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Paul Sweeting

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The Pensions Institute
Cass Business School
City University
106 Bunhill Row London
EC1Y 8TZ
UNITED KINGDOM

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Paul Sweeting[1,2]
Fidelity Investments, University of Bristol

1 Introduction

The literature into employee choice in relation to DB and DC pension schemes is substantial. Yang (2005) looks at the factors influencing employee choice between DB and DC pension schemes; similarly, Choi et al (2002) and Huberman et al (2004) look at the factors influencing individuals to join DC pension arrangements whilst Clark et al (1998) consider this question and the question of how individuals decide how much to contribute if they do join. Holden and VanDerhei (2001) and Papke (2002) also looks at factors affecting the level of employee contributions, whilst Bernartzi and Thaler (2001), Poterba (2003) and Holden and VanDerhei (2003) consider the investment strategies chose by DC pension plan participants. These studies are largely carried out from the employees' point of view.

However, little research has been carried out into what influences companies to offer DB or DC pension plans to employees. This is of interest because according to the NAPF Annual Survey (2005), the number of private sector pension schemes providing defined benefits has fallen from over 80% in 1996 to below 50% in 2005. There are a number of reasons advanced for this. First, falling bond yields, increasing longevity and increasingly guaranteed pension benefits have led to an increase in the cost of benefits being earned. Furthermore, assets held in respect of benefits already earned have not increased in value as much as the liabilities, which has led to pension

1 Fidelity Investments; paul.sweeting@uk.fid-intl.com
2 University of Bristol; paul.sweeting@bristol.ac.uk

scheme deficits. These factors have led to firms reducing the extent of DB provision where possible; however, many firms that have come into being in recent years have offered only DC pension benefits.

Bodie et al (1988) point out that the major advantage of DB plans over DC arrangements is in the benefit stability that they provide to employees. The protection offered to employees is, though, also a risk borne by the employer. However, Bodie et al propose that at least part of this risk is diversifiable to employers, whilst remaining non-diversifiable to employees. For a firm, DB pension scheme investment risk is just one of many financial risks taken, most of which are in the course of either running or funding the business. For example, firms face risk relating to the price charged for goods or services sold; the volume of business; the cost of sales; the cost of financing; and so on. However, for many individuals DC pension scheme investment risk will be the largest, if not the only, financial risk taken. Most individuals will not have significant non-pensions savings; for most people, future wage inflation will be reasonably stable; and house purchases only result in significant financial risk if short-term interest rates are particularly volatile or if repayment is through an investment vehicle such as an endowment policy.

Kruse (1995) finds that in the US, only a small proportion of new defined contribution participation has come from firms that have terminated their defined benefit plans, whilst Papke (1999) finds that around 20% of US sponsors have dropped their defined benefit plans in favour of defined contribution arrangements.

Munnell et al (2006) offer four possible explanations why employers are closing pension schemes in the US. The first is that some firms are attempting reduce total compensation bills as a response to global competition; the second is that the reduction in pensions cover is a response to the increasing cost of accrued health benefits; the third relates to the high levels of economic risk, longevity risk, regulatory risk and accounting standards risk present in DB pension plans; and the fourth is that traditional pension benefits have become irrelevant to senior directors whose overall compensation packages have grown hugely in recent years. Munnell et al propose that all contribute to the trend in the US; it is also clear that the first and third reasons are equally relevant to the UK. Looking at the move from DB to DC, the cost issue is evidenced by the Government Actuary's Department (2006) which finds that the average employer contribution rate for private DB pension plans is 16.0% of members' salaries, but only 6.3% of salaries for private DC arrangements.

The analysis of the general factors leading to the shift from DB to DC pension provision is interesting; however, it is also useful to consider the characteristics of the firms making these choices, and it is this that I aim to do in this paper.

2 Data

My dataset consists of UK non-financial companies in the FTSE 100. I look at the reasons that firms might choose to offer DB or DC pension schemes to UK employees. I use only non financial firms because DB pension schemes can be regarded as affecting the leverage of a firm, and many of the factors I consider involve this link to company leverage. I include leverage as an explanatory variable. Given that leverage is more difficult to analyse in the context of financial firms, as noted by Feldstein and Seligman (1981), Fama and French (1992), Rajan and Zingales (1995) and Garvey and Hanka (1999), I exclude these firms from my analysis. This leaves the following FT Economic Groups:

- Cyclical Consumer Goods ("CCG");

- Non-Cyclical Consumer Goods (“NCCG”);

- Cyclical Services (“CS”);

- Non-Cyclical Services (“NCS”);

- Resources (“R”);

- Basic Industries (“BI”);

- General Industrials (“GI”);

- Utilities (“U”); and

- Information Technology (“IT”).

Obtaining pensions data from the accounts of such companies has not always been straightforward; however, Statement of Standard Accounting Practice (“SSAP”) 24, which came into effect for periods after 1 July 1988, provided the first attempt in UK accounting to standardise both the calculation of pension costs and the disclosure of information relating to this calculation, particularly relating to DB pension schemes. This also meant that is became easier to determine which firms actually had DB pension schemes and which did not.

SSAP 24 sets out the principles to be followed in calculating pension costs and the disclosures required. It also gives the nature of the pensions arrangements – DB or DC.

For accounting periods ending after 22 June 2001, firms are required to disclose additional pensions information required by FRS 17. However, although firms could adopt FRS 17 in place of SSAP 24 from this date if they chose, reporting under SSAP 24 was still an option until accounting years ending on or after 1 January 2005.

SSAP 24 was superseded by Financial Reporting Standard ("FRS") 17 for all accounting years ending on or after 1 January 2005, although a number of firms continued to account under the earlier standard after this date.

A number of firms have DB pensions arrangements but do not account for pensions under SSAP 24 or FRS 17. In almost all cases this is because they are accounted for under International Accounting Standard ("IAS") 19 or another non-UK standard such as the US Financial Accounting Standard ("FAS") 87, where the nature of the pensions arrangement is still clear; however, in 1989 and, to a lesser extent, 1990, the firms not using a UK accounting standard were using no standard at all, being late to adopt SSAP24.

Table 1 – Number of Firms Split by Scheme Type and Reporting Standard

	1989	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**Total**
No DB Scheme	1	3	1	1	1	1	2	3	4	7	11	14	8	7	7	8	9	**88**
DB Reporting under SSAP24	22	69	76	79	75	75	74	74	67	63	61	58	62	59	57	46	44	**1,061**
DB Reporting under FRS17	0	0	0	0	0	0	0	0	0	0	0	0	0	4	6	19	16	**45**
No UK GAAP DB Reporting	55	7	4	2	2	2	2	2	2	2	3	3	4	3	3	3	5	**104**
Total	**78**	**79**	**81**	**82**	**78**	**78**	**78**	**79**	**73**	**72**	**75**	**75**	**74**	**73**	**73**	**76**	**74**	**1,298**

I use data for whole years following the introduction of SSAP 24, so I look at the constituents of the FTSE100 on every 31 December from 1989 to 2005 inclusive, and use information from the accounts produced that would be available at that date assuming a three month publication lag, so for inclusion in analysis as at 31/12/XXXX, I use data from accounts with year ends up to and including 30/09/XXXX. As alluded to earlier, I look at the difference between firms that provide DB pension schemes for their UK employees and those that do not. The numbers of schemes falling into these categories are shown in Table 1.

