Three Essays on Chinese and UK Defined Benefit Pension Schemes

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To my family, with love

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Time flies, in a twinkling, I spent four rich and meaningful years at the ICMA Centre, Henley Business School, University of Reading. These four years of doctoral life have made me realize the breadth and profundity of finance. At the same time, my knowledge level, teaching and practical abilities have been improved, and my life has a new direction as well.

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Abstract

This thesis contributes to the quantitative and qualitative analysis of optimal asset-liability portfolio allocations for the Chinese basic pension fund (BPF) pillar 1B, based on various investment constraints; investigations of the determinants of the equity asset allocations of UK defined benefit (DB) pension schemes and the reasons for a hard freeze decision by these DB schemes.

The first contribution is the application of an asset-liability model (ALM) to compare the effects of various investment constraints on the efficient portfolio of the BPF. Using an ALM, we investigate the effects of different investment limits, pooling investment by the national social security fund (NSSF) and raising retirement age, on asset allocations. We find that an ALM is superior, and removing the limits on investment in domestic assets would be beneficial, as would transferring the assets to the NSSF and raising the retirement age.

The second contribution is the first empirical analysis of the effects of non-linear default risk, leverage, cash flow volatility, company or sponsor size and pension scheme maturity on the asset allocation of DB schemes. We investigate the determinants of the equity allocation of UK pension funds using a panel of 125 FTSE 100 companies from 2003 to 2019. Seven variables have a significant effect on the equity allocation with the biggest effects coming from scheme maturity, the scheme's funding ratio and a time trend.

The third contribution is the first empirical analysis of the reasons for a hard freeze decision of UK DB schemes. Using an expanded panel from the last study, we find that

five variables have a significant effect on the probability of making a hard freeze decision. The results suggest that a hard freeze may also have led to some movement in their post-freeze values of these variables back towards their pre-freeze values.

Table of Contents

List of Tables

List of Figures

1. Chapter One: Introduction

1.1. Background for the thesis

There are two main types of occupational pension scheme - defined benefit (DB) and defined contribution (DC). Employers sponsoring a DB scheme promise to pay members a pension for the rest of their lives (effectively a lifetime annuity) based on each member's final or average salary. This pension promise is independent of the risks arising from investment returns, interest rates, longevity, salary levels, inflation rates and regulations. All these risks are assumed by the employer, and only employer default risk is borne by the members. In contrast, DC schemes do not create any risks for the employer, as they just pay a proportion of each member's salary into that member's pension pot, with all the risks falling on the members (Bassett, Fleming, and Rodrigues 1998).

Global DB schemes, in both public and private sectors, have been facing a series of challenges, such as the rising longevity, an increasing dependency (non-workers to workers) ratio, economic slowdowns, and increasing associated costs and risks due to the nature of DB schemes.

To alleviate the problems caused by these challenges, the government authorities have launched reforms to public DB pension schemes, for example, raising the retirement age which results in more contributors and fewer pensioners (James 2002; Queisser, Reilly, and Hu 2016; Imrohoroglu and Zhao 2018), easing the investment regulations to allow higher equity investment limits or investments in alternative asset (Hu, Fiona, and Yermo 2007), pooling the investment of separated schemes for accessing more investment expertise and achieving economies of scale (Mitchell and Andrews 1981; Chemla 2004; Dyck and Pomorski 2011; Bikker 2017).

In 2015, there were two changes to the regulations governing the investment of the Chinese basic pension fund (BPF) assets by the provinces. The upper and lower limits on the proportions of assets invested in different asset classes were changed (State Council 2015), and the provinces were allowed to transfer their BPF assets to the Council of National Social Security Fund (NSSF). As a DB cash balance pension plan, the pillar 1B of the BPF's goal is to accumulate enough assets to meet their liabilities, not to maximise their returns; and so, asset performance relative to the liabilities is more important than beating a benchmark (Sutcliffe 2016). Board and Sutcliffe (2007) find that including the liabilities affects the optimal portfolio weights, and managers of DB pension funds should not ignore the liabilities when investing the funds. Hoevenaars et al. (2008) conclude that an assets-only model tends to select short-term assets (e.g. T-bills) because of their low risk in the short run, and good diversification with stocks in the long run. But when liabilities are added to the model, long-term investment assets tend to be selected, as they provide a better hedge against the duration mismatch risk with respect to the liabilities. These lead to four main questions to be answered for the Chinese BPF pillar 1B in this thesis: how the asset allocation and performance of the BPF is affected by the inclusion of the BPF liabilities in the portfolio model; what the effects of the various investment regulations on the BPF's optimal asset allocation and performance; will transferring the funds to the NSSF improve the asset performance; and what would be the effects of raising the retirement age to 65 on the asset allocation, liabilities and investment performance of the BPF?

The asset allocation of DB pension schemes is one of the most important decisions taken by such schemes. It has a major effect on their investment performance, which then affects the scheme's funding ratio and contribution rates. DB pension scheme asset allocation has been the subject of a very active debate by trustees, actuaries, fiduciary managers, sponsors, fund managers, academics and regulators. Theory indicates that three factors affect the asset allocation of DB pension schemes. The tax arbitrage strategies of Black (1980) and Tepper (1981) imply 100% investment in bonds, while the under-priced default insurance model of Sharpe (1976) leads to 100% investment in equities.

In addition to these three factors, a pension fund's asset allocation may be affected by the default risk of the sponsor (Rauh 2009). A further influence on a pension fund's asset allocation is the degree to which the asset allocation is re-balanced in response to price changes (Bikker, Broeders, and De Dreu 2010; Rauh 2009). High levels of leverage tend to increase the risk of default by the sponsor, and Davis and De Haan (2012) found that Dutch DB pension funds with a more highly levered sponsor have a lower equity allocation. Various studies have found that DB pension funds with a large sponsor also tend to have higher equity allocations (US – Amir and Benartzi 1999; Netherlands – Bikker et al. 2012; Netherlands – Davis and De Haan 2012; Switzerland – Gerber and Weber 2007; Kenya – Ngugi and Njuguna 2018; US – Rauh 2009). Another factor that has been found to influence asset allocations is the volatility of the sponsor's cash flows (Amir and Benartzi 1999). The maturity of a scheme's liabilities may also affect a pension fund's asset allocation (Amir and Benartzi 1999; Friedman 1983; Lucas and Zeldes 2009).

The results for other countries do not necessarily apply to the UK due to institutional differences. The asset allocation decision is affected by UK pension legislation, the requirements of the Pension Regulator and UK institutions such as the Pension Protection Fund (Yuan and Lui 2016), as well as by the different circumstances of each scheme. Therefore, this thesis aims to deliver a better understanding of the determinants of asset allocation within the UK context that will help both those making this decision, and those regulating and insuring pension schemes, as well as investors in DB scheme sponsors.

As for employers or sponsors from the private sector, they want to escape from a DB scheme's costs and risks, thus choosing to freeze their DB schemes. There are two main types of freeze: a soft freeze occurs when no-one can join the scheme, but existing active members can continue making contributions and accruing benefits; a hard freeze is when no-one can join the scheme, and active members cannot make any further contributions or accrue new benefits. Freezing DB schemes has been widely adopted in both the UK and US. From about 1990 onwards, UK companies have been freezing their DB schemes in increasing numbers and replacing them with defined DC schemes. In 2006 the proportion of open DB schemes was 66%, but by this had dropped to 24% by 2020 (Pension Protection Fund 2020). Over the 2003-2013 period, there was a rapid increase in the proportion of US schemes that were hard frozen, and by 2013 hard frozen schemes were much more common in the US than soft frozen schemes (PBGC 2008, 2013).

Previous research on scheme closures has used US data (Atanasova and Hrazdil, 2010; Beaudoin, et. al, 2010; Begley, et. al, 2015; Choy, et. al, 2014; Comprix and Muller, 2011; Hwang and Hong, 2021; Kim, et. al, 2015; Munnell and Soto, 2007; Rauh, et. al, 2020; Silverstein, forthcoming; Vafeas and Vlittis, 2018; Yu, 2016). They find it is a positive function of the probability of employer bankruptcy, employer credit risk, a loss making employer, the scheme's level of annual benefit accrual, the projected benefit obligation (PBO) minus the accumulated benefit obligation (ABO), the ratio of (pensioners/total participants), scheme assets are less than the PBO, the proportion of independent directors of the employer, the introduction of accounting standard SFAS 158, the number of schemes sponsored by the company, the employer's age, the percentage of other companies in the same industry that have DC schemes, an increase in disclosure requirements, and after an increase in the employer's sales. The probability of a freeze is decreased by scheme size, the ABO, the ratio of (actives/total employees), the unemployment rate, the unionization of the employer's workforce, CEO accumulated pension benefits, and the employer's size, fixed assets, intangible assets, debt/equity ratio, (operating income/total assets) ratio, the employer's interest coverage, the length of tenure of the employer's CEO, and after an increase in dividends paid by the employer. Previous studies have reached opposite conclusions on whether a higher funding ratio increases or decreases the probability of a freeze.

There has been a recent study (Li, Liu and Newton, 2021) of the reasons for freezing UK DB schemes, and their conclusions are different from those of the US studies. The freeze decision appears to be governed by a wide range of factors, which does not permit the simple conclusion that employers in a weak financial position with poorly funded schemes are more likely to freeze their DB schemes to reduce their costs and risk. Since there are substantial differences in the DB pension regulatory and institutional environment between countries, the US results may not be generalizable to the UK or other countries, and hence this thesis focuses on exploring the reasons for the closure decisions made by UK-listed companies.

1.2. Overview of the thesis

This thesis provides the applications of the asset-liability model (ALM) to the Chinese BPF on the basis of different investment constraints, which are aimed at comparing the effects on the efficient frontiers. At the same time, this thesis offers estimates of the determinants of equity asset allocation and causes of hard freeze decisions by DB pension plans in the UK.

First, this thesis defines pillar 1B of the Chinese BPF as a DB cash balance scheme. Only a few authors have considered whether pillar 1B of the BPF is a DB or DC scheme. Although OECD (2017) describe the individual accounts of pillar 1B as DC, these accounts are largely notional, with interest credited at a rate set by the government, and benefits received as a lifetime annuity (Bateman and Liu 2017). The government, in the form of the province, is responsible for investing the money in these accounts, and for any deficits (Dorfman et al. 2013; Wang, Beland, and Zhang 2014a). Meanwhile, since the sponsor of pillar 1B invests the assets and bears the investment risk (Cahill and Soto 2003), pillar 1B is operating as a DB cash balance scheme.

Unlike other institutional investors, the goal of DB schemes is to accumulate enough assets to meet their liabilities, not to maximise their returns; and so, asset performance relative to the liabilities is more important than beating a benchmark (Sutcliffe 2016). Thus, the asset allocation decision of DB schemes can be treated as a portfolio problem, where the aim is to invest the funds to minimise the combined asset and liability risk, subject to a given rate of return. As a first step, we calculate the actuarial liabilities for six different types of member– active members and pensioners, each in three groups (male employees, female officials in public institutions and female blue-collar workers). Together with assumptions of the notional rate of return for each type of liability, average age for each type of pension member and their average annual salary, we find that the total actuarial liability has exceeded the total accumulated assets in pillar 1B since 2001, and the deficit had grown to around US$200 billion in 2016. This fiscal burden for the government is forecast to increase further in the future, since the accelerating growth of the pillar 1B deficit is consistent with the rapid ageing of the Chinese population.

