, the selection on unobservables is not likely to affect our treatment effect estimation. Indeed, results are relatively robust to an unobserved variable that would increase between 20% and 35% the probability of receiving treatment – i.e. being a member of a DC pension scheme – depending on the matching algorithm considered. This does not imply the

[18] See Becker and Caliendo (2007) for STATA code description, Rosenbaum (2002) for a detailed description of the methodology and Aakivik (2001) for the use of Mantel-Haenszel test statistics in the case of dichotomous outcome. See also Caliendo et.al. (2005) for an empirical application of this methodology.

[19] We consider a 5% significance level.

absence of hidden bias but that the existence of unobserved confounders that would change our estimation results is relatively unlikely.

TABLE 5

Summary of Results:

Sensitivity Analysis for Unobserved Heterogeneity

Sample/ Method	**Treatment Effect** $^{\zeta}$	**Mantel-Haenszel Statistic**†	**Critical Value**‡
Kernel h=0.1	5.38%	3.28619	1.3-1.35
Nearest Neighbour NN=10	6.40%	3.07156	1.3-1.35
Radius δ=0.01	5.33%	3.08522	1.25-1.3

Notes:

- ζ Difference in employee turnover between DC and DB pension scheme members.
- † Mantel-Haenszel test compares the number of treated individuals with its expected number under the hypothesis of the absence of treatment effect. In this case we present the Mante-Haenszel test for the case of absence of unobserved heterogeneity, i.e. when the odds ratio between two matched individuals is 1.
- ‡ Odds ratio of differential assignment due to selection on unobservables assuming the overestimation of treatment effect.

In sum, we found that workers in DC schemes are more likely to switch jobs than those in DB schemes and that selection in unobservables is relatively unlikely to happen. The latter is in line with Meally and Pudney (1996) and contrary to evidence found by Andrietti (2004) when comparing workers participating in occupational pension plans with non-participants. Our results suggest that the lower turnover rate of workers in DB relative to workers in DC pension schemes is a consequence of the facts that DB schemes have less incentives for job mobility or are more generous than DC ones, not because of the fact that more mobile workers are more likely to choose to belong to DC pension schemes.

4. Concluding Remarks

This paper presents evidence not only that occupational pension coverage implies a lower employee turnover rate but also, in hand with an early study, that the selection on unobservables is not likely to affect this pattern. Moreover, we go into detail to present evidence of the different effect that DB occupational pension schemes have on job mobility relative to DC ones.

Using data from the two available waves of the English Longitudinal Study of Ageing (ELSA) we study not only the effect of pension provision on employee turnover, but also analyze the different behaviour of workers in DB and those in DC occupational pension schemes. We follow two different empirical approaches. First, we applied a probit model with sample selection for the probability of employee turnover. Consistent with early studies, our results confirm that pension covered workers tend to have lower turnover rates than non-covered workers. However, we go farther and find that not only coverage plays an important role in explaining job mobility but also the type of pension is a key determinant. Indeed, our findings confirms the hypothesis that DC members are more mobile than DB peers, suggesting that the low portability of pension rights could be an impediment to job mobility.

Secondly, by applying matching methods we study the different pattern in terms of job mobility between DB and DC covered workers but testing at this stage for the potential endogeneity of pension choice. Results confirm our findings using the probit model with sample selection: DC occupational pension scheme members are more likely to switch job than DB ones. Moreover, we test the sensitivity of our results to the presence of unobservable selection and find that the existence of unobserved confounders that would change our estimation results is relatively unlikely.

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Appendix

TABLE A.1
Pension Scheme Coverage

Pension Status	Individuals	%
Offered Occupational Pension	***2,055***	***71.86***
Joined, DB	*1,079*	*37.73*
Joined, DC	*414*	*14.48*
Not Joined	*562*	*19.65*
Not Offered Occupational Pension	***805***	***28.15***
Total Sample	**2,860**	**100**

Source: English Longitudinal Study of Ageing, Wave 1 and Wave 2.

TABLE A.2

Selection Equation

Chance of Being Working (Wave 1 and Wave 2)

Regressor	Coeff.	Standard Error
Individual Characteristics		
Age	-0.112*	0.003
Female	-0.169*	0.033
Married	-0.029	0.037
Degree or Above	0.109*	0.043
Child	0.177*	0.035
Fair/Poor Health	-0.775*	0.043
Wealth		
Savings	-0.019*	0.004
State Pension Wealth	0.061*	0.005
Private Pension Wealth	0.002*	0.004
Observations	8,179	

Notes:

- * indicates significance at 1% confidence level
- ** indicates significance at 5% confidence level
- *** indicates significance at 10% confidence level
- Savings and both State and Private pension wealth are in £10,000s
- Standard Errors are robust to heteroskedasticity.
- The coefficient on Female is with respect to Male. The coefficient on Married is with respect to the omitted category: Not Married. The coefficient on Degree or Above level of education is with respect to Below Degree/Other education level. The coefficient on Child is with respect to No Child at household. The coefficient on Fair/Poor Health is with respect to Excellent/Very Good/Good self-reported health status.