Most pension scheme data for UK firms is not available on databases. I therefore extract the information that I use directly from the pensions notes in the accounts. I use electronic versions of the accounts and, when these are unavailable, hard copies from the British Library, the London Business School Library and the Strathclyde Business School Library. All other data are taken from Datastream. Data for the required variables are available for almost every firm in every year; however, the coverage is not universal. I therefore exclude the observations for which complete data are not available, giving the number of observations available as shown in Table 2.

Table 2 – Number of Firms Split by Scheme Type and Reporting Standard with Dependent Variables

	1989	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**Total**
No DB Scheme	1	1	1	1	1	1	2	3	3	5	9	12	8	6	6	8	9	**77**
DB Reporting under SSAP24	19	66	71	75	71	71	71	71	64	59	58	56	59	57	56	44	42	**1,010**
DB Reporting under FRS17	0	0	0	0	0	0	0	0	0	0	0	0	0	3	5	18	15	**41**
No UK GAAP DB Reporting	49	4	3	1	1	1	2	2	2	2	3	3	4	3	3	3	5	**91**
Total	**69**	**71**	**75**	**77**	**73**	**73**	**75**	**76**	**69**	**66**	**70**	**71**	**71**	**69**	**70**	**73**	**71**	**1,219**

The data available for analysis constitute an unbalanced panel, since different firms are available for analysis in different years. However, as shown in Table 2, no more than three firms were without any UK DB provision in each year until 1998, and only one firm was without any DB provision from 1989 to 1994. There is, therefore, merit in combining all of the data into a single dataset for some parts of the analysis.

Since only two firms out of those analysed had no DB pension scheme for only some of the years in which they featured, it is straightforward to exclude these firms and divide the rest into those firms that had a DB pension scheme and those that did not. This means that although there are over 1,000 observations, there are only 161 unique firms, 161. As well as analysis on the full data, I also perform analysis on a combined set. The division of firms by type (and for whom information on dependent variables is available) is given in Table 3.

Table 3 – Number of Discrete Firms Split by Scheme Type and Reporting Standard with Dependent Variables

No DB Scheme	16
DB Reporting under SSAP24	126
DB Reporting under FRS17	8
No UK GAAP DB Reporting	11
Total	**161**

As mentioned above, little work has been carried out on the choice of whether to offer employees DB or DC pension provision. However, given that DB pension schemes can be viewed as an extension of capital structure, as discussed by many authors including Graham and Dodd (1951), Bagehot (1972), Sharpe (1976), Ippolito (1981) and Exley et al (1997), it is reasonable to expect that the literature relating to capital structure might also affect decision relating to the pension scheme. Analysis on choices of funding and asset allocation in DB pension schemes might also provide insights into the decision as to whether to provide a DB or a DC pension scheme. Finally, I include some additional suggestions unrelated to these two sources.

Smaller firms might be expected to incur proportionally higher cost running a DB pension scheme, so might be expected to be less likely to want to offer DB provision. Also, younger firms are likely to be smaller firms. Since the cost of offering DB accrual rose sharply in the 1990s due to reasons such as falling real bond yields (from 3.9% on 5 April 1995 to 1.6% on 5 April 2000 for the benchmark 30 year Index Linked Gilt), newer firms could be forgiven for a reluctance to set up new

DB pension schemes. The increasing costs of DB pension schemes are discussed in more detail in Sweeting (2006). This too could be expected to lead to a positive relationship between firm size and the likelihood of offering a DB pension plan. The proxies I consider for firm size are total balance sheet assets, equity market value and sales. Total balance sheet assets is more stable from year to year than either of the other options which are more prone to change with market sentiment (market value) or the economic cycle (sales). A variable related to total assets also better reflects the true size of an undertaking; market values reflect expectations of future growth as much as the current size of an organisation, and a large sales volume can be generated by a comparatively small firm in some industries; however, all three options are considered.

Bradley, Jarrell and Kim (1984) point out that if a high proportion of a firm's assets are intangible, then the lack of collateral might make it expensive to raise debt. This could be expected to persist if the issue is simply that a firm has limited assets of any kind. Such a situation could mean that a DB pension scheme became attractive since it would offer the opportunity to run a pension scheme deficit (in other words, defer employee remuneration) providing an attractive way to raise funds (effectively borrowing from the workforce). I therefore use the ratio of sales to total assets as a proxy for the asset base of the firm.

It might be attractive to a firm with a high marginal tax rate to set up a DB pension scheme since such an arrangement offers significant opportunity to manage tax exposure. The ratio of earnings before interest and tax ("EBIT") divided by total assets might be regarded as a proxy for the marginal tax rate. However, Francis and Reiter (1987) recognise that riskier firms are more likely to under-fund their pension schemes, since the put option that the firm has on the deficit, outlined by Sharpe (1976), is more valuable. If EBIT over total assets is instead regarded as a risk proxy, then it might be concluded that firms with a low level of this variable might be more likely to set up a DB scheme in order to gain the option of running a pension scheme deficit.

DeAngelo and Masulis (1980) note that non-debt tax shields reduce attraction of leverage. This is because one attraction of leverage is that the interest payments on debt are tax deductible, and if there are already significant non-debt tax shields then this advantage is lessened. A defined benefit pension scheme – in particular, the ability to over-fund such a scheme – offers the opportunity to manage corporate tax bills. However, if there are already significant non-debt tax shields, then there is less need to set up a pension scheme to help to manage tax bills. A common and significant non-debt tax shield is depreciation, so I use this as a proxy after initially standardising by dividing by EBIT before depreciation, depletion and amortisation ("EBITDA"). This is the most common denominator used in the literature for standardisation.

"Growth" firms might be more inclined than "value" firms to want to use DB provision, since offering such a scheme gives such a firm the opportunity to defer payment by creating a pension scheme deficit, thus providing additional funding. This is, of course, unless such firms find that it is simply cheaper to use DC provision, and the workforce is unable to correctly value the difference between this and DB provision. A number of potential variables can be used as growth proxies, the main one being the earnings to price ratio, the ratio of book to market value and the dividend yield. None of these three proxies is without problems: the earnings to price and market to book ratios both have a tendency to throw up extreme values for some firms, whilst the earnings to price ratio and dividend yield are low for both very young growth firms (which are growing too fast to produce substantial if any earnings or dividends) and very mature firms (which are in decline so have depressed earnings and dividends). Indeed, Blume (1980) finds that returns are higher for those firms paying higher dividends or no dividends at all. I therefore consider all three variables.

Finally, Francis and Reiter (1987) note that funding derived from a pension scheme deficit might be cheaper than that derived externally once external funding has reached a particular level. This might also imply that firms with high leverage might be more likely to have a DB scheme rather than a DC scheme since deficits are only possible with the former. I therefore include leverage as an explanatory variable, using the ratio of book debt over the sum of book debt and the market value of equity. I use book debt because it is more readily available than the market value of debt, and more likely to include all debt. It also measure the obligation rather than the market value of the obligation, which is what leverage is intended to measure. I use the market value of equity since this gives a better indication of the value of the firm. The independent variables I therefore consider are:

- a firm size proxy, for which I use total assets ("TotA"), market value ("MV") and sales ("Sales");
- an asset base proxy, for which I use the ratio of sales to total assets ("SoA");
- a firm risk and marginal tax proxy, for which I use the ratio of EBIT to total assets ("EBIToA");
- a non-debt tax shield proxy, for which I use depreciation, depletion, amortisation over EBITDA ("DAoEBTIDA");
- a "growth"/"value" firm proxy, for which I use the dividend yield ("DY"), earnings to price ratio ("EtoP") and the market to book ratio ("MtoB"); and
- leverage ("Leverage"), which I define as the ratio of the book value of debt over the sum of the book value of debt and the market value of equity.