And then we address this portfolio problem through expanding and adjusting the traditional Markowitz portfolio model to include these liabilities to create a single period ALM (Board and Sutcliffe 2007; Sharpe and Tint 1990). Additionally, to ease the challenges pillar 1B faces, several types of reforms have been discussed and implemented, such as delaying retirement (James 2002; Queisser, Reilly, and Hu 2016), more lenient investment restrictions (Faugere and Shawky 2003; Hu, Fiona, and Yermo 2007) and pooled investment of the BPF assets (Bikker 2017; Dyck and Pomorski 2011;

NSSF 2018; Shen et al. 2019).

In 2015, the government not only introduced new investment regulations to ease the restrictions, but also encouraging provinces to transfer their BPF pillar 1B assets to the NSSF to invest in a pooled manner. We thus compare the efficient frontiers of pillar 1B asset under five different investment constraints: 1) post-2015 limits; 2) pre-2015 limits; 3) instantaneous raising retirement age to 65; 4) NSSF limits; and 5) no limits. We find that the shape of the ALM frontier is different, and has substantially higher risk for every level of return, due to the inclusion of the six types of liabilities. Thus, an ALM is preferable to an assets-only approach, if only because it reveals the correct risks and returns of the scheme, and prevents fund managers and the government from thinking the current investment regulations are compatible with boosting the previous sluggish performance. After the comparison between pre-2015 and post-2015 limits, we conclude that the post-2015 limits help alleviate the problem of empty individual accounts due to higher investment returns. It also suggests there may be further benefits from an additional relaxation of the restrictions. Thus, we remove all investment constraints, and find that allowing unlimited investment in foreign equities and fixed-income products would provide no benefit; but relaxation of the restrictions on domestic equities and corporate bonds would achieve a higher expected return. Pooled management by the NSSF will also increase returns due to more favourable investment limits, superior investment expertise and economies of scale. We also find that an instantaneous increase in the retirement age to 65 is a challenging pension reform option for China in short term. If the Chinese retirement age is increased to 65, we find that the liabilities of active members will increase by over 40%. When we include these liabilities, compared to the ALM with current retirement ages, while the expected returns of the asset–liability portfolios are largely unchanged, their risk increases considerably.

Second, this thesis measures the scheme maturity using the effective duration of DB pension liabilities. There is no agreed way of measuring scheme maturity, and a large number of alternative definitions have been used in previous empirical studies (Chandler 2017; Defau and De Moor 2018; Lucas and Zeldes 2009; Rauh 2009 and so on). Most of these measures of maturity simply group participants according to their age or membership status. However, this ignores substantial differences in the magnitude of the benefits accrued by participants of the same age or membership status. Since scheme maturity influences a pension fund's asset allocation via its effect on when the scheme's liabilities fall due for payment, what is needed is a summary measure of the timing of future pension payments, irrespective of the age or membership status of participants. We therefore follow McCaulay (2013) and calculate effective duration to measure the duration of pension liabilities. There is a clear downward trend in the average maturity of pension liabilities per year for our sample companies, dropping from 21.2 years in 2003 to 17.8 years in 2019.

Besides the effective duration (*ED*), we include nine different explanatory variables to empirically estimate the effects on the equity asset allocations of 125 UK-listed companies: 1) the funding ratio (*FR*) and 2) the funding ratio squared (FR^2) to allow for a non-linear relationship between the funding ratio and equity allocation (Bader 1991);

3) the financial leverage ratio (*LEV*) to capture the effect of debt (Amir, Guan, and Oswald 2010); 4) the standard deviation of operating cash flows (*SDCF*) to capture the associated risks of fluctuate operating cash flows; 5) the natural logarithm of the sponsor's market capitalization (*Size (SMC)*), or the natural logarithm of the pension assets (*Size (PA)*), alternatively, to capture the effect of company or plan size (De Dreu and Bikker 2012; Gorter and Bikker 2013); 6) an indicator variable (*Close*) to capture the effect of hard closure (Butt 2011); 7) a dummy variable (*EHB*) to capture the effect of higher total return on equity index than that on bond index. 8) an indicator variable (*Overseas*) to capture the effect of pension assets in overseas schemes, since these schemes are subject to different regulations and tend to have younger membership structure; 9) and a time trend (*T*) to control the time effect of equity allocation changes in the UK (Sutcliffe 2005).

The empirical results show that, when size is denoted by company size, equity allocation is increased by 1.232% when the *ED* of DB pension liabilities is increased by one year. The positive coefficient on the *FR* (0.431) and the negative coefficient on the FR^2 (-0.004) indicate that increases in the funding ratio of the DB schemes have a net positive effect on the equity asset allocation but at a decreasing rate, when funding ratios are less than 54% (only 2.84% of observations are within this range). However, for funding ratios above 54%, the equity allocation decreases, presenting an inverted *U*-shaped relationship, thus supporting a risk shifting empirical reality in the UK. As expected, more levered companies (*LEV*) have lower equity allocations (the coefficient equals 0.089), the coefficient (-3.413) of *Close* means hard closed schemes have a lower equity asset allocation, and those companies with more than 20% of their pension assets in foreign schemes (*Overseas*) have equity allocations that are 4.900% higher. The negative coefficient (-1.178) on *Size (SMC)* and the negative coefficient (-2.097) on *T* reveal that larger schemes have responded more strongly to the general trend for de-risking in the UK. When we measure size using total pension asset, the main conclusions stay the same.

To further measure the importance of each explanatory variable. We also use sensitivity analysis to quantify the effect of a one standard deviation change in the value of each significant non-dummy explanatory variable on the predicted average equity allocation. The dependent variable is most sensitive to variations in *T* (24%), closely followed by variations in *FR* (−21% for an increase, and 13% for a decrease of one standard deviation). Variations in *ED* have half the effect (12%) of *T* and *FR* on the equity allocation. Variations in *LEV* have a much smaller effect (4%), and *Size* has an even smaller effect (below 1%). Overall, the results support positive effects for *ED*, *FR* *LEV, Size* and *Overseas,* and negative effects for FR^2, *Close* and *T.* Apart from *Size,* the signs of other significant variables are in accord with our prior expectations.

Finally, the thesis estimates the probability of a freeze decision made by UK DB pension schemes. The freeze decision appears to be governed by a wide range of factors, which does not permit the simple conclusion that employers in a weak financial position with poorly funded schemes are more likely to freeze their DB schemes to reduce their costs and risk. Previous evidence for US DB schemes has found that there is a wide range of elements that cause a freeze[1]. For example, it is a positive function of employer's credit risk, scheme assets are less than scheme liabilities, the employees' average age, and an increase in the sales revenue. The probability of a freeze is also decreased by scheme size, sponsor's size, the unionization rate of the employer's workforce, and an increase in dividend pay-outs. A recent study of the causes of freezing UK DB schemes has reached opposite conclusions from those of US studies, e.g. the probability of a hard freeze is a positive function of the funding ratio, employer and scheme sizes; and is decreased by the employer's leverage and annual level of benefit accrual (Li, Liu and Newton 2021). It suggests that there are essential differences between the freeze decision in the US and UK.

Our sample for the empirical analysis is 125 companies with a DB pension scheme that were members of the FTSE 100 at some point between 2003 to 2019. This research focuses on hard freezes because they have the largest effect on the employer. We regress the hard freeze dummy on 13 explanatory variables in the empirical model to explore the reasons for a hard freeze decision. They are the funding ratio, company size, operating cash flows, whether the employer suffered a loss from the previous year, effective duration (as a proxy for pension plan maturity, following Zhao and Sutcliffe (2021)), unionization rate of the workforce, leverage ratio, whether the schemes have been soft frozen, changes in CEO, sales revenue, dividend pay-outs, R&D expenses, and capital expenditures. We compute that the proportion each year of companies in

[1] Atanasova and Hrazdil 2010; Beaudoin et. al, 2010; Begley et. al, 2015; Choy et. al, 2014; Comprix and Muller 2011; Hwang and Hong 2021; Kim et. al, 2015; Munnell and Soto 2007; Rauh, et. al 2020; Silverstein 2021; Vafeas and Vlittis 2018; Yu 2016.

our sample with a hard frozen scheme. There is a clear upward trend, increasing from 2% in 2003 to 60% in 2019. And in 2011, the number of employers who hard froze their DB scheme jumped to a higher annual rate that was maintained for the next seven years. Most hard freezes are concentrated in the industries of consumer services, financials and industrials.

To prevent confounding the effects of a freeze with the causes of a freeze, we first remove the post-freeze observations from the panel regression. The empirical results show that large employers with a small operating cash flow and a highly unionized workforce are less likely to hard freeze their scheme; while those who have previously soft frozen their scheme and whose sales revenue has increased are more likely to freeze their scheme. The other explanatory variables are not significant, showing that hard freezes are not motivated solely by financial pressures. To further investigate the sensitivity of our empirical findings, we re-estimate the model with two types of modified dependent variables, the freeze dummy is set to one in both the year of the freeze and in all subsequent years, and the freeze dummy is set to one in the freeze year and zero in all post-freeze years. These results of these robustness tests not only further confirm the findings of the exclusion of post-freeze observations, but also suggest that a hard freeze is followed by an increase in the funding ratio and R&D expenditure; an increase in leverage, which reduces the probability of a hard freeze; and that the freeze may have led to some movement in their post-freeze values of these variables back towards their pre-freeze values.

1.3. Contributions of the thesis

There have been increasing issues and concerns regarding the investment performance, asset allocations, and risks for public and private DB pension plans, because of the growing challenges (e.g. rising longevity). Sponsors in both developed and emerging countries from public and private sectors have initiated reforms and adjustments to their DB pension plans to mitigate the negative effects on these plans or sponsors. The regulatory authorities, policy makers, trustees, plan sponsors and members will benefit from an exploration of the effects of these reforms and adjustments. This thesis, consisting of three main chapters, contributes to the quantitative and qualitative analysis of optimal asset-liability portfolio allocations for Chinese BPF pillar 1B based on various practical and hypothetical investment regulations and constraints, investigations of the determinants of the equity asset allocations of UK DB pension schemes and the causes of a hard freeze decision by these DB pension schemes.

First, the contributions of the application of ALMs to the Chinese BPF include: we compare the assets-only efficient frontier to that of an ALM with six groups of pension liabilities; we use an ALM to compare the effects of the pre-2015, post-2015 and no investment restrictions on the efficient portfolio of the BPF; we use an ALM to analyse the effects of outsourcing the BPF investment of pension funds to the NSSF; we investigate the effects on the efficient frontier of an ALM of raising the retirement age of the BPF to 65.