TABLE A.3

Probit Model with Sample Selection

Chance of Job Mobility

Regressor	Coeff.	Standard Error	Marginal Effect
Pension Coverage			
No Occupational Pension	0.330*	0.077	0.100*
Individual Characteristics			
Female	-0.154***	0.081	-0.047**
Age	-0.035	0.049	-0.010
Age Squared	0.0003	0.0005	0.0001
Married	-0.071	0.079	-0.022
Employment			
Full Time	-0.143***	0.079	0.043***
Employment Income	-0.010*	0.022	-0.003*
2-99	0.086	0.084	0.026
100-499	0.085	0.109	0.026
500-999	0.339*	0.130	0.102**
Wealth			
Savings	0.015***	0.008	0.005***
House	-0.0008	0.031	-0.0002
Observations	Uncensored	Censored	Total
	2,080	6,099	8,179
Log-Likelihood	-3620.60		
Wald	79.00		
Selection Correlation	-0.239	0.146	p-value 0.1016

Notes:

- * indicates significance at 1% confidence level
- ** indicates significance at 5% confidence level
- *** indicates significance at 10% confidence level
- Employment income is in £1,000s, Savings are in £10,000s, and Housing wealth is in £100,000s.
- Standard Errors are robust to heteroskedasticity.
- The coefficient on No OP is with respect to Occupational Pension. The coefficient on Female is with respect to Male. The coefficient on Married is with respect to the omitted category: Not Married. The coefficient on Full Time is with respect to Part Time. The omitted category for the number of employees is more than 1,000.

TABLE A.4
Number of Treated and Control Members
By pre-defined stratum

Minimum Propensity Score	**Treated (DC)**	**Control (DB)**	**Total**
0.0632	24	269	293
0.15	157	466	623
0.35	19	32	51
0.40	86	94	180
0.60	86	56	152
Total	**372**	**917**	**1,289**

TABLE A.5
Propensity Score Estimation: Logit Model:
P(DC=1)

Regressor	Coefficient	Std.Error
Individual Characteristics		
Female	-0.463*	0.195
Age	-0.014	0.170
$(\text{Age})^2$	0.0003	0.0016
Degree or above	-0.644*	0.180
Married	-0.052	0.164
Employment		
Earnings	-1.043**	0.452
$(\text{Earnings})^2$	2.3085	2.108
Full Time	0.280	0.194
Female*Full Time	0.181	0.302
2-99 employees	1.995*	0.188
100-499 employees	1.095*	0.197
500-999 employees	1.061*	0.239
Wealth		
Savings	-0.054**	0.026
Observations	1,262	
Log Likelihood	-658.45	
Pseudo-R^2	0.1346	

Notes:

- * indicates significance at 1% confidence level
- ** indicates significance at 5% confidence level
- *** indicates significance at 10% confidence level
- Employment income is in £1,000s, Savings are in £10,000s
- Standard Errors are robust to heteroskedasticity.
- The coefficient on Female is with respect to Male. The coefficient on Married is with respect to the omitted category: Not Married. The coefficient on Full Time is with respect to Part Time. The coefficient on Degree or above education is with respect to the omitted category Below Degree education. The omitted category for the number of employees is more than 1,000. The coefficient on Female*Full Time is wit respect to Male working part time.

TABLE A.6
Standardized Bias (SB) Before and After Matching for Different Matching Algorithms

Variable	Before Matching	After Matching											
		Kernel				*Nearest Neighbour*				*Radius*			
		h=0.01	*h=0.03*	*h=0.06*	*h=0.1*	*NN=1*	*NN=10*	*NN=15*	*NN=20*	δ*=0.001*	δ*=0.005*	δ*=0.01*	δ*=0.05*
GENDER	27.2	4.8	3.4	5.7	7.4	4.9	7.1	9.1	8.7	4.3	6.5	4.2	5.9
AGE	22.3	0.9	2.4	2.6	1.7	8.5	1.7	2.0	0.6	10.5	1.1	0.6	2.5
AGE^2	22.5	1.1	2.5	2.9	2.0	9.6	1.9	2.0	0.8	10.8	1.4	0.7	2.8
EARNINGS	21.5	6.8	8.7	6.8	5.0	10.6	8.5	6.1	5.5	0.7	5.9	6.2	6.7
$EARNINGS^2$	16.6	2.5	3.7	3.0	2.0	2.0	1.6	0.7	0.8	1.0	2.3	2.4	2.9
MARRIED	3.6	6.3	10.6	8.8	6.9	13.4	11.5	9.6	8.1	10.4	7.5	6.6	8.5
NOEMP	75.1	3.4	3.8	3.8	5.8	2.9	3.0	2.7	3.3	2.2	2.2	3.5	3.8
EDUCATION	29.2	6.4	5.1	4.1	2.4	8.4	6.5	4.9	3.8	7.2	6.0	6.2	4.1
SAVINGS	17.4	1.9	0.2	0.4	0.2	0.8	1.5	0.6	1.0	0.9	1.4	2.1	0.5
FULL TIME	19.0	4.8	6.3	7.1	7.7	11.6	10.6	9.5	8.7	1.8	3.8	4.1	7.3
GENDER*FULL TIME	5.2	0.1	0.6	0.1	0.4	1.7	2.3	1.8	1.8	6.3	1.5	0.9	0.1
Mean Std. Bias	**23.6**	**3.5**	**4.3**	**4.1**	**3.8**	**6.8**	**5.1**	**4.5**	**3.9**	**5.1**	**3.6**	**3.4**	**4.1**