This gives us the raw data, and I give the characteristics of these data in Table 4. I include the Bera-Jarque statistic, designed by Bera and Jarque (1981) to measure the normality of a dataset.

This considers the skew and kurtosis of a distribution. The statistic is calculated as:

$$(1) \qquad BJ = \frac{\hat{\tau}^2}{6} + \frac{(\hat{\kappa}-3)^2}{24} \sim \chi_2^2$$

Table 4 – Data Characteristics: Raw Data

	MV*	**TotA***	**Sales***	**SoA**	**EBIToA**	**DDAoEBITDA**	**DY**	**EtoP**	**MtoB**	**Leverage**
Number of Observations = 1,219										
Maximum	158.54	171.70	154.68	6.64	0.67	34.90	1.05	3.52	131.86	0.84
95th Percentile	24.87	24.91	18.68	1.95	0.27	0.72	0.07	0.13	5.02	0.46
90th Percentile	15.09	16.59	11.22	1.71	0.21	0.50	0.05	0.11	3.16	0.39
75th Percentile	7.56	7.17	6.14	1.29	0.15	0.35	0.04	0.08	1.64	0.27
50th Percentile	3.99	3.65	3.21	0.93	0.11	0.24	0.03	0.06	1.07	0.18
25th Percentile	2.33	1.96	1.77	0.61	0.08	0.17	0.02	0.04	0.69	0.10
10th Percentile	1.64	1.13	0.98	0.34	0.04	0.13	0.01	0.01	0.49	0.04
5th Percentile	1.30	0.82	0.66	0.27	0.01	0.10	0.00	-0.02	0.40	0.02
Minimum	0.08	0.04	0.01	0.05	-0.87	-7.42	0.00	-2.05	0.02	0.00
Mean	8.04	7.79	6.34	0.99	0.12	0.40	0.03	0.06	1.89	0.20
Standard Deviation	14.61	15.48	12.96	0.56	0.09	1.48	0.06	0.19	5.14	0.14
Skew	5.50	6.27	7.07	1.73	-1.39	15.76	12.95	10.49	16.74	0.92
Excess Kurtosis	36.27	48.79	60.71	10.07	21.31	321.30	201.76	205.64	369.32	0.94
Bera-Jarque Statistic	59.86	105.75	161.9	4.72	19.24	4,342.79	1,724.05	1,780.31	5,729.85	0.18
> Mean + 3 St Dev	25	24	17	8	10	14	7	4	12	9
< Mean – 3 St Dev	0	0	0	0	8	1	0	3	0	0

*data in £bn

There are clearly issues with these data, both in relation to skew and leptokurtosis. Both are a source of extreme variables, which are an issue if they result in high leverage points that distort the results of a regression. With 1,219 observations, no more than one or two observations should be more than three standard deviations from the mean; no variable has data falling within this range. Furthermore, the critical value of the statistic – from the χ^2 distribution with 2 degrees of freedom – is 9.21 at the 1% level of confidence, a level that all variables except SoA and Leverage miss by some margin. Even SoA is non-normal at the 10% level of confidence, where the critical value is

4.61.

There are a number of approaches than can be used to deal with extreme variables. One common approach is Winsorizing, where extreme variables beyond particular limits are set to those limits. The limits are frequently specified in terms of numbers of standard deviations from the mean. However, if there are a large proportion of extreme variables, then this approach risks discarding a large amount of information. Accounting ratios in particular produce distributions with large numbers of extreme observations. Kolari, McInish, and Saniga (1989) and Buckmaster and Saniga (1990) find range of non-normal distribution shapes in ratios – J, reverse J, U – all of which suggest lots of outliers, certainly too many for Winsorizing. Furthermore, the presence of extreme values can itself artificially inflate the standard deviation used to determine the Winsorization cut-off points, meaning that too many extreme variables might remain.

Table 5 – Data Characteristics: Transformed Data

	lnMV	**lnTotA**	**lnSales**
Number of Observations = 1,219			
Maximum	5.07	5.15	5.04
95th Percentile	3.21	3.22	2.93
90th Percentile	2.71	2.81	2.42
75th Percentile	2.02	1.97	1.82
50th Percentile	1.38	1.30	1.17
25th Percentile	0.84	0.67	0.57
10th Percentile	0.49	0.12	-0.02
5th Percentile	0.26	-0.20	-0.42
Minimum	-2.56	-3.23	-4.35
Mean	1.51	1.37	1.20
Standard Deviation	0.94	1.07	1.06
Skew	0.65	0.29	0.03
Excess Kurtosis	1.68	1.16	2.01
Bera-Jarque Statistic	0.19	0.07	0.17
> Mean + 3 St Dev	18	9	11
< Mean – 3 St Dev	4	4	7

For variables which always take values greater than zero and where positive skew is the issue, logarithms can be taken. This approach is suitable for the data given as absolute values (rather than ratios), namely the three size proxies: MV, TotA, and Sales. Taking the natural logarithms of these variables does reduce skew and brings the Bera-Jarque statistics to levels such that there is no statistically significant non-normality. Summary information for the transformed data is given in Table 5, the prefix "ln" indication that logarithms-transformed data has been used.

Clearly, whilst the Bera-Jarque statistics are much more satisfactory, there are still a number of data points beyond three standard deviations of the mean; however, given that the variables span seventeen years and are not dimensionless (unlike the remaining ratio variables which are), some change in the mean of annual observations is to be expected from year to year, and the result is likely to be leptokurtosis. In the regression analysis later on, year-to-year change is taken care of by using dummy variables for all but one of the years; however, for this to be the only change needed there would need to be only a limited incidence of extreme observations within each year for these variables. Looking at deviations from the mean on a year-by-year basis, the number of extreme variables is much lower with only a single observation being more than four standard deviations from a mean (4.01 standard deviations, to be precise). A summary of year-by-year results is given in Table 6.

Table 6 – Annual Deviations from the Mean: Transformed Data

		1989	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**Total**
lnMV	**+ 3 St Dev**	0	0	0	0	0	0	0	0	0	1	1	2	3	0	1	1	1	**10**
	– 3 St Dev	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**4**
lnTotA	**+ 3 St Dev**	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	**3**
	– 3 St Dev	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	**2**
lnSales	**+ 3 St Dev**	0	0	0	0	0	0	1	1	1	1	0	0	0	1	2	1	0	**8**
	– 3 St Dev	1	0	0	0	0	0	0	0	0	0	1	2	0	0	0	1	1	**6**
Number		**69**	**71**	**75**	**77**	**73**	**73**	**75**	**76**	**69**	**66**	**70**	**71**	**71**	**69**	**70**	**73**	**71**	**1,219**

Having dealt with the size proxies, I next turn to the remaining variables, all of which are ratios. A transformation that can be used to rescale extreme observations where some of the values are less than or equal to zero – and one that reduces skew in many cases – is to take the inverse tangent of the raw observations. However, as discussed above, ratios often have distributions such that even this transform still leaves a large number of extreme variables, and that does appear to be the case when the transform is applied here: skew is generally reduced, but excess kurtosis still appears to be a problem, and the Bera-Jarque statistics for almost all variables still suggest significant non-normality.