Second, the contributions of the study of the determinants of the equity asset allocation of DB pension schemes include: we analyse the effects of ten explanatory variables on the equity allocation, while previous studies for other countries have used only a few explanatory variables; we study the effects of non-linear default risk, leverage, cash flow volatility, size of the sponsor (or scheme) and maturity on the asset allocation of UK schemes; we include four new variables – scheme closure to new contributions, overseas pension assets, a time trend and equity returns exceeding bond returns; we measure the maturity of DB pension schemes using effective duration, which we argue is the best available measure of scheme maturity.

Third, the contributions of estimating the causes of hard freeze decisions in the UK include: we are only the second non-US study of the reasons for the closure decision, and the first study of this issue in the UK with 13 different explanatory variables; to prevent confounding the effects of a freeze with the causes of a freeze, we remove all post-freeze observations and then re-estimate the sensitivity of the model with modified dependent variables (all post-freeze dummies equal to one, or all post-freeze dummies equal to zero).

1.4. Structure of the thesis

The rest of the thesis is structured as follows: Chapter 2 applies the ALM to the Chinese BPF with six different groups of pension liabilities, and it also compares the effects of different investment constraints on the efficient portfolio of the BPF; Chapter 3 investigates the determinants of the equity allocation of UK DB pension schemes, with the first use of the effective duration of pension liabilities as a proxy to the maturity of DB schemes; Chapter 4 analyses the reasons of a hard freeze decision of UK DB pension schemes; and Chapter 5 summaries the main findings and conclusions, and presents the potential research directions based on the essays discussed in this thesis.

In order to achieve a better reading experience and logical consistency, we separately construct each main chapter to be self-contained, thus we (re)introduce variables in each chapter in isolation. We try to follow the consistent notations, explanations and signs in the whole thesis as much as possible.

2. Chapter Two: Asset-liability models and the Chinese basic pension fund

2.1. Introduction

After over 40 years of economic reform China has established a three-pillar pension system for urban employees. This system faces the challenges of rising longevity, an increasing ratio of non-workers to workers, an economic slowdown and considerable underfunding. Additional challenges include negative real returns on pension investments and a fragmented pension system. The focus of our research is on the investment of the assets of the first pillar of the basic pension fund (BPF), which is by far the largest of the three pillars. The BPF was designed to be a national state pension scheme, with the assets in the individual accounts invested by the provinces. The provinces make their own local decisions, which loosely follow a common set of national regulations; and the central government remains ultimately responsible for any deficits generated by the provinces. In 2015, there were two changes to the regulations governing the investment of BPF assets by the provinces. The upper and lower limits on the proportions of assets invested in different asset classes were changed, and the provinces were allowed to transfer their BPF assets to the Council of National Social Security Fund (NSSF) to invest on their behalf in a pooled manner, subject to national investment restrictions.

The four main questions on which we focus are: how are the asset allocation and performance of the BPF affected by the inclusion of the BPF liabilities in the portfolio model; what are the effects of the various investment regulations on the BPF's optimal asset allocation and performance; will transferring the funds to the NSSF improve the asset performance; and what would be the effects of raising the retirement age to 65 on the asset allocation, liabilities and investment performance of the BPF? To answer our first question, we compare the results of a conventional assets-only mean-variance model with that of an asset–liability model (ALM). For our second question, we solve the ALM with three different sets of investment restrictions. Our third question investigates the extent to which the NSSF's superior investment performance is due to their different investment restrictions, or to other factors. Finally, we use an ALM to study the effects of raising the retirement age to 65 to answer our last question. We compute the optimal asset allocations in 2016 using annual data for the asset and liability classes from 2001 to 2016. For both active members and pensioners, we disaggregate the liabilities into male employees, female officers in public institutions and female blue-collar workers, making six groups in total.

This is the first study of the BPF to compare the assets-only efficient frontier to that of an ALM with six groups of pension liabilities, and the first to use an ALM to compare the effects of the pre-2015, post-2015 and no investment restrictions on the efficient portfolio of the BPF. We are also the first to use an ALM to analyse the effects of outsourcing the BPF investment of pension funds to the NSSF, and the first to investigate the effects on the efficient frontier of an ALM of raising the retirement age of the BPF to 65.

We find that using an ALM is preferable to an assets-only analysis, and that the pre-2015 investment limits were very restrictive. Relaxing the post-2015 limits on domestic assets, but not foreign assets, would allow an improvement in the performance; and removing all limits would permit much higher returns, but also lead to much higher risk. Investment of pillar 1B funds by the NSSF would probably improve investment performance. Instantaneously raising the retirement age would worsen the funding ratio, but a phased change should improve the funding ratio. The notional rate of return of over 8% on the investment accounts set recently by the government (MOHRSS 2017c) will probably worsen the funding ratio as it exceeds likely investment returns.

This chapter is structured as follows: it first provides background information on the Chinese pension system, the investment restrictions, the challenges it faces and the various reforms. Next, it introduces the ALM approach to setting the asset allocation for defined benefit (DB) pension schemes. It then presents our ALM model. The following two sections describe the calculation of the liabilities, and report the asset data we use. Our results follow in the next section, and the final section concludes.

2.2. Background

2.2.1. Three-pillar pension system in China

Starting with the economic reforms in the 1980s, a multi-pillar pension fund system was established in urban China (Oksanen 2012). This system can be divided into three pillars – the BPF (pillar 1), the enterprise annuities (pillar 2) and the private annuities (pillar 3) (Dong and Wang 2016). There are some differences between those who work in the public and private sectors, and between those who live in urban and rural areas. All those who work in for-profit enterprises must participate in the BPF, which is also called Basic Old Age Insurance. Civil servants working in non-profit public institutions must join the Public Employee Pension (PEP), which was merged into the BPF in 2015. By the end of 2016, the BPF had 278.26 million active members and 101.03 million pensioners (MOHRSS 2017a). The BPF is divided into two parts: pillar 1A operates as a DB scheme on a pay-as-you-go (PAYG) basis, and pillar 1B is designed to be fully funded by individual accounts.

Only a few authors have considered whether pillar 1B of the BPF is a DB or defined contribution (DC) scheme. The OECD (2017) describes the individual accounts of pillar 1B as DC. But these accounts are largely notional, with interest credited at a rate set by the government, and benefits received as a lifetime annuity (Bateman and Liu 2017). The government, in the form of the province, is responsible for investing the money in these accounts, and for any deficits (Dorfman et al. 2013; Wang, Béland, and Zhang 2014a). DC schemes are not run in this way. For example, members of American 401(k) schemes are responsible for deciding how to invest their pension pots and may decide how much to contribute. They also decide how and when to receive benefits, and bear all the investment risk (Bassett, Fleming, and Rodrigues 1998). The operation of pillar 1B resembles a cash balance scheme, which is somewhere between DB and DC. Because members typically have an individual account and receive benefits as a lump sum at retirement, cash balance schemes look like DC schemes. But they are generally classified as a type of DB scheme, as the sponsor invests the assets and bears the investment risk (Cahill and Soto 2003). Therefore, in this study, we define pillar 1B as a DB cash balance scheme.

Pillar 1 of the BPF covers urban employees in full-time jobs or with permanent contracts. In 2009, the New Rural Resident Pension (NRP) was established for self-employed rural residents, and in 2011, the Urban Resident Pension (URP) was created for self-employed urban residents. Ning et al. (2016) find that the NRP does not improve the wellbeing of the elderly, particularly those in poor health. In 2014, the merger of these two voluntary schemes into the Resident Pension was announced, and by 2017, this scheme had 512.6 million participants (Fang and Feng 2018). It is not part of the three-pillar system.

In 1991, pillar 2, the employer-sponsored Enterprise Annuities (EA), was introduced for employees of large state-owned enterprises (SOEs). As a DC scheme, the EA is increasingly offered by employers, and has the advantage that the sponsor is not responsible for the level of pension benefits. At the end of 2016, the EA had 23.3 million members, which was only 5.8% of the number of BPF participants (Fang and Feng 2018). Pillar 3 (private annuity insurance) is intended to be complementary to the other two pillars, and most products in pillar 3 are DC schemes, with a few old DB schemes. It has been growing rapidly, and according to the annual report of the Chinese insurance market, the private annuity market expanded by 16.9% each year from 2001 to 2014 (Chinese Insurance Regulation Commission 2015). But this pillar is still in its infancy. According to Fang and Feng (2018), most existing private annuity products are treated as wealth management products, and not held for long periods. Therefore, these products are unlikely to provide an income in retirement. To develop the private annuity insurance market, on 1 May 2018 a pilot policy of tax relief was launched in the cities of Shanghai and Suzhou and in Fujian province. Investment gains are tax exempt, and

25% of the annuity payments are also tax exempt. Table 2.1 summaries the Chinese three-pillar pension system.

Table 2.1: The structure of the three pillars in China

Scheme	Pillar	Type of Scheme	Contribution Rate	Mandatory
BPF: Social Pool	1A	PAYG	Enterprise: 20%	YES
BPF: Individual Accounts	1B	DB Funded*	Individual: 8%	YES
Enterprise Annuities	2	DC Funded	Enterprise and Individual ≤ 12%	NO**
Private Annuity Insurance	3	DB/DC Funded	Individual: N.A.	NO

Notes: *Pillar 1B should be fully funded, but in practice it operates with notional accounts (Liu and Sun 2016). **Only large state-owned enterprises offer enterprise annuities to their employees, and they are voluntary for these employees (Hu, Gregorio and Li 2009; Cai and Cheng 2014).
Data sources: Feldstein (1999), Song (2009), MOHRSS (2017a) and Fang and Feng (2018).

2.2.2. Challenges to pillar 1B

Over the coming decades most countries will face a higher dependency ratio (non-workers/workers) due to rising longevity and falling birth rates. This issue will be more severe in China than any other countries due to its very large population and one-child policy[2] (Li and Mérette 2005). Peng (2008) forecasts that the demographic shift in China will be rapid, with the proportion of those over 60years old increasing from 6.9% in 2000 to 15.7% in 2030. Leung (2003) estimates that a '4-2-1' dependency ratio will appear in 2030: that is, the caring responsibility for two parents and four grandparents will rely on a solo adult child. This challenges the financial sustainability of the pillar 1A PAYG system. In 2030, cash outflows from the PAYG pillar 1A are forecast to exceed its cash inflows, and by 2037 the scheme's reserve fund will be exhausted (Xu et al. 2017). So, on current projections, from 2037 onwards pillar 1A will have insufficient funds to meet its obligations. Since the provinces are responsible for paying the pillar 1A pensions, funding problems will emerge earlier in provinces with a

[2] In 2016 the one-child policy was replaced by the two-child policy (Feng, Gu and Cai 2016).

recession.

The individual accounts in pillar 1B have suffered from the fragmentation of the BPF across provinces, and their excessively conservative investment policies. Pillar 1B funds are pooled at the provincial level, or even at the county level; and each local government has considerable autonomy in operating the BPF and investing its assets (Barr and Diamond 2010; Frazier 2010). Some local governments in poor areas, or those with a recession, have used the accumulated assets in pillar 1B to finance their current payments to pillar 1A pensioners (Sin 2005; Liu and Sun 2016). Therefore, the individual accounts in some provinces are notional, with no assets in the individual accounts (empty accounts[3]). There are also significant differences in the pension payments and conditions of pensioners of the urban, rural, SOEs, public institutions and civil service schemes, leading to unfairness (Lin 2004; Wang, Béland and Zhang 2014b; Jia 2017).