Notes: Following Rosenbaum and Rubin (1985) and Caliendo and Kopening (2005), we define:

$$\text{SB } \textit{before} \text{ matching} = 100\times\frac{(\overline{X}_{DC}-\overline{X}_{DB})}{\sqrt{\frac{1}{2}\times[V_{DC}(X)+V_{DB}(X)]}}\;;\quad \text{SB } \textit{after} \text{ matching} = 100\times\frac{(\overline{X}_{DC,M}-\overline{X}_{DB,M})}{\sqrt{\frac{1}{2}\times[V_{DC,M}(X)+V_{DB,M}(X)]}}$$

Where: $\overline{X}_{DC}$ ($V_{DC}(X)$) is the mean (variance) among DC pension scheme members (treated group) and $\overline{X}_{DB}$ ($V_{DB}(X)$) is the mean (variance) among DB pension scheme members (untreated group) before matching; On the other hand, $\overline{X}_{DC,M}$ ($V_{DC,M}(X)$) is the mean (variance) among DC pension scheme members (treated group) and $\overline{X}_{DB,M}$ ($V_{DB,M}(X)$) is the mean (variance) among DB pension scheme members (untreated group) after matching.

TABLE A.7

Pension Type Effect on Employee Turnover Rates

Sample/ Method	Observations	Treated (DC)	Control (DB)	Treatment Effect ζ	Std. Error	p-value‡	% Benchmark
Unmatched	1,289	17.47%	10.58%	6.90%	0.02030	0.000	-
Kernel							
h=0.01	1,230	17.15%	12.02%	5.13%	0.02556†	0.045	74.3%
h=0.03	1,257	17.49%	11.28%	6.20%	0.02816†	0.028	89.9%
h=0.06	1,262	17.44%	11.88%	5.56%	0.03035†	0.067	80.6%
h=0.1	1,262	17.44%	12.06%	5.38%	0.02395†	0.025	78.0%
Nearest Neighbour							
NN=1	1,262	17.44%	10.08%	7.36%	0.03506†	0.036	106.7%
NN=10	1,262	17.44%	11.03%	6.40%	0.02650†	0.016	92.8%
NN=15	1,262	17.44%	11.15%	6.29%	0.03389†	0.064	91.2%
NN=20	1,262	17.44%	11.78%	5.65%	0.03094†	0.068	81.9%
Radius							
δ=0.001	865	17.13%	9.42%	4.09%	0.03827†	0.063	59.3%
δ=0.005	1,196	17.37%	10.53%	6.83%	0.03073†	0.026	99.0%
δ=0.01	1,230	17.15%	11.82%	5.33%	0.02820†	0.059	77.2%
δ=0.05	1,262	17.44%	11.96%	5.48%	0.03153†	0.082	79.4%

Notes:

- ζ Difference in employee turnover between DC and DB pension scheme members
- † Bootstrapped standard errors with 50 replications.
- Note that average treatment effect over treated differs in some cases due to the fact some observations for the untreated and the treated are off common support. Though, the percentage of observations that are off common support is not high except for the case of Radius Matching with δ=0.001.
- ‡ Estimated p-value for the treatment effect – difference in means –.

TABLE A.8

Sensitivity Analysis for Unobserved Heterogeneity

Sample/ Method	**Treatment Effect** $^{\zeta}$	**Mantel-Haenszel Statistic**†	**Critical Value**‡
Kernel			
h=0.01	5.13%	3.08522	1.25-1.3
h=0.03	6.20%	3.33882	1.3-1.35
h=0.06	5.56%	3.28619	1.3-1.35
h=0.1	5.38%	3.28619	1.3-1.35
Nearest Neighbour			
NN=1	7.36%	2.39781	1.2-1.25
NN=10	6.40%	3.07156	1.3-1.35
NN=15	6.29%	3.33317	1.35-1.4
NN=20	5.65%	3.27895	1.3-1.35
Radius			
$\delta=0.001$	4.09%	2.99542	1.3-1.35
$\delta=0.005$	6.83%	3.2919	1.3-1.35
$\delta=0.01$	5.33%	3.08522	1.25-1.3
$\delta=0.05$	5.48%	3.28619	1.3-1.35

Notes:

- ζ Difference in employee turnover between DC and DB pension scheme members.
- † Mantel-Haenszel test compares the number of treated individuals with its expected number under the hypothesis of the absence of treatment effect. In this case we present the Mante-Haenszel test for the case of absence of unobserved heterogeneity, i.e. when the odds ratio between two matched individuals is 1.
- ‡ Odds ratio of differential assignment due to selection on unobservables assuming the overestimation of treatment effect.