An approach suggested by Kane and Meade (1998) specifically for dealing with financial ratios is to use ranks instead. In particular, they find that models using this approach have more explanatory and predictive power than those using data converted with other transformations. I therefore transform all ratio data using this approach. Another advantage of transforming data to ranks is that it is straightforward to combine combinations across years for each firm, thus transforming the panel data into a cross-sectional dataset. I therefore also transform the three size proxies by ranking as well.

With this approach there will be, by definition, no extreme variables. Given that the distributions of all of these variables are identical – uniform from 1 to 1219 – the summary data would be trivial, so they are not given in a separate table.

Since ranking the data does remove some information from the dataset, and since the log transformations on the size proxies do appear to provide a good dataset, I carry out analysis using both types of transformed size proxy in the analysis on the full dataset in order to determine the extent to which the ranking process affects the usefulness of these proxies.

As alluded to earlier, I analyse aggregated data as well as considering each observation by year and firm separately. Since no firm changes from being one which offers a DB pension scheme to one that does not (or vice versa), there is merit in carrying out this aggregation. The combination of the ranked data into an aggregated, cross-sectional dataset is done by ranking the explanatory variables within each year, and then taking the average of these ranks for each variable for each firm. Considering the rank within each year has the advantage of removing any impact of the year of the observation. For example, an observation which is low for a particular firm in a particular year, but occurs in a year where all observations are high, may nonetheless have a high rank when considered as part of the full dataset. However, I also experiment by aggregating the data by taking the average of the ranks calculated relative to the full dataset, and find the coefficients and levels of significance to be very similar for both approaches (once the coefficients have been adjusted for the difference in average value).

It is worth noting that since the highest value in any series will have a rank of 1 and the lowest a rank of (in this case) 1,219, the order of ranked variables is the reverse of the order of the raw variables. For the aggregated data, the series can have a minimum of 1 and a maximum of 76 (the largest number of firms in any one year).

3 Analysis

As discussed above, the full data available for analysis constitute an unbalanced panel. I therefore use logit analysis, counting firms without a DB pension scheme as 1 and those with a DB pension scheme as 0, and using not only the variables described below, but also the year of the observation as a dummy variable. This means that since observations are taken from years 1989 to 2005, sixteen dummy variables are required (the number of years minus 1), each taken a value of 1 if the dependent variable is from that year and 0 otherwise. In this analysis, there are 1,219 observations.

The logit analysis for the aggregated data is similar, except that no year dummies are required. In this analysis there are 161 observations.

However, before carrying out these calculations, I perform some more basic analysis of the data. First, I give a correlation matrix showing the links between the independent variables. Correlations for raw variables are shown in Table 7, for transformed data in Table 8 and for aggregated transformed data in Table 9. The correlations between rank-transformed variables are equivalent to Spearman's Rank Correlation Coefficient; however, this is not the case for the aggregated transformed data since the dependent variables are no longer pure ranks. In this and all subsequent analysis, the prefix "ln" indicates that a proxy has been log-transformed, and the prefix "r" indicates that rank transformation has been used.

Table 7 – Correlation Matrix: Raw Data

	MV	**TotA**	**Sales**	**SoA**	**EBIToA**	**DDAoEBITDA**	**DY**	**EtoP**	**MtoB**	**Leverage**
Number of Observations = 1,219										
MV	1.000	0.774	0.643	-0.083	0.016	0.044	-0.038	-0.051	0.048	-0.171
TotA	0.774	1.000	0.734	-0.163	-0.160	0.088	0.059	-0.030	-0.084	0.068
Sales	0.643	0.734	1.000	0.097	-0.046	0.002	0.082	0.017	-0.070	0.009
SoA	-0.083	-0.163	0.097	1.000	0.269	-0.035	-0.061	-0.002	0.079	-0.310
EBIToA	0.016	-0.160	-0.046	0.269	1.000	-0.161	-0.033	0.260	0.189	-0.314
DDAoEBITDA	0.044	0.088	0.002	-0.035	-0.161	1.000	-0.012	-0.051	0.007	-0.008
DY	-0.038	0.059	0.082	-0.061	-0.033	-0.012	1.000	0.812	-0.103	0.231
EtoP	-0.051	-0.030	0.017	-0.002	0.260	-0.051	0.812	1.000	-0.050	0.064
MtoB	0.048	-0.084	-0.070	0.079	0.189	0.007	-0.103	-0.050	1.000	-0.264
Leverage	-0.171	0.068	0.009	-0.310	-0.314	-0.008	0.231	0.064	-0.264	1.000

Looking first at the raw data, the correlations between most variables are low, with few absolute correlations being above 0.500. Those that are are generally between variables where only one would be use as a proxy. For example, the correlations between MV, TotA and S are all quite high (between 0.615 and 0.833); however, only one of these would be used in any single regression. Similarly, the correlations between DY and EtoP are high, but both are value/growth proxies. The exception is MtoB (another value/growth proxy), which is highly negatively correlated with Leverage.

Table 8 – Correlation Matrix: Transformed Data

	lnMV	**lnTotA**	**lnSales**	**rMV**	**rTotA**	**rSales**	**rSoA**	**rEBIToA**	**rDDAoEBITDA**	**rDY**	**rEtoP**	**rMtoB**	**rLeverage**
Number of Observations = 1,219													
lnMV	1.000	0.673	0.615	-0.941	-0.647	-0.595	0.118	-0.040	-0.141	0.114	0.211	-0.221	0.218
lnTotA	0.673	1.000	0.833	-0.635	-0.952	-0.793	0.317	0.355	-0.300	-0.351	-0.123	0.506	-0.365
lnSales	0.615	0.833	1.000	-0.579	-0.776	-0.942	-0.233	0.143	-0.233	-0.327	-0.147	0.333	-0.177
rMV	-0.941	-0.635	-0.579	1.000	0.660	0.596	-0.130	0.044	0.116	-0.101	-0.201	0.227	-0.193
rTotA	-0.647	-0.952	-0.776	0.660	1.000	0.804	-0.350	-0.373	0.286	0.345	0.101	-0.508	0.397
rSales	-0.595	-0.793	-0.942	0.596	0.804	1.000	0.210	-0.186	0.240	0.301	0.094	-0.333	0.186
rSoA	0.118	0.317	-0.233	-0.130	-0.350	0.210	1.000	0.351	-0.102	-0.082	0.020	0.305	-0.354
rEBIToA	-0.040	0.355	0.143	0.044	-0.373	-0.186	0.351	1.000	-0.576	-0.176	0.335	0.571	-0.441
rDDAoEBITDA	-0.141	-0.300	-0.233	0.116	0.286	0.240	-0.102	-0.576	1.000	0.112	-0.333	-0.280	0.221
rDY	0.114	-0.351	-0.327	-0.101	0.345	0.301	-0.082	-0.176	0.112	1.000	0.437	-0.592	0.531
rEtoP	0.211	-0.123	-0.147	-0.201	0.101	0.094	0.020	0.335	-0.333	0.437	1.000	-0.374	0.257
rMtoB	-0.221	0.506	0.333	0.227	-0.508	-0.333	0.305	0.571	-0.280	-0.592	-0.374	1.000	-0.771
rLeverage	0.218	-0.365	-0.177	-0.193	0.397	0.186	-0.354	-0.441	0.221	0.531	0.257	-0.771	1.000