2.2.3. Reforms of pillar 1B

The literature has discussed possible reforms to pillar 1B to ease the challenges it faces, such as raising the retirement age, pooling investment of the assets, and more flexible investment constraints.

2.2.3.1. Delaying retirement

Raising the retirement age is a direct remedy for pension underfunding, which has been used by pension schemes in many other countries. A higher retirement age means there

[3] These accounts only have numbers displayed. There is no money left to invest and accumulate, since the money have been transferred to support the insufficient pay-as-you-go pillar 1A or misused to support local fiscal expenditures in some recession areas.

will be more contributors and fewer pensioners. In China, the mandatory retirement age is currently low at 60 for male workers, 55 for female officials in public institutions, and 50 for female blue-collar workers (Liu et al. 2015). In practice, the average male retirement age is 56, and that of females is around 50 (James 2002). Simulation results indicate that raising these retirement ages to 65 can postpone the time when the cash flow of the pillar 1A PAYG system becomes negative by 15 years (Wang et al. 2004).

However, these simulations implicitly assume that, if their retirement age is raised, members will continue to be employed. Fang and Zhang (2018) recently challenge this assumption. They show that the growth rate of the productivity of Chinese workers is much higher than that in developed countries. In the manufacturing and textile industries there is a surfeit of workers, and so the Chinese economy does not need to employ elderly workers to increase output. Moreover, for full-time workers in China there is a strong positive correlation between age, or years of service, and salary. Therefore, organisations may be reluctant to hire elderly workers on higher salaries. In consequence, an increase in the retirement age might not be successful, as older workers may be unable to find employment.

2.2.3.2. More lenient investment restrictions

To provide 'absolute safety' to pensioners, until 2015 investment by the pillar 1B scheme was restricted to bank deposits, domestic treasury bills and Chinese government bonds (Hu, Fiona, and Yermo 2007). These assets were too conservative to beat inflation, and the provincial pillar 1B funds experienced average negative real returns from 2011 to 2015. During this period, the average nominal return on pillar 1B assets was 2.5%, while the average inflation rate was 2.7% (Dong and Wang 2016; Zhang and Harte 2017).

Table 2.2: Chinese investment restrictions on pillar 1B funds and the social security fund[4]

Provincial investment of pillar 1B funds, pre-2015:
At least 20% in domestic fixed income and money market instruments with a maturity of under one year.
At least 20% in government bonds with a maturity of at least one year.
Provincial and NSSF investment of pillar 1B funds, post-2015:
At least 5% in domestic fixed income and money market instruments with a maturity of under one year.
Not more than 30% in domestic equity
NSSF investment of the Social Security Fund, 2006 onwards:
At least 50% in domestic and foreign bank deposits and government bonds
Not more than 10% in domestic and foreign corporate bonds
Not more than 40% in domestic and foreign equity
Not more than 20% in total foreign investments

Note: No investment is permitted in any asset not mentioned in the regulations.

Data sources: Hu, Fiona, and Yermo (2007), Leckie and Pan (2007) and State Council (2015).

With the introduction of new investment regulations for the pillar 1B individual accounts in 2015, the investment restrictions started to be eased. According to the new constraints, in contrast with the pre-2015 limits, the minimum investment in short-term investment vehicles (the duration of the investment is less than one year) decreased from 20% to 5%. The minimum proportion of 20% of assets under management (AUM) in one-year plus fixed income investments was removed; and the asset classes in this section were no longer limited to government bonds and term deposits (Hu, Fiona, and Yermo 2007). An allocation of the pillar 1B assets to equities was allowed for the first time, with a maximum proportion of 30%, but only in domestic equities (State Council

[4] The Social Security Fund was established in 2000, and the Chinese government described it as a 'strategic reserve fund' and 'the last ditch to the problem of ageing'. The assets of the Social Security Fund come from four sources: allocations from the central government's treasury, equities of SOEs, state lottery proceeds and its own investment revenues (Leckie and Pan, 2007). The Social Security Fund was the only fund managed by the NSSF before pooled investment of the BPF pillar 1B funds was permitted in 2015.

2015). Not only is the investment by pension funds in domestic equities likely to improve the investment performance of pension portfolios, but it also helps stabilise and expand the Chinese equity market and improve market efficiency (Faugere and Shawky 2003; Bohl, Brzeszczyński, and Wilfling 2009; Alda 2017). The investment restrictions (including those of the Social Security Fund) are summarised in Table 2.2.

2.2.3.3. Pooled investment of the BPF assets

The fragmented nature of the BPF has resulted in a series of problems, e.g. portability risk, and higher administration and investment costs. When migrant workers switch jobs from rural to urban areas, or from one province to another, they have to give up a proportion of the accumulated contributions in their individual accounts to transfer their pensions to the new scheme (Yang and Zhou 2017). In some cases, they may have to give up all the accumulated benefits in their pillar 1B pensions (Zuo 2014). This is because, when a migrant worker switches his/her job from one province to another, only the actual money (often less than the notional value of the individual account) is transferred, due to the problem of empty accounts. This discourages labour mobility in China.

In 2015, the State Council of China issued the ‘Regulations on the Basic Pension Fund Investment Management’. From December 2016, these regulations permit provinces to transfer their BPF pillar 1B assets to the NSSF to invest in a pooled manner, subject to the pillar 1B investment regulations. By the end of 2017, nine provinces had transferred about 430 billion Chinese yuan (accounting for 12% of the total assets in pillar 1B) to the NSSF (NSSF 2018). The central government is currently encouraging the other provinces to outsource the investment of their pillar 1B pension funds to the NSSF.

The NSSF, which is not part of any pillar of the pension system, has a better historical investment performance than the BPF (NSSF 2018). The NSSF has managed the Chinese Social Security Fund since 2000, achieving an average annual return of 8.37%. The returns of the NSSF are higher than almost all the wealth management products in China, and higher than the weighted average return of the enterprise annuities (7.57%) over the same period (Hu 2017). The NSSF uses both internal and external fund managers, and Shen et al. (2020) show that from 2000 to 2016 the external fund managers of the Social Security Fund earned better risk-adjusted returns than the internal managers, with five generating positive alphas, while funds managed internally by the NSSF failed to achieve a positive alpha. Shen et al. (2020) find that private information and alumni networks at fund management companies contributed to the total investment performance of the Social Security Fund, even though insider trading is not allowed in China. Although the Social Security Fund is subject to investment restrictions different from those to the BPF, these results suggest that pooled management by the NSSF of the pillar 1B funds has the potential to bring better investment performance. Pooled management of pension portfolios by the NSSF will also reduce the growth of the problem of notional individual accounts, as provinces will find it hard to remove money from the NSSF, except for the purpose of paying pillar 1B pensions. This should improve labour mobility, as individual accounts will be less empty.

The fragmentation of the BPF into many small pension pools has led to higher overall investment costs. Large pension funds can benefit from economies of scale, such as lower administration expenses, the attraction of in-house experts and access to additional types of assets, e.g. direct property, infrastructure, hedge funds and private equity. Evidence of this can be found in the large Canadian and US DB schemes that access asset classes unavailable to smaller schemes (Mitchell and Andrews 1981; Chemla 2004; Bikker 2017). In-house expertise can bring further cost reductions and boost returns for large pension funds (Dyck and Pomorski 2011). Pooled investment of the BPF assets by the NSSF offers the advantages of much more professional management[5], lower investment costs due to economies of scale, and greater exposure to equities.

2.3. ALMs of DB pension schemes

DB schemes have different objectives from other institutional investors. The goal of DB schemes is to accumulate enough assets to meet their liabilities, not to maximise their returns; and so, asset performance relative to the liabilities is more important than beating a benchmark (Sutcliffe 2016). A scheme has a fully hedged position if it can make its pension benefit payments, no matter how the values of its assets and liabilities fluctuate. The asset allocation decision of DB schemes can be treated as a portfolio problem, where the aim is to invest the funds to minimise the combined asset and liability risk, subject to a given rate of return. This can be addressed by expanding the traditional Markowitz portfolio model to include the liabilities, creating a single period

[5] Only a few coastal provincial administrative regions, such as the city of Shanghai and Shandong province, have experience of selecting and hiring external asset managers.

ALM (Sharpe and Tint 1990; Ezra 1991; Craft 2001, 2005).

Board and Sutcliffe (2007) use annual data from 1981 to 2002 in an ALM to optimise the asset allocation of the Universities Superannuation Scheme (USS), which is the largest UK DB pension scheme. They find that inclusion of the liabilities altered the efficient frontier. The assets-only efficient frontier lay to the northeast of the ALM efficient frontier, with different portfolio weights for any given level of risk or return. This shows that including the liabilities affects the optimal portfolio weights, and managers of DB pension funds should not ignore the liabilities when investing the funds. Using assets-only and ALM portfolio models, Hoevenaars et al. (2008) explore the intertemporal covariance structure of US assets and liabilities. They conclude that an assets-only model tends to select short-term assets (e.g. T-bills) because of their low risk in the short run, and good diversification with stocks in the long run. But when liabilities are added to the model, long-term investment assets tend to be selected, as they provide a better hedge against the duration mismatch risk with respect to the liabilities.

In the only previous study of the asset allocation of pillar 1B, Jin (2017) uses an ALM to compute the optimal asset allocations from 2009 to 2014. He concludes that pillar 1B has a low funding ratio (below 70%), and to remove this underfunding without central government subsidies, more assets need to be allocated to equity markets, or the government contribution rate should be raised. However, his model does not include the investment restrictions on pillar 1B investments which have an important effect on the asset allocation. The retirement age, annuity factor, salaries, average age at the valuation, and life expectancy differ as between active members and pensioners, males and females, and job types; but Jin's model does not disaggregate the liabilities.

2.4. Methodology

2.4.1. Calculation of the actuarial liabilities

Calculation of the actuarial liabilities is the first step in constructing an ALM model of Chinese individual accounts (pillar 1B). Board and Sutcliffe (2007) divide the liabilities into three parts: active members, deferred pensioners and pensioners. Because the retirement age is based on gender and occupation in China, we divide the individual account liabilities of pillar 1B into three groups: male members (retirement at 60), female officials in public institutions (retirement at 55) and female blue-collar workers (retirement at 50). We further divide the calculation of the actuarial liability for each group into two sections: active members and pensioners[6]. As membership of pillar 1B is mandatory for urban employees, it has no deferred pensioners.

We use extended versions of the formulae for actuarial liabilities provided by the Actuarial Education Company (2002), adapted for a cash balance scheme. Our actuarial model for active members is:

$$AL_{ai} = N_{ai} \times \left(\frac{Pot_{Pi}}{AF_i}\right) \times \left\{\frac{(1+g_i)}{(1+h)}\right\}^{R_i - G_i} \times \left\{\frac{\left[1-\left(\frac{1+h}{1+p}\right)^{-W_i}\right]}{\left(\frac{1+h}{1+p}-1\right)}\right\} \tag{1a}$$

where i = 1 represents male employees, i = 2 stands for female officials in public institutions and i = 3 is for female blue-collar workers; AL_{ai} represents the actuarial

[6] We aggregate the liabilities in these six groups across all the provinces. Since the proportions of these six liabilities and their age distributions differ as between provinces, our ALM solutions apply to China as a whole, and may differ at the provincial level.

liability for the active members in each group; N_{ai} is the number of active members in each group; P_i is the average length of service of each member at the valuation date for each group; AF_i is the annuity factor for each group; g_i is the annual forecast nominal salary growth rate for each group between now and retirement; h is the nominal discount rate between now and retirement; Pot_{Pi} is accumulated notional value of a member's individual account at the valuation date for each group; R_i is the statutory retirement age in China for each group; G_i is the average age of members in each group at the valuation date; W_i is the life expectancy of members in each group at retirement; and p is the growth rate of the price level.

The term Pot_{Pi} can be expressed as:

$$Pot_{Pi} = C[S_{i,m} + S_{i,m-1}(1+NR_{i,m}) + S_{i,m-2}(1+NR_{i,m})(1+NR_{i,m-1}) + \cdots + S_{i,1}(1+NR_{i,m})(1+NR_{i,m-1}) \ldots (1+NR_{i,2})] \tag{1b}$$

where C is a constant contribution rate, which equals to 8% according to Table 2.1; $S_{i,m}$ is average member's annual salary for each group in period m ($1 \leq m \leq P_i$); and $NR_{i,m}$ is the notional rate of return for each group in period m.

Our model of the actuarial liability for pensioners is:

$$AL_{pi} = N_{pi} \times PEN_i \times \left\{ \frac{\left[1 - \left(\frac{1+h}{1+p}\right)^{-WA_i}\right]}{\left(\frac{1+h}{1+p} - 1\right)} \right\} \tag{2}$$

where AL_{pi} is the actuarial liability for the pensioners in each group; N_{pi} represents the current number of pensioners in each group; WA_i is the life expectancy of pensioners at the valuation date; and PEN_i is the average annual current pension for each group at the valuation date. Therefore, the total actuarial liability (AL_T) of the scheme is the sum of the liabilities for these six groups:

$$AL_T = \sum_{i=1}^{n=3} (AL_{ai} + AL_{pi}) \tag{3}$$

2.4.2. Forecasting salaries

The Chinese economy has made rapid progress since its reform in 1978, and its GDP experienced double-digit growth until 2010. The annual average salary growth rate for Chinese urban employees from 2002 to 2016 was similar to the growth in GDP, with an average annual growth rate of 12.32% (MOHRSS 2017a). However, it would be unreasonable to adopt this historic growth rate as a forecast of the future growth rate, as it is unlikely that the Chinese economy will keep expanding at such a high rate over the next 25–30 years. To estimate a more realistic salary growth rate, we use a logistic growth model with an upper bound to forecast annual salaries, which is a modified version of Fan (2010):

$$y_t = \frac{K}{1 + \alpha e^{-\beta \Delta t}} \tag{4a}$$

where y_t is the average annual salary in year t; K is the upper bound on average annual salary; α is a coefficient; β is the annual salary growth rate in the previous year; Δ_t is the number of years since 1990; and e is the mathematical constant.

Equation (4a) can be rewritten as:

$$\ln\left(\frac{K}{y_t} - 1\right) = \ln(\alpha) - \beta \Delta t \tag{4b}$$

The strategic objective of China's economic development is to become a medium-level developed country by the mid-21st century. Therefore, following Wei and Qiu (2014), we assume the ceiling on average annual salary (K) is 305,875 yuan (US$50,000). They apply linear regression to Equation (4b), using the average annual salaries of urban employees in Sichuan province from 1991 to 2012. Their estimates of the coefficients in Equation (4b) can be transformed back into Equation (4a):

$$y = \frac{305875}{1 + 154.3774e^{-0.1444\Delta t}} \tag{4c}$$

where α is significant at the 10% level, and $\beta = 0.1444$ is significant at the 5% level.

We use Equation (4c) to forecast salaries. The forecast salary growth rate per annum (g_i) is the average logarithmic return on the forecast annual salaries between the valuation date and retirement. Since the three liability groups in China entered employment at different average ages and have different statutory retirement ages, the average salary growth rates for each group are different.

2.4.3. Asset-liability model

DB schemes must meet their obligations to present and future pensioners in full, and so the liabilities are included in the extended version of the traditional portfolio model. Assuming that the value of the actuarial liabilities is unaffected by the fund's asset allocation (Inkmann, Blake, and Shi 2017), the ALM can be stated in mean-variance terms with the addition of the covariances between the liabilities and asset classes, and the rates of change in the value of the liabilities.

We expand Sharpe and Tint (1990) model by dividing the total liability into six groups, which have different correlations with the various asset classes. We identify three groups (male employees, female officials in public institutions and female blue-collar workers) and two types of members (active members and pensioners).

The extended portfolio model with six types of liability is:

$$Minimise\ V_{AL} = \sum_{j=1}^{N+B} \sum_{k=1}^{N+B} x_j x_k COV_{jk} \tag{5a}$$

$$Subject\ to: R_{AL} = \sum_{j=1}^{N} x_j R_j \tag{5b}$$

$$\sum_{j=1}^{N} x_j = 1 \tag{5c}$$

$$x_j \geq 0, \qquad j = 1,2,3,\dots,N \tag{5d}$$

$$x_k = \frac{-AL_{ai}}{A_0}\ or\ \frac{-AL_{pi}}{A_0}, \qquad k = ai, pi \tag{5e}$$

plus any additional constraints on the asset weights (x_j), where V_{AL} is the variance of the asset–liability portfolio; j and k represent asset and liability classes; N and B are, respectively, the number of assets and liabilities; COV_{jk} are the covariances of returns on asset or liability classes j and k; R_{AL} is the expected return of the asset–liability portfolio; R_j is the expected return on each asset class; x_j is the portfolio weight of each asset class; x_k is the initial ratio of each type of actuarial liability to the initial value of the assets, it has a negative sign and is fixed; A_0 is the current value of the fund's assets; AL_{ai} represents the actuarial liability for the active members in each group; and AL_{pi} is the actuarial liability for the pensioners in each group.

By repeatedly solving this quadratic problem for a range of portfolio returns (R_{AL}), an asset–liability efficient frontier can be computed for comparison with the conventional assets-only efficient frontier. This is computed in a similar way to the ALM frontier, but with the liability terms removed from the model. According to the BPF investment regulations, short selling is prohibited to avoid the risks involved, and this has an important effect on the optimal asset allocation (Sutcliffe 2005). Because the liability weights are fixed, changes in the value of the liabilities and covariances between the various types of liability have no implication for the asset weights of the efficient frontier, and can be set to zero.

2.4.4. Hedging effectiveness

After computing the asset–liability efficient frontier, we use Ederington's (1979) statistic to measure the hedging effectiveness of the portfolios. This is the reduction in the variance of the asset-liability portfolio, relative to the variance of the liabilities, and can be expressed as follows:

$$HE = 1 - \frac{V_{AL}}{V_L} \tag{6}$$

where *HE* is the hedging effectiveness; V_{AL} denotes the variance of the asset–liability portfolio; and V_L represents the variance of the fund's actuarial liabilities.

2.5. Estimating the liabilities

To estimate the actuarial liabilities for each group of active members and pensioners for 2001–2016, we use data from the China Labour Statistical Yearbooks (2002–2017)[7]. For example, the number of active members and pensioners, and the average pension benefits are collected from these yearbooks. The average age of each group at the valuation date is estimated using the educational attainment of urban employees in these yearbooks. For those with no senior school qualifications, we assume an entry age of 16, which is the minimum legal working age in China. For senior school and medium vocational education graduates, we assume an entry age of 18; and for those with a high-level vocational education and college graduates we assume an entry age of 21. For bachelor's degree holders, we assume 22, and for master's and PhD degree holders

[7] We assume the pension contributions in year t in the individual accounts will be increased by at the notional rates of return in year t+1.

we assume 25. We find that the average entry age gradually increased between 2001 and 2016 for both genders, reflecting the increasing academic qualifications of employees. In 2015, the average entry age of female employees overtook that of male employees. This may be because Chinese companies tend to prefer men when they hire skilled workers and non-customer-oriented managers; and to overcome this preference women need higher academic qualifications (Kuhn and Shen 2013).

Life expectancy at retirement for male and female employees from 2001 to 2016 was collected from the World Bank's (2018) database. The database of the National Bureau of Statistics of China (2018) provides the average annual salary of urban employees, and the annual consumer price index for calculating the inflation rate. In urban China, the salary gap between male and female employees has been rising since the 1980s. The China Urban Labour Survey (CULS) of 2001 find that the average hourly earnings of females were almost 20% lower than for males, and 84% of this difference cannot be explained by differences in individual endowments. This large difference can be viewed as evidence of gender discrimination against females, although other unknown factors may also contribute to this gap (Wang and Cai 2008). We follow the CULS survey and assume that the average annual salary of women is around 16% lower than that of men. We estimate the average annual salaries of males and females in each of the three groups using the proportions of male and female employees in each group.

Chinese monthly pension payments are computed by dividing the final value of a member's accumulated pension pot by an annuity factor, as in Equation (1). Because the retirement age and average life expectancy are different for each group, the annuity factors are also different. It is 139 for male workers, 170 for female officials in public institutions and 195 for female blue-collar workers (MOHRSS 1997; Li and Lin 2019). For each liability estimation, the discount rate is the current ten-year Chinese government bond yield in each year. Summary statistics of the demographic data used to calculate the actuarial liabilities of the six groups are displayed in Appendix 2.1.

The computation of the six liabilities each year allows for changes in the number of active members and pensioners in each group, the level of inflation, the average salary and other demographic factors (e.g. life expectancy), and changes in the notional rate of return. According to the regulations[8], to diminish the unfairness of the fragmented pillar 1B system, every province must update the balance of individual accounts each year by at least the one-year commercial bank deposit rate (MOHRSS 2017b). However, this rate is lower than the inflation rate for some periods. Before the launch of this regulation, each provincial or city-level authority could set their own notional rate of return. We use the ten-year Chinese government bond yield as the notional rate of return for each liability estimate, except for 2014–2016. Based on the policy notice of MOHRSS (2017c), the notional rate of return on individual accounts (pillar 1B) of urban employees is uniformly set at 5% for 2014–2015 and 8.31% for 2016.

The total actuarial liability has exceeded the total accumulated assets in pillar 1B since 2001, and when required, government subsidies have enabled the provinces to

[8] Measures for Unifying and Standardising the Notional Rate of Return on the Individual Accounts of Urban Employees' BPF.

meet their obligation to pay pensions. The deficit has grown to 1,405,645 million yuan (around US$200 billion) in 2016 and, in contrast to Jin (2017), this fiscal burden for the government is forecast to increase further in the future. The accelerating growth of the pillar 1B deficit is consistent with the rapid ageing of the Chinese population, which challenges not only the notional individual accounts, but also the sustainability of the pillar 1A PAYG system (Peng 2008).