Moving on to the transformed data, the first point to note is that the correlations between the ranked variables and those that have been log-transformed generally reverse. However, the results in this analysis are similar to those for the raw data, although here the absolute value of the correlation between rEBIToA and rDDAoEBITDA rises above 0.500. In addition, the correlation between rLeverage and lnTotA rises above 0.500, and the correlation between rMtoB and all three of rLeverage, rTotA and rDY climbs to this level. This suggests that the results of any regressions involving these combinations of variables should be treated with caution. This is important since high correlations between explanatory variables can result in multicolinearity. It is also important to note that the correlations between combinations of variables involving the log-transformed size proxies are very close to those involving the rank-transformed ones (albeit with the signs reversed).

Table 9 – Correlation Matrix: Aggregated Transformed Data

	rMV	rTotA	rSales	rSoA	rEBIToA	rDDAoEBITDA	rDY	rEtoP	rMtoB	rLeverage
Number of Observations = 161										
rMV	1.000	0.653	0.495	-0.213	0.037	0.086	-0.158	-0.295	0.223	-0.181
rTotA	0.653	1.000	0.742	-0.351	-0.371	0.241	0.328	0.223	-0.536	0.432
rSales	0.495	0.742	1.000	0.294	-0.085	0.135	0.315	0.279	-0.369	0.230
rSoA	-0.213	-0.351	0.294	1.000	0.447	-0.156	0.010	0.102	0.214	-0.271
rEBIToA	0.037	-0.371	-0.085	0.447	1.000	-0.487	-0.088	0.152	0.549	-0.421
rDDAoEBITDA	0.086	0.241	0.135	-0.156	-0.487	1.000	-0.011	-0.194	-0.274	0.210
rDY	-0.158	0.328	0.315	0.010	-0.088	-0.011	1.000	0.692	-0.599	0.505
rEtoP	-0.295	0.223	0.279	0.102	0.152	-0.194	0.692	1.000	-0.619	0.481
rMtoB	0.223	-0.536	-0.369	0.214	0.549	-0.274	-0.599	-0.619	1.000	-0.780
rLeverage	-0.181	0.432	0.230	-0.271	-0.421	0.210	0.505	0.481	-0.780	1.000

Finally, I consider the aggregated transformed variables. The correlations between the three size proxies are generally over 0.5, as are the correlations between the three growth/value proxies. Since only one of each of the size and growth/value proxies will be used in any one regression, this is not an issue. However, the correlation between rMtoB and both rEBIToA and rLeverage is above 0.5. This should be allowed for when considering the regression results.

I turn next to the differences between the independent variables for firms with and without DB pension schemes. The log-transformed size proxies have distributions which are broadly normal, according to the data in Table 5. I therefore compare the means under this assumption. Having calculated the means, I then calculate the standard deviations and degrees of freedom in order to carry out a two-tailed t-test. I give the results for these variables in Table 10.

Table 10 – Difference between Means for Firms With and Without DB Pension Schemes: Log-Transformed Data

x	Predicted Difference	E(x) No DB Scheme	E(x) DB Scheme	Joint Standard Deviation	Joint Degrees of Freedom	Two-Tailed p Value	Significance
lnMV	<	1.72	1.50	0.08	101.38	0.0062	***
lnTotA	<	0.50	1.43	0.14	84.45	0.0000	***
lnSales	<	0.18	1.27	0.15	83.56	0.0000	***
Number		**77**	**1,142**				

Significance codes: *** 1%; ** 5%; * 10%.

The analysis here suggests that there are significant differences between the two groups of firms. It adds weight to the theory that smaller firms are more likely to only offer DC pensions, but only on the basis of lnSales and lnTotA, the difference between all paired groups of size proxies being significant at the 1% level for the transformed data. The difference between the average market value for the two groups is also significant – but in the other direction. This difference is a result of the boom in tech stocks, which entered the FTSE 100 in large numbers in the late 1990s with high market values (but limited assets and sales). Such young firms were less likely to have defined benefit pension schemes.

For the rank-transformed variables, a different approach is needed, and I use the Mann-Whitney U-test as derived by Mann and Whitney (1947). This involves manipulating the ranks to give a statistic that can be tested to see whether the null hypothesis that, that two samples of observations come from the same distribution, can be rejected at a reasonable level of significance. The U-test statistic is calculated as the lower of:

(2) $$U_{No\,DB} = n_{No\,DB} n_{DB} + \frac{n_{No\,DB}(n_{No\,DB}+1)}{2} - R_{No\,DB}$$

and

$$U_{DB} = n_{DB} n_{No\,DB} + \frac{n_{DB}(n_{DB}+1)}{2} - R_{DB} \tag{3}$$

where $n_{No\,DB}$ is the number of firms without a DB pension scheme, n_{DB} is the number of firms with a DB pension scheme and $R_{No\,DB}$ and R_{DB} are the sums of ranks for the variables relating to firms without and with defined benefit pension schemes. An adjustment is made for tied ranks. For large samples such as the ones being investigated here, the test statistic can be regarded as having an approximately normal distribution with a mean $n_{No\,DB} n_{DB}/2$ and variance $n_{No\,DB} n_{DB}(n_{No\,DB}+n_{DB}+1)/12$. The calculations of the significance of U are given in Table 11 below. The calculation of U is such that large values for the underlying pre-ranked data result in large values of U.

Table 11 – Results of U Test for Firms With and Without DB Pension Schemes: Ranked Data

x	Predicted Difference	$U_{No\,DB}$	U_{DB}	Expected Value of U	Standard Deviation of U+	Two-Tailed p Value	Significance
rMV	<	53,208.0	34,726.0			0.0020	***
rTotA	<	24,571.5	63,362.5			0.0000	***
rSales	<	22,067.5	65,866.5			0.0000	***
rSoA	<	37,906.5	50,027.5	↑	↑	0.0427	**
rEBIToA	</>	50,989.5	36,944.5	43,967.0	2,990.0	0.0187	**
rDDAoEBITDA	>	46,521.0	41,413.0	↓	↓	0.3929	
rDY	</>	15,406.0	72,528.0			0.0000	***
rEtoP	</>	22,687.5	65,246.5			0.0000	***
rMtoB	</>	69,813.5	18,120.5			0.0000	***
rLeverage	<	22,257.5	65,676.5			0.0000	***
Number		**77**	**1,142**				

Significance codes: *** 1%; ** 5%; * 10%.
+The standard deviation actually used in the calculations is adjusted for tied ranks.

The ranked size proxies reflect the results of the log-transformed proxies, with the rTotA and rSales being smaller for firms without DB pension schemes than those with such arrangements, the reverse being true for rMV. The data suggest that SoA is smaller for those firms with no DB pension scheme than it is for those firms offering such an arrangement. This supports the asset tangibility argument discussed earlier, since firms with a high level of sales relative to assets have a small asset base and should be more likely to want to make use of a DB pension scheme.

The risk/tax proxy is significantly different for the two groups of firms. The transformed EBIToA variable is higher for those firms without DB pension schemes, suggesting that this variable is a proxy for risk rather than tax.

All value/growth proxies are significantly different for the DB/no DB pension scheme groups, all suggesting that "value" firms are by far the more likely than "growth" firms to offer DB pension schemes. "Value" firms are also typically mature and unionised, and these factors are also likely to affect these results. These results imply that the requirement for additional finance from "growth" firms is typically met through the fact that DC contributions are typically lower than DB contributions, rather than through the running of a DB pension scheme deficit.

Finally, those firms without DB pension arrangements appear to have significantly lower leverage than those with such schemes, supporting the argument that pension scheme deficits used to supplement firm leverage.

It would be possible to calculate a U statistic for the aggregated rank-transformed data; however, it is not clear what the distribution of this statistic would be, so it is impossible to determine the level of significance of the calculated statistics. It does, though, appear unlikely that the aggregated rank-transformed data are normally distributed, so nor do I aim to calculate the differences between the means as I did for the log-transformed data. I do not, therefore, carry out any univariate analysis on the aggregated data.

Next, I look at whether there is a significant difference across economic groups when it comes to the provision of a DB pension schemes. This is interesting in its own right, but also useful for assessing the extent to which the results above are not more a reflection of sector biases. I use the binomial distribution rather than an approximation. To do this, I use the following approach:

- I first divide firms by FTSE economic group;
- next, I choose an economic group and calculate the proportion of firms in that group that had no DB pension scheme;
- I then calculate the proportion of firms in all other economic groups combined that have no DB pension scheme;
- using this proportion as the population probability, I then calculate the cumulative binomial probability for the chosen economic group and assess the statistical significance of any difference; and
- I repeat this for all economic groups.

I carry out this analysis both counting each observation individually (with 1,219 observations) and counting each unique firm only once (with 161 observations). The is because firms do not generally change economic group, and counting a single firm a number of times simply because it features in more years might bias the results in relation to that firm's economic group. I give the results for multiply-counted firms in Table 12 and for uniquely-counted firms in Table 13.

Table 12 – Difference in Incidence of Firms With and Without DB Pension Schemes between Economic Groups: Multiply-Counted Firms

	Number in Group	Number in Group with No DB Scheme	Two-Tailed p Value	Significance
BI	134	0	0.0001	***
CCG	22	0	0.2316	
CS	353	28	0.0468	**
GI	87	0	0.0022	***
IT	33	17	0.0000	***
NCCG	247	13	0.2450	
NCS	122	6	0.3183	
R	106	13	0.0079	***
U	115	0	0.0002	***
Total	**1,219**	**77**		

Significance codes: *** 1%; ** 5%; * 10%.

Table 13 – Difference in Incidence of Firms With and Without DB Pension Schemes between Economic Groups: Singly-Counted Firms

	Number in Group	Number in Group with No DB Scheme	Two-Tailed p Value	Significance
BI	19	0	0.1032	
CCG	4	0	0.6505	
CS	46	2	0.0695	*
GI	11	0	0.2892	
IT	10	6	0.0000	***
NCCG	28	2	0.4230	
NCS	13	2	0.3520	
R	14	4	0.0228	**
U	16	0	0.1540	
Total	**161**	**16**		

Significance codes: *** 1%; ** 5%; * 10%.

The difference between the two tables is clear – in particular, counting each unique firm only once reduces the number of economic groups that are significantly different. Using all observations, firms in the BI, GI and U economic groups appear to be more likely than average to have a defined benefit pension scheme, whereas the firms in the CS, IT and R economic groups are less likely than other firms to have one; however, using the unique-firm dataset only CS, IT and R remain significantly different. This supports the idea that counting many firms more than once distorts the results.

Some of the differences between economic groups should not be surprising: Information Technology is a relatively new industry with relatively young firms and, for reasons mentioned earlier, younger firms could reasonably be expected to be less likely to have put DB pension arrangements in place; also, a number of newly listed FTSE firms based overseas are Resources firms such as Antofagasta (Chile and Peru) and Kazakhmys (Kazakhstan).

Next, I carry out regression analysis on the data, using a logit regression approach. As described earlier, a level of 0 for the dependent variable denotes a firm with a DB pension scheme, and a level of 1 denotes a firm with no DB pension scheme. First, I consider the the transformed data, and then I move on to the aggregated transformed data.

I include the explanatory variables described earlier, together with a number of dummy variables. First, there are those arising from the economic group analysis above. The economic groups CS, IT and R appear to be the most suitable: indeed, if all six economic groups highlighted in the earlier analysis are included as dummy variables, then the additional dummy variables are not even close to be statistically significant. In the transformed data, I also include dummy variables for all but one year (1989 to 2004, excluding 2005), in order to exploit the panel-based nature of the data. I have also experimented with including dummy variables for all but one of the 161 firms in this regression, but the lack of variability in the dependent variable in a logit regression, together with the small number of observations where there is no defined benefit scheme (71 in total), means that including the additional 160 dummy variables results in the regression failing to converge on an optimal solution. The resulting variance/covariance matrix has a number of singularities involving the intercept term and the year dummies, and cannot be inverted. This means that a Hausman test cannot be carried out, although given these problems it seems reasonable to conclude that excluding company fixed effects will not result in omitted variable bias.

The equation used in this part of the analysis is given in two parts. The first, in (4), gives the basic structure of the regression; the second part of the equation, given as (5), converts the equation into the logit format. The term “SizeProxy” can be six different variables: lnMV, lnTotA, lnSales, rMV, rTotA or rSales. Only the last three of these are used in the aggregated transformed data. The term “ValueProxy” can be three different variables: rDY, rEtoP and rMtoB. This means that eighteen regressions are needed for the transformed data, and nine for the aggregated transformed data.

(4)
$$\begin{aligned} y^* &= x_0 + x_1 SizeProxy + x_2 rSoA + x_3 rEBIToA + x_4 rDDAoEBITDA \\ &+ x_5 ValueProxy + x_6 rLeverage + \sum_{i=7}^{22} x_i YearDummy_i + x_{23} CS + x_{24} IT + x_{25} R \end{aligned}$$

(5)
$$P(\text{No DB Pension Scheme}) = \frac{e^{y^*}}{1+e^{y^*}}$$

In order to avoid giving 27 separate tables of results, I give only the results with lnTotA as the size proxy and rDY as the growth value proxy when analysing the transformed data, and rTotA and rDY as proxies in the summarised transformed data. The results for the transformed data are given in Table 14 and for the aggregated transformed data in Table 15. For each regression I also give the pseudo-R^2 as defined by McFadden (1974), and the adjusted pseudo-R^2 as defined by Ben-Akiva and Lerman (1985). The formulae are given as (6) and (7) respectively:

(6)
$$R^2 = 1 - \frac{\ln \hat{L}(M_{Full})}{\ln \hat{L}(M_{Intercept})}$$

(7)
$$R^2_{adj} = 1 - \frac{\ln \hat{L}(M_{Full}) - k}{\ln \hat{L}(M_{Intercept})}$$

where $\ln \hat{L}(M_{Full})$ is the estimated log likelihood function of the model as given, $\ln \hat{L}(M_{Intercept})$ is the estimated log likelihood function of the model as calculated with only an intercept, and k is the number of explanatory variables.