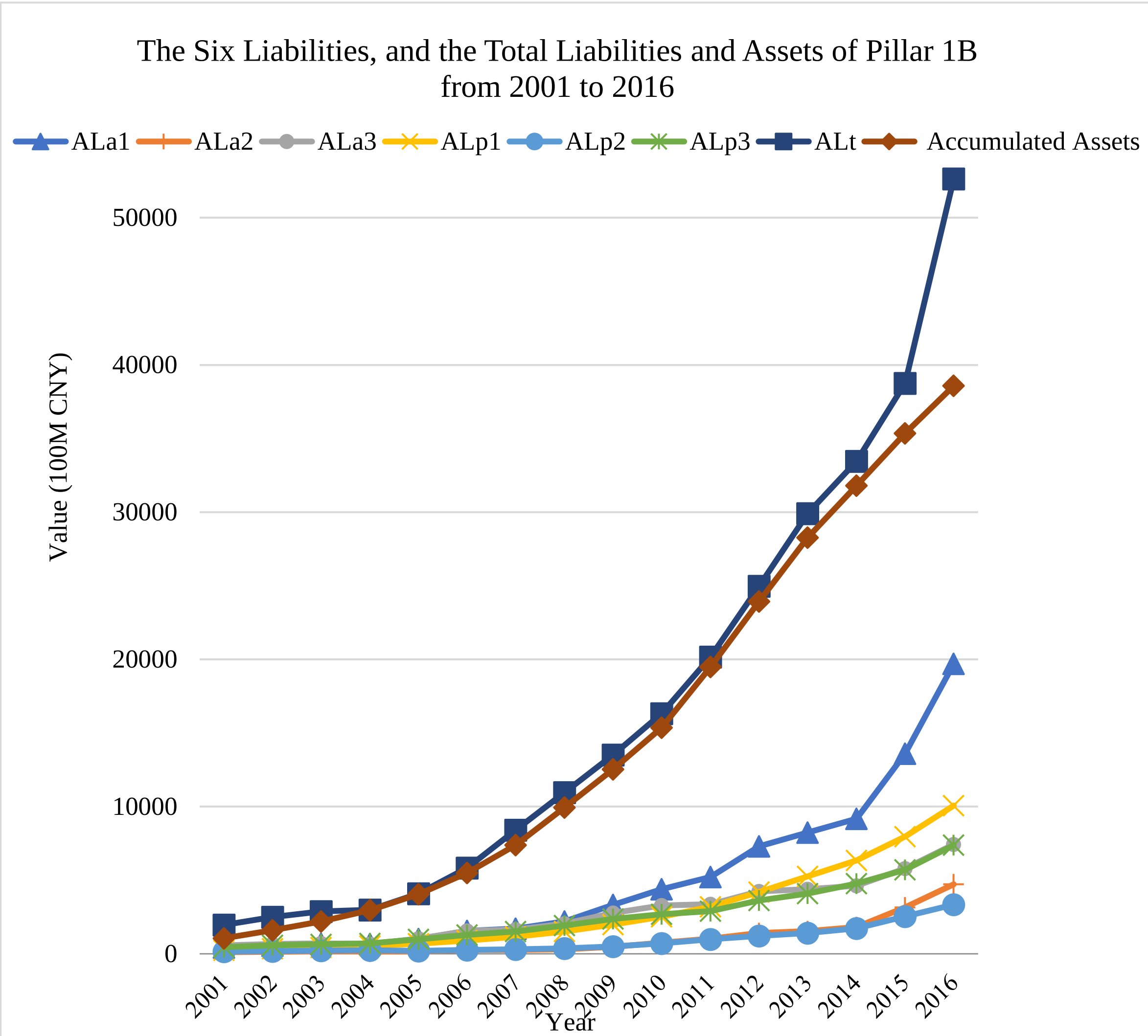

Figure 2.1: Liabilities and total assets

The actuarial liabilities of male employees are larger than for females because there are more male employees. The total actuarial liability of female active officers in public institutions is smaller than for active female blue-collar workers; but their average growth rate is much higher. At the end of 2016, the actuarial liabilities of the three groups of active members, as a proportion of the total scheme assets, were: males x_{a1} = -51.04%, female officials in public institutions x_{a2} = -12.24%, and female blue-collar workers x_{a3} = -19.26%. For pensioners, they were males x_{p1} = -26.10%, female officials in public institutions x_{p2} = -8.66% and female blue-collar workers x_{p3} = -19.14%. The total actuarial liability was around 1.36 times the assets, i.e. a funding ratio of 73.50%. The time series of the estimated liabilities for the six liability groups in pillar 1B, together with the total values of the assets and liabilities, are plotted in Figure 2.1.

2.6. Asset data

In compliance with the BPF investment regulations, we include the following assets: the MSCI China A-level Onshore[9] Growth total returns index[10] in CNY, the MSCI China A-level Onshore Value total returns index[11] in CNY, yields on ten-year China government bonds, the three-month China interbank offered rate provided by DataStream, and yields on the China Corporate Bond Index from S&P, with yields on the China Corporate Bond (AAA) Index[12] from China Bond as a supplement due to the shorter time span of yields from the S&P. The MSCI World Index[13] in CNY, yields on FTSE World Government Bond Index – Developed Markets[14] in CNY and yields

[9] MSCI China A-level Onshore Index captures 537 large and mid-cap constituents of Chinese equities listed on the Shanghai and Shenzhen Exchanges (MSCI 2019a).

[10] The growth index captures the equities in MSCI China A-level Onshore Index, which exhibits growth style characteristics (MSCI 2019b).

[11] The value index captures the equities in MSCI China A-level Onshore Index, which exhibits value style characteristics (MSCI 2019c).

[12] The yield curve of the China Corporate Bond (AAA) Index from China Bond: https://www.chinabond.com.cn/cb/eng/zzsj/cywj/syqx/sjxz/zzqyzqx/list.shtml, last viewed on 31 July 2018.

[13] The MSCI World Index contains 1,632 large and mid-cap constituents across 23 developed markets. It covers around 85% of the market capitalisation in each market (MSCI 2019d).

[14] The FTSE World Government Bond Index – Developed Markets measures the performance of fixed-rate, local currency, investment-grade sovereign bonds issued in developed markets (FTSE Russell 2018).

on the FTSE WorldBIG Corporate Bond Index[15] in CNY are used to test the effects of relaxing the restriction on overseas investment. We use annual data from 2001 to 2016 for all the asset classes.

We estimate the actuarial liability for each group and the total actuarial liability using the actuarial models in Equations (1) – (3). We also estimate the rates of change, standard deviations and correlations for the six types of actuarial liability, the expected returns, standard deviations and correlations for each asset class, and the correlations between the asset classes and liabilities (Table 2.3). All the expected returns and correlations are tax exempt, and in Chinese yuan.

2.7. Model results

We investigate the effects on the investment performance and asset allocation of pillar 1B for four situations – including liabilities in the portfolio model, changing the investment restrictions, outsourcing investment to the NSSF and increasing the retirement age.

2.7.1. Including liabilities in the model

For the assets-only model, we compute the efficient frontier using five assets (MSCI China A-level Onshore Growth Index, MSCI China A-level Onshore Value Index, China Corporate Bond Index, ten-year government bond, and the China three-month interbank deposit rate). Table 2.4 contains 12 efficient asset allocations when the post-2015 regulatory constraints of the BPF apply, together with their expected returns and

[15] FTSE WorldBIG Corporate Bond Index is one of the sub-indices of FTSE World Broad Investment-Grade Bond Index, which is a multi-asset, multi-currency benchmark that provides a broad-based measure of the global fixed income market (FTSE Russell 2019).

risk. The BPF 2017 annual report gives a broad indication of its opening asset allocations, 5.5% of the assets under management (AUM) were invested in short-term vehicles, 16% in long-term government bonds, 48.5% in corporate bonds, and 30% in stocks (NSSF 2018), which complies with the regulatory constraints. The expected returns and standard deviations of returns for the actual BPF portfolio computed using our data appear in Table 2.4.

In addition to the five asset classes, the ALM with post-2015 restrictions also includes the six fixed liabilities, and Table 2.4 shows the asset weights and performance of 12 efficient portfolios. Our ALM returns do not include expected liability returns as the liabilities are exogenous.