Table 14 – Logit Analysis of Firms With and Without DB Pension Schemes: Transformed Data

	Predicted Sign	Estimate	Standard Error	Significance
Number of Obserations = 1, 219				
Pseudo-R^2: 0.3841; Adjusted Pseudo-R^2: 0.3388				
(Intercept)	?	-4.7220	1.0850	***
lnTotA	–	-0.6081	0.1756	***
rSoA	+	0.0022	0.0006	***
rEBIToA	+/–	-0.0012	0.0005	**
rDDAoEBITDA	–	-0.0014	0.0005	**
rDY	+/–	0.0024	0.0006	***
rLeverage	+	0.0012	0.0005	**
$YearDummy_{1989}$	?	-2.6806	1.1687	**
$YearDummy_{1990}$	?	-1.7669	1.1598	
$YearDummy_{1991}$	?	-2.1286	1.1610	*
$YearDummy_{1992}$	?	-2.4795	1.1409	**
$YearDummy_{1993}$	?	-2.3652	1.1393	**
$YearDummy_{1994}$	?	-2.3223	1.1263	**
$YearDummy_{1995}$	?	-1.5466	0.8766	*
$YearDummy_{1996}$	?	-1.2409	0.7755	
$YearDummy_{1997}$	?	-1.2171	0.7784	
$YearDummy_{1998}$	?	-0.3537	0.6783	
$YearDummy_{1999}$	?	-0.5740	0.6571	
$YearDummy_{2000}$	?	-0.5595	0.6404	
$YearDummy_{2001}$	?	-0.2854	0.6609	
$YearDummy_{2002}$	?	0.2314	0.6994	
$YearDummy_{2003}$	?	0.0583	0.6816	
$YearDummy_{2004}$	?	0.0476	0.6580	
CS	?	1.0536	0.3743	***
IT	?	1.9765	0.6017	***
R	?	1.3404	0.4963	***

Significance codes: *** 1%; ** 5%; * 10%.

Table 15 – Logit Analysis of Firms With and Without DB Pension Schemes: Aggregated Transformed Data

	Predicted Sign	Estimate	Standard Error	Significance
Number of Obserations = 161				
Pseudo-R^2: 0.4616; Adjusted Pseudo-R^2: 0.3657				
(Intercept)	?	-9.5681	2.4359	***
rTotA	+	0.0107	0.0264	
rSoA	+	0.0337	0.0259	
rEBIToA	+/–	-0.0111	0.0263	
rDDAoEBITDA	–	-0.0102	0.0229	
rDY	+/–	0.0949	0.0401	**
rLeverage	+	0.0174	0.0263	
CS	?	0.2887	1.0409	
IT	?	2.3207	1.0313	**
R	?	1.8270	1.1379	

Significance codes: *** 1%; ** 5%; * 10%.

First, I consider the transformed data before any aggregation. With these data, the results are remarkably consistent across the various proxies used: in particular, using ranked size proxies rather than log-transformed alternatives does not significantly alter the results, either in terms of the significance of the variables, or in terms of general goodness-of-fit. The pseudo R^2 and adjusted pseudo R^2 values suggest that the models using lnTotA/rTotA and lnSales/rSales as size proxies give the best results, whereas using rDY as the value/growth proxy is also successful. These conclusions are reflected in the results below.

Looking first at the size proxies, the log-transformed versions always have negative coefficients whilst the ranked proxies have positive coefficients in all but one instance (rMV in a single regression, although not at any reasonable level of significance), consistent with the proposition that smaller firms might be more likely to offer DC pension schemes. The coefficient on rMV is never significant at any reasonable level, and that on lnMV is also frequently insignificant; however, apart from the one regression involving rMV, these proxies do have the predicted sign. This is in contrast to the earlier single-dimensional analysis, suggesting that the presence of other explanatory and dummy variables is countering the "tech stock boom" effect. All other size proxies are significant at the 1% level of confidence.

Turning next to rSoA, the capital base proxy, the coefficient on this variables is always positive and significant at either the 1% or the 5% level. This suggests that firms with a low level of rSoA, or a strong asset base, are more likely to have no DB pension scheme. This is in line with the Bradley, Jarrell and Kim (1984) asset base argument for DB provision, and consistent with the earlier results.

The coefficient for rEBIToA is consistently negative and almost always significant. This again suggests that it reflects a risk rather than a tax proxy and that risky schemes do (or perhaps that firms with DB pension schemes are less likely to be profitable). The results are best when rEtoP is the growth/value proxy, and worst when rMtoB fulfils this role. The low (or absent) significance when rMtoB is the growth/value proxy is a result of multicolinearity arising from the relatively high correlation between these two variables (0.571). Its significance is also lower when either lnMV or rMV is the size proxy.

The coefficient on rDDAoEBITDA is always negative and, unlike the earlier analysis, almost always significant. This supports the hypothesis that firms with low levels of non-debt tax shields are more likely to want to have a defined benefit pension fund – firms with large non-debt tax shields are less likely to need the tax-deferral flexibility offered by a DB pension scheme.

Next, it is time to look at the growth/value proxies. The coefficients on rDY and rEtoP are always positive, whereas those on rMtoB are always negative. This supports the hypothesis that growth firms are less likely to offer a DB pension scheme, so are attracted by the (generally) lower cost of DC schemes rather than the prospect of contribution flexibility in DB arrangements. Within these results, the coefficient on rDY is always strongly significant, where as those on rEtoP and rMtoB are significant mainly when either lnMV or rMV is the size proxy.

Finally for the "main" variables, the coefficient on Leverage is always positive and almost always significant at a reasonable level. This supports the theory that DB pension schemes are used as borrowing once the maximum level of debt issuance has been reached.

Next, I look at year proxies. The coefficients on many of these are significant, sometimes as early as 1989, sometimes as late as 1997, and always from 1992 to 1995. The range of years with significant coefficients is generally longer when rEtoP is the growth/value proxy. It might be thought that these proxies mainly control for the variation in the log-transformed size proxies over time; however, the proxies are at least as significant when ranked size proxies are used, where there is no change in the average level of proxy over time. Instead, it seems that the proxies are controlling for the low number of firms without DB pension schemes up to and including 1997: up to this point in time there were no more than three firms per year without a DB pension scheme; after 1997, there were no fewer than five.

Finally for this part of the analysis, the three industry dummy variables are all significant in all regressions, at levels of at least 5% and usually at 1%.

Next, I consider the aggregated transformed data. The pseudo R^2 values are much higher in these regressions, although the difference between the values of the two sets of adjusted pseudo R^2 numbers – which gives a fairer comparison – is smaller, although the results from regressions using rDY as the growth/value proxy are much better using the aggregated data. An interesting difference is that the aggregated results seem much less affected by changes to the size proxy.

The results here are less positive in terms of the number of significant variables. In many cases there are changes to the coefficients on the explanatory variables, but the main cause is the fact that the standard errors have increased by a factor of around three, as might be expected given that the number of observations has fallen by around ten.

None of the size proxies are significant at any reasonable level. However, the coefficient on the asset base proxy rSoA is significant at the 10% level in four of the nine regressions. In all regressions, rSoA has a positive coefficient, supporting the earlier analysis.

The coefficients on neither rEBIToA nor rDDAoEBITDA are significant. However, the growth/value proxies give better results – the coefficients on rMtoB and rDY are always significant at a reasonable level, and the coefficient on rEtoP is significant in one of the three regressions in which it appears. The coefficients on rDY and rEtoP are positive, and the ones on rMtoB are negative. This supports the earlier analysis suggesting that growth firms are less likely to have DB pension schemes. The coefficients on rLeverage are never significant.

The coefficients on the economic group proxies are significant in many instances: in all regressions for Information Technology and in all but one for Resources.

The results are similar if the explanatory variables are obtained by aggregating the ranks relative all data rather than the ranks within each year – in fact, the only differences are that rSoA is significant more frequently (in six of the nine regressions) and that the economic group proxies feature less often.

The results from the aggregated data perhaps suggests that useful information is being lost in the process of aggregation, or alternatively that the unbalanced nature of the panel is leading to a level of significance being shown that is higher than is accurate.

6 Conclusion

There are significant differences between the firms that offer DB pension schemes and those that offer DC arrangements. The first to note is the difference between industries. In particular, Information Technology and Resources firms seem less likely than others to offer a DB pension scheme. However, even after controlling for industry, other differences remain between firms. The unbalanced panel data analysis suggests that small firms are much less likely than other firms to offer defined benefit pension schemes, possibly because small firms are young and can better appreciate the true cost of such an arrangement: the cost of running a DB pension scheme has increased significantly over the last ten years or so, as discussed in Sweeting (2006), so younger firms might be less likely to commit themselves to this type of arrangement if given a choice. Having said this, these results are not found when the aggregated data are used.

Firms with a small asset base are more likely to offer defined benefit pension arrangement due to the financial opacity offered by such arrangements. This result is seen in almost all of the regressions carried out.

There is evidence in the panel data that unprofitable firms tend to avoid offering DC pensions, suggesting that the flexibility of DB pension contributions is appreciated by firms making less profit (although it could be that the high cost of DB pension provision has led firms offering such schemes to be less profitable than those offering DC arrangements). The panel data also show that this flexibility is also appreciated by firms with low levels of non-debt tax shields, who are able to use such schemes as a way of managing their tax positions.

“Value” firms are much more likely than “growth” firms to offer DB pension arrangements, suggesting that the lower cost of DC is more important to “growth” firms than the financial flexibility offered by DB. This is seen both in the panel data, and in the aggregated data. Finally, high leverage seems to coincide with the offer of a defined benefit pension scheme, suggesting that such schemes are used as a source of debt funding, although this is seen only in the panel data.

In summary, the type of pension arrangement chosen by a sponsoring employer appears to say a lot about that firm.

References

Bera, A. and Jarque, C. (1981). "Efficient Tests for Normality, Heteroskedasticty, and Serial Independence of Regression Residuals: Monte Carlo Evidence," *Economics Letters, 7*, 313–318.

Bernartzi, S. and Thaler, R., (2001). "Naïve Diversification Strategies in Defined Contribution Saving Plans," *American Economic Review, 91*, 79–98.

Blume, Marchall E., (1980). "Stock Returns and Dividend Yields: Some More Evidence," *Review of Economics and Statistics*, *62*, 567-577.

Bodie, Z., Marcus, A. and Merton, R., (1988). "Defined Benefit vs. Defined Contribution Pension Plans: What are the Real Trade-Offs?," *in Z. Bodie, J. Shoven, and D. Wise (eds), Pensions in the U.S. Economy,* University of Chicago Press.

Bradley, M., Jarrell, G. A., and Kim, E. H., (1984). "On the Existence of an Optimal Capital Structure: Theory and Evidence," *Journal of Finance*, *39*, 857–878.

Buckmaster, D., and Saniga, E., (1990). "Distributional Forms of Financial Accounting Ratios: Pearson's and Johnson's Taxonomies." *Journal of Economic and Social Measurement*, 16, 149–66.

Choi, J., Laibson, D., Madrian, B. C. and Metrick, A., (2002). "Defined Contribution Pensions: Plan Rules, Participation Decisions, and the Path of Least Resistance," *in J. Poterba (ed), Tax Policy and the Economy Volume 16*, MIT Press.

Clark, R. L. and Schieber, S. J., (1998). "Factors Affecting Participation Rates and Contribution Levels in 401 (k) Plans," *in O. Mitchell and S. Schieber (eds), Living with Defined Contribution Pensions: Remaking Responsibility for Retirement,* University of Pennsylvania Press.

DeAngelo, H. and Masulis, R. W., (1980). "Optimal Capital Structure under Corporate and Personal Taxation," *Journal of Financial Economics*, *8*, 3–29.

Francis, J. R. and Reiter, S. A., (1987). "Determinants of Corporate Pension Funding Strategy," *Journal of Accounting and Economics*, *9*, 35–59.

Government Actuary's Department, (2006). *Occupational Pension Schemes 2005 – The Thirteenth Survey by the Government Actuary*.

Holden, S. and VanDerhei, J., (2001). "Contribution Behavior of 401(k) Plan Participants," *Investment Company Institute Perspective*, *7.*

Holden, S. and VanDerhei, J., (2003). "401(k) Plan Asset Allocation, Account Balances, and Loan Activity in 2001," *Investment Company Institute Perspective*, *9.*

Huberman, G., Sheena S. I. and Wei J., (2004). "Defined Contribution Pension Plans: Determinants of Participation and Contribution Rates," *working paper, Columbia University*.

Kane, G. D. and Meade, N. L., (1998). "Ratio Analysis using Rank Transformation", *Review of Quantitative Finance and Accounting*, 10, 59-74.

Kolari, J., McInish, T. H. and Saniga, E., (1989). "A Note on the Distribution types of Financial Ratios in the Commercial Banking Industry", *Journal of Banking and Finance*, 13, 463–471.

Kruse, D. L., (1995). “Pension Substitution in the 1980s: Why the Shift Toward Defined Contribution Plans?” *Industrial Relations*, *34,* 218–241.

Mann, H. B. and Whitney, D. R., (1947). “On a test of whether one of two random variables is stochastically larger than the other”, *Annals of Mathematical Statistics, 18*, 50-60.

Munnell, A. H., Golub-Sass, F., Soto, M. and Vitagliano, F., “Why are Healthy Employers Freezing their Pensions?”, w*orking paper, Center for Retirement Research, Boston College*, 2006.

National Association of Pension funds, (2005). *Annual Survey*.

Papke, L. E., (1999). “Are 401(k) Plans Replacing Other Employer-Provided Pensions?”, *Journal of Human Resources*, *34*, 346–368.

Papke, L. E., (2002). “Choice and Other Determinants of Employee Contributions to Defined Contribution Plans,” w*orking paper, Center for Retirement Research, Boston College*.

Poterba, J. M., (2003). “Employer Stock and 401(k) Plans,” *American Economic Review*, *93*, 398–404.

Sweeting, P., (2006). “The Cost and Value of Defined Benefit Pension Schemes”, *Pensions Institute Working Paper PI-0618.*

Yang, T., (2005). “Understanding the Defined Benefit versus Defined Contribution Choice”, *working paper PRC WP 2005-4, Pension Research Council*.