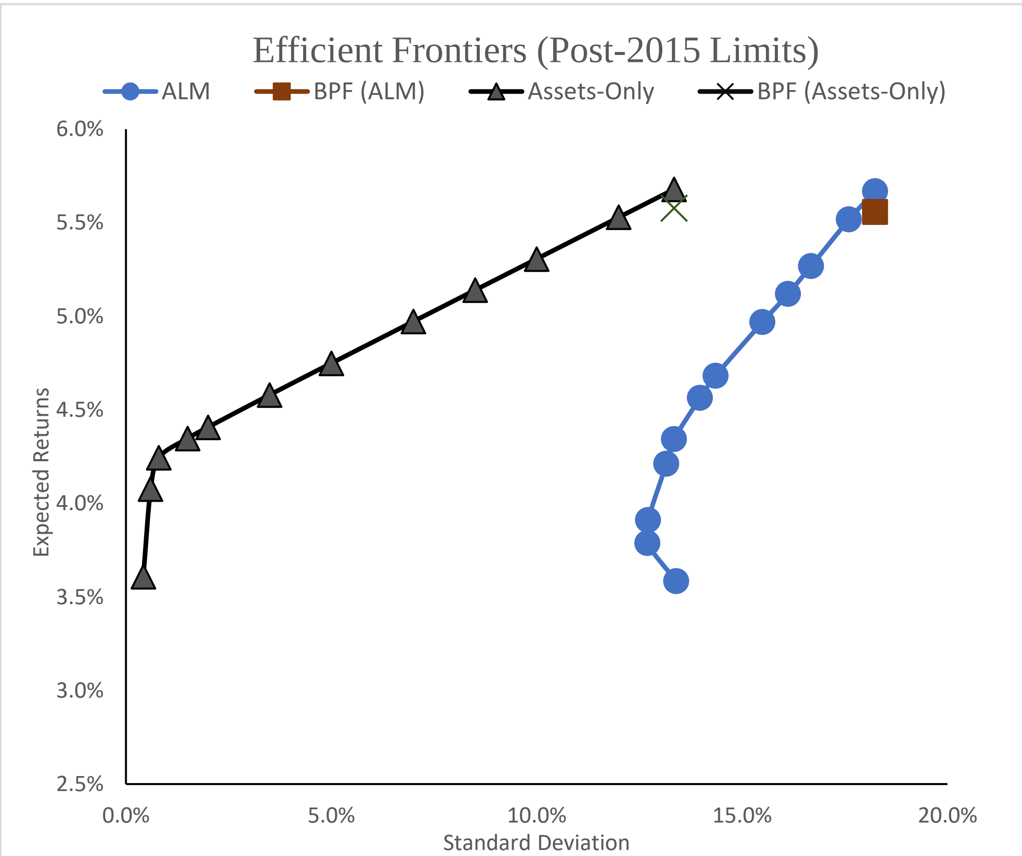

Figure 2.2: Assets-only and asset–liability efficient frontiers

Table 2.3: Correlation matrix, expected returns and standard deviations

	MSCI China A onshore value	MSCI China A onshore growth	MSCI world	FTSE world government bond yield-DM	FTSE world big corporate yield	China corporate bond index yield	China 10Y government bond yield	China inter-bank 3M offered rate	Liability standard deviation
MSCI China A onshore value	1.00								
MSCI China A onshore growth	0.98	1.00							
MSCI world	0.65	0.69	1.00						
FTSE world government bond yield-DM	-0.08	-0.04	-0.38	1.00					
FTSE world big corporate yield	-0.14	-0.12	-0.37	0.13	1.00				
China corporate bond index yield	-0.12	-0.18	-0.01	-0.49	-0.07	1.00			
China 10Y government bond yield	-0.12	-0.15	-0.12	0.10	-0.02	0.57	1.00		
China inter-bank 3M offered rate	-0.26	-0.36	-0.28	-0.31	-0.21	0.82	0.47	1.00	
ALa1	0.03	0.08	-0.01	-0.16	0.27	-0.44	-0.66	-0.47	14.21%
ALa2	0.15	0.18	0.10	-0.46	0.28	-0.20	-0.66	-0.23	18.40%
ALa3	0.03	0.09	-0.05	0.04	0.23	-0.46	-0.44	-0.50	14.88%
ALp1	-0.23	-0.17	-0.42	0.49	0.30	-0.33	-0.52	-0.25	4.04%
ALp2	0.18	0.18	0.00	-0.40	0.25	0.08	-0.39	0.11	12.94%
ALp3	-0.05	-0.03	-0.22	0.22	0.10	-0.38	-0.36	-0.38	7.77%
Expected Return	9.19%	5.47%	4.83%	2.30%	3.42%	4.22%	3.60%	3.63%	
Standard Deviation	46.24%	46.77%	20.33%	0.80%	1.22%	0.71%	0.44%	1.04%	

Note: The correlations between changes in the six liabilities and their expected returns have no impact on determining the efficient frontier and are not included in the table.

Table 2.4: Assets-only and asset-liability portfolios (post-2015 limits)

	Assets only		Efficient asset proportions					ALM (post-2015 limits)			Efficient asset proportions for ALM				
	Expected return	Standard deviation	MSCI China A onshore value	MSCI China A onshore growth	China corporate bond	China 10Y government bond	China inter-bank 3M rate	Expected return	Standard deviation	Effectiveness	MSCI China A onshore value	MSCI China A onshore growth	China corporate bond	China 10Y government bond	China inter-bank 3M rate
1	3.61%	0.42%	0.00%	0.18%	0.12%	94.70%	5.00%	3.58%	13.40%	-10.26%	0.00%	0.00%	0.00%	95.00%	5.00%
2	4.08%	0.60%	0.00%	0.31%	75.98%	18.71%	5.00%	3.79%	12.70%	0.94%	0.00%	0.00%	0.00%	82.70%	17.30%
3	4.24%	0.80%	1.15%	0.00%	93.85%	0.00%	5.00%	3.91%	12.71%	0.69%	0.00%	0.00%	0.00%	0.00%	100.00%
4	4.35%	1.50%	3.21%	0.00%	91.79%	0.00%	5.00%	4.21%	13.16%	-6.39%	4.88%	0.00%	90.12%	0.00%	5.00%
5	4.41%	2.00%	4.43%	0.00%	90.57%	0.00%	5.00%	4.34%	13.35%	-9.45%	9.03%	0.00%	85.97%	0.00%	5.00%
6	4.58%	3.50%	7.90%	0.00%	87.10%	0.00%	5.00%	4.56%	13.98%	-20.03%	12.83%	0.00%	82.17%	0.00%	5.00%
7	4.75%	5.00%	11.29%	0.00%	83.71%	0.00%	5.00%	4.68%	14.36%	-26.61%	16.38%	0.00%	78.62%	0.00%	5.00%
8	4.97%	7.00%	15.79%	0.00%	79.21%	0.00%	5.00%	4.97%	15.50%	-47.59%	19.74%	0.00%	75.26%	0.00%	5.00%
9	5.14%	8.50%	19.16%	0.00%	75.84%	0.00%	5.00%	5.12%	16.12%	-59.67%	22.96%	0.00%	72.04%	0.00%	5.00%
10	5.31%	10.00%	22.52%	0.00%	72.48%	0.00%	5.00%	5.27%	16.68%	-70.91%	26.06%	0.00%	68.94%	0.00%	5.00%
11	5.53%	12.00%	26.99%	0.00%	68.01%	0.00%	5.00%	5.52%	17.61%	-90.40%	29.08%	0.00%	65.92%	0.00%	5.00%
12	5.68%	13.34%	30.00%	0.00%	65.00%	0.00%	5.00%	5.67%	18.24%	-104.37%	30.00%	0.00%	65.00%	0.00%	5.00%
BPF*	**5.58%**	**13.35%**	**30.00%**	**0.00%**	**48.50%**	**16.00%**	**5.50%**	**5.56%**	**18.24%**	**-104.39%**	**30.00%**	**0.00%**	**48.50%**	**16.00%**	**5.50%**

Notes: *In the BPF 2017 annual report, the investment rate of return was 5.23% (the realised rate of return after transaction costs was 4.55%), which is close, but a little lower than the result of 5.58% using our assets-only data. This is because we cannot separate the stock investments of the BPF into value stocks and growth stocks due to the limited information.

Including the expected liability returns in Figure 2.2 would shift the ALM frontier downwards by 20%, making it difficult to compare the ALM and assets-only frontiers. Therefore, the figures considerably overstate the expected returns on the combined portfolio of assets and liabilities. This may mislead fund managers and the government into thinking that the current investment regulations are compatible with boosting the sluggish performance of the past.

The assets-only and ALM efficient frontiers, together with the actual asset allocation of pillar 1B of the BPF, are plotted in Figure 2.2. This shows that the ALM frontier is not simply a linear transformation of the assets-only frontier. Due to the inclusion of the six types of liabilities, the shape of the ALM frontier is different, and has substantially higher risk for every level of return. The big increase in risk which shifts the ALM frontier to the right in Figure 2.2 is due to the incorporation of liability risk in the ALM but not the assets-only frontier. The hedging effectiveness of the ALM is included in Table 2.4 and shows that portfolio 2 with the funds invested in 82.7% of ten-year government bond and 17.3% of the China Interbank 3M rate offers the best hedge by reducing the liability risk by 0.94%. For portfolios 4–12, and the actual BPF portfolio, the negative hedging effectiveness means these portfolios are riskier than just the liabilities. For the assets-only model, portfolio 1 is the risk minimising portfolio, with 94.7% of the funds in ten-year government bonds. Despite their different plots in Figure 2.2, the asset weights for the five asset classes exhibit only small differences between the two models. The BPF portfolio plots just below the top end of both the assets-only and ALM efficient frontiers. This shows that the BPF's asset allocation is more or less on the efficient frontier, with almost the highest available expected returns and risks.

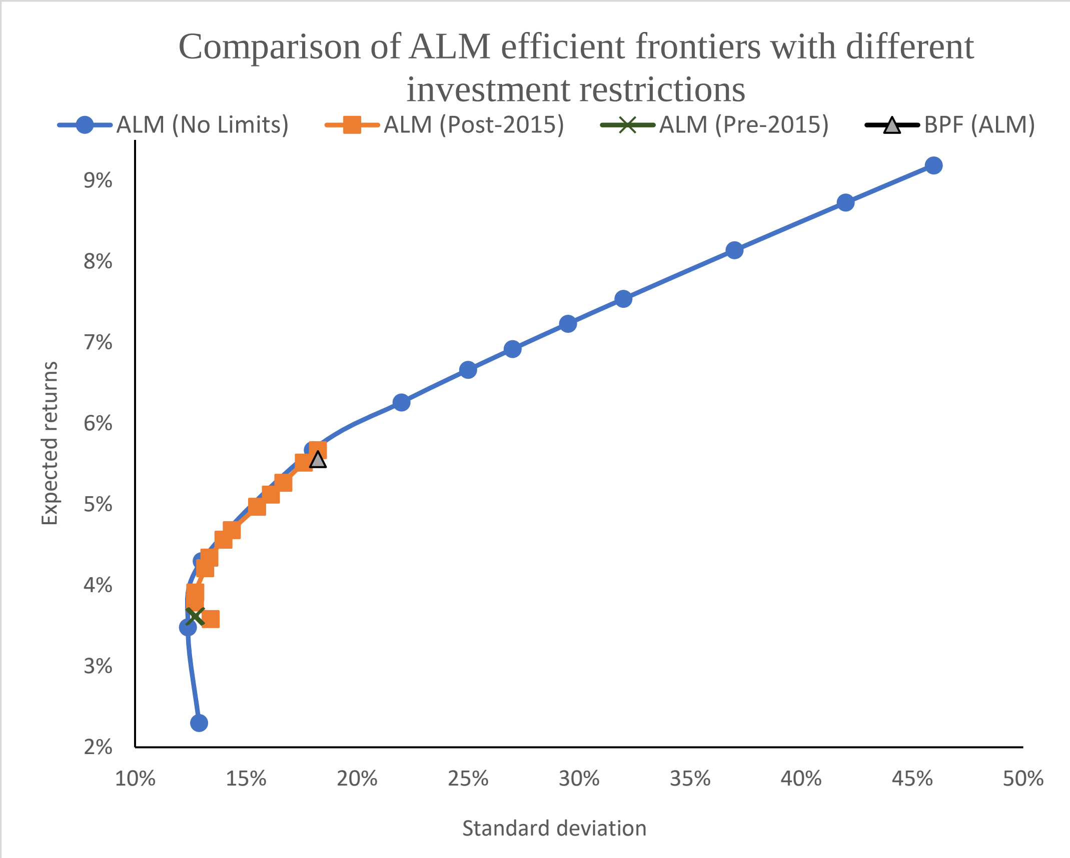

Figure 2.3: Asset-liability efficient frontiers

2.7.2. ALM with different investment restrictions

Table 2.2 summarises the various sets of investment restrictions pre- and post-2015 for pillar 1B and the Social Security Fund. In the section 'Including liabilities in the model', we compute the ALM efficiency frontier for the post-2015 regulations, and we now compute the efficient frontiers for the pre-2015 pillar 1B regulations, and with no investment restrictions. These plots appear in Figure 2.3. The differences between these plots reveal the implied cost of these regulations, in terms of their effect on the risk and return of efficient portfolios.

2.7.2.1. ALM with pre-2015 pillar 1B investment restrictions

The pre-2015 pillar 1B investment limits were very conservative, which caused the negative real return on its investments from 2011 to 2015, contributing to the problem of empty individual accounts. In this subsection, we compute the ALM efficient frontier under the pre-2015 constraints to see the cost, in terms of risk and return, of pursuing 'absolute safety' with investment in only government bonds and interbank deposits exposures. The efficient portfolios and related hedging effectiveness are included in Table 2.5. It can be seen that all 12 portfolios have positive effectiveness, and portfolio 12 provides the largest reduction of 1.70%; but the expected returns for portfolios 2–12 are lower than those for the post-2015 portfolios. While the asset allocation varies, the expected returns and risk of the 12 portfolios with pre-2015 limits are very similar to each other, effectively a single point, which is because the two available assets have similar characteristics. The pre-2015 investment regulations ruled out almost all of the efficient frontiers made available by the introduction of the post-2015 limits. The post-2015 BPF asset allocation in Figure 2.3 shows that once these very restrictive rules were loosened, the BPF moved to a higher risk and return portfolio by transferring 78.5% of its assets into the newly permitted asset classes. This helped alleviate the problem of empty individual accounts due to higher investment returns. The benefits from relaxing the investment restrictions in 2015 suggest there may be further benefits from additional relaxation.

2.7.2.2. ALM with no investment restrictions

Two previous studies of Chinese pensions have found that allowing investment in foreign assets worsens the Sharpe ratio. In the assets-only investment liberalisation analysis of Hu, Fiona, and Yermo (2007), the four hypothetical and arbitrary pension portfolios which allowed investment in foreign assets achieved lower Sharpe ratios than a portfolio with no foreign investment that complied with the pre-2015 investment limits. Pfau (2011) uses an assets-only portfolio model with a risk aversion parameter of five to compute efficient portfolios. He finds that adding foreign assets to a portfolio of domestic equities and bank deposits led to 99.78% of the funds being invested in foreign assets. This increased Chinese returns by 60%, but also increased their standard deviation by 66%, which implies a small reduction in the Sharpe ratio.

We now apply the ALM with no investment limits (except for banning short sales), together with eight asset classes, and the results appear in Figure 2.3 and Table 2.5. The three additional assets we include are the MSCI World Index, the FTSE World Government Bond – Developed Markets Index and the FTSE WorldBIG Corporate Bond Index. Figure 2.3 shows that the post-2015 investment constraints on pillar 1B investment remove a large part of the efficient frontier. Portfolios 1 and 2 provide positive liability risk hedging, with 1.21% and 5.78% reductions, respectively. Portfolios 3–12 with no limits only invest in domestic value stocks and domestic corporate bonds. This shows that the ban on foreign equities and fixed-income products in the post-2015 investment limits is not a binding constraint, and its relaxation would provide no benefit. If the BPF wishes to deal with its substantial underfunding, the removal of investment limits on domestic equities and domestic corporate bonds would enable the BPF to achieve a much higher expected return, although this is accompanied by additional risk.

2.7.2.3. Assets-only model with social security fund limits

The NSSF accesses foreign investments through international fund managers. The Social Security Fund has performed much better than the BPF (Leckie and Pan 2007), with an average return of 7.1% from 2011 to 2016, and 8.37% since 2000 (Zhang and Harte 2017). This superior performance may be for two different reasons. First, the NSSF benefits from superior investment expertise, economies of scale, personal connections, the use of external fund managers and access to additional types of assets; and these can also benefit pooled investment by the NSSF of the pillar 1B assets. Second, the Social Security Fund benefits from less restrictive limits on investment in domestic equities and is allowed to invest in foreign equities and bonds (Table 2.2). This advantage is not available to those provinces who transfer their funds to the NSSF, as transferred funds remain subject to the pillar 1B investment limits. To quantify the size of this second advantage, we compare the assets-only efficient frontiers (plotted in Figure 2.4) for the Social Security Fund using both its own investment limits and the post-2015 pillar 1B limits[16]. Figure 2.4 shows that the post-2015 efficient frontier lies to the left of the frontier with Social Security Fund limits, indicating that investment of pillar 1B funds by the NSSF will increase returns for two reasons – more favourable investment limits, and superior investment expertise, economies of scale, and insider trading. Details of the assets-only efficient portfolio with Social Security Fund limits appear in Table 2.6, and like the ALM portfolio with no investment limits, there is no allocation to foreign assets, except for portfolios 1–3.

[16] For example, ALM portfolio 11, which plots close to the actual BPF portfolio, has an expected return of -25.52%, not 5.52%, when the liability returns are included.

Table 2.5: Asset-liability portfolios (pre-2015 limits and no limits)

	ALM (pre-2015 limits)		Effectiveness	Efficient asset proportions		ALM (no limits)		Effectiveness	Efficient asset proportions							
	Expected return	Standard deviation		China 10Y government bond	China inter-bank 3M rate	Expected return	Standard deviation		MSCI China A onshore value	MSCI China A onshore growth	MSCI world	FTSE world government bond-DM	FTSE world big corporate bond	China corporate bond	China 10Y government bond	China inter-bank 3M rate
1	3.63%	12.77%	-0.16%	20.00%	80.00%	2.30%	12.68%	1.21%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
2	3.62%	12.75%	0.18%	30.00%	70.00%	3.48%	12.38%	5.78%	0.00%	2.80%	0.00%	0.00%	97.20%	0.00%	0.00%	0.00%
3	3.62%	12.74%	0.34%	35.00%	65.00%	4.30%	13.00%	-3.82%	4.32%	0.00%	0.00%	0.00%	16.83%	78.85%	0.00%	0.00%
4	3.62%	12.73%	0.50%	40.00%	60.00%	5.67%	18.00%	-99.03%	29.23%	0.00%	0.00%	0.00%	0.00%	70.77%	0.00%	0.00%
5	3.62%	12.72%	0.66%	45.00%	55.00%	6.26%	22.00%	-197.32%	41.10%	0.00%	0.00%	0.00%	0.00%	58.90%	0.00%	0.00%
6	3.62%	12.71%	0.81%	50.00%	50.00%	6.66%	25.00%	-283.94%	49.17%	0.00%	0.00%	0.00%	0.00%	50.83%	0.00%	0.00%
7	3.62%	12.70%	0.97%	55.00%	45.00%	6.92%	27.00%	-347.82%	54.34%	0.00%	0.00%	0.00%	0.00%	45.66%	0.00%	0.00%
8	3.61%	12.69%	1.12%	60.00%	40.00%	7.23%	29.50%	-434.59%	60.64%	0.00%	0.00%	0.00%	0.00%	39.36%	0.00%	0.00%
9	3.61%	12.68%	1.27%	65.00%	35.00%	7.54%	32.00%	-529.04%	66.81%	0.00%	0.00%	0.00%	0.00%	33.19%	0.00%	0.00%
10	3.61%	12.67%	1.41%	70.00%	30.00%	8.14%	37.00%	-740.97%	78.89%	0.00%	0.00%	0.00%	0.00%	21.11%	0.00%	0.00%
11	3.61%	12.66%	1.56%	75.00%	25.00%	8.73%	42.00%	-983.62%	90.73%	0.00%	0.00%	0.00%	0.00%	9.27%	0.00%	0.00%
12	3.61%	12.65%	1.70%	80.00%	20.00%	9.19%	45.96%	-1197.81%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

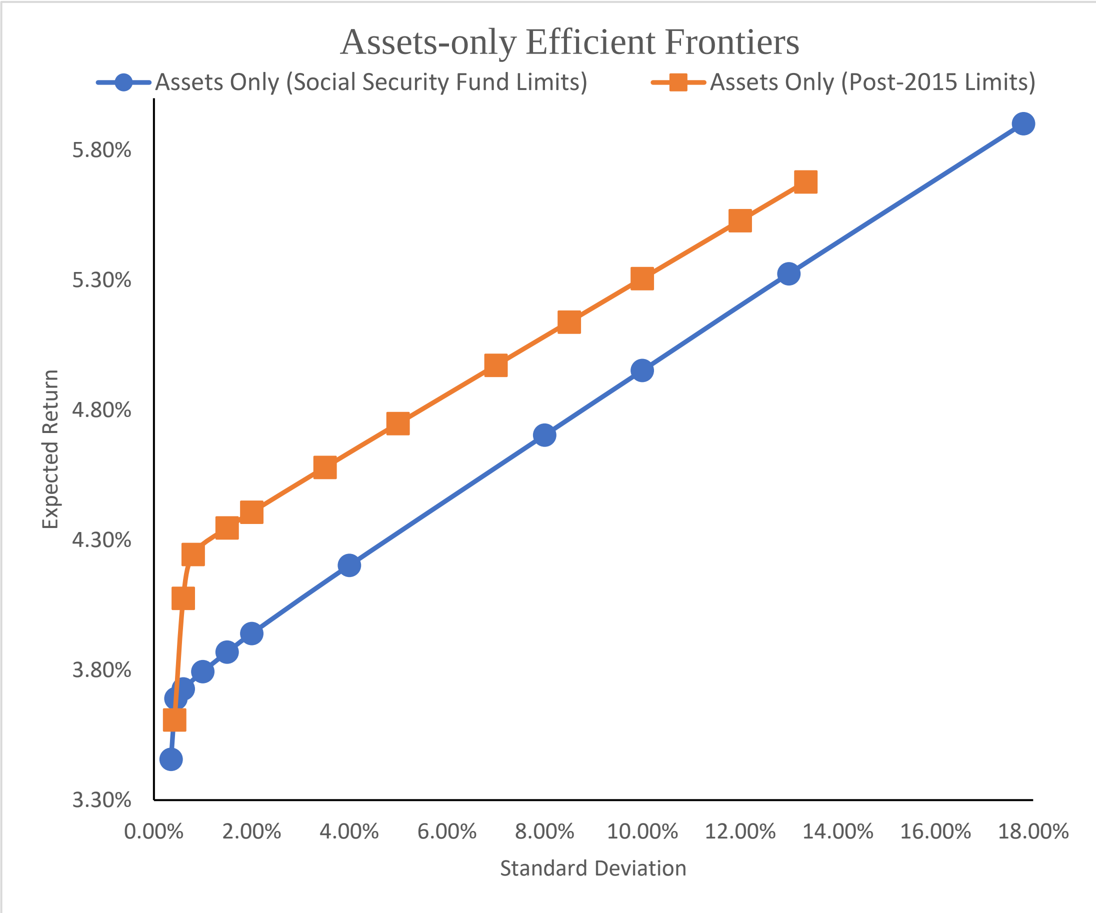

Figure 2.4: Assets-only efficient frontiers for social security fund and post-2015 limits

Table 2.6: Assets-only portfolios (social security fund limits) and asset-liability portfolios (65)

	Assets only (Social Security Fund limits)		Efficient asset proportions								ALM (65)			Efficient asset proportions				
	Expected return	Standard deviation	MSCI China A onshore value	MSCI China A onshore growth	MSCI world	FTSE world government bond-DM	FTSE world big corporate bond	China corporate bond	China 10Y government bond	China inter-bank 3M rate	Expected return	Standard deviation	Effectiveness	MSCI China A onshore value	MSCI China A onshore growth	China corporate bond	China 10Y government bond	China inter-bank 3M rate
1	3.34%	0.39%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	3.60%	21.35%	0.47%	0.00%	0.00%	0.00%	95.00%	5.00%
2	3.46%	0.39%	0.00%	0.07%	0.29%	12.42%	6.96%	0.00%	89.64%	0.00%	3.63%	21.34%	0.58%	0.00%	1.64%	0.00%	93.36%	5.00%
3	3.69%	0.49%	0.68%	0.00%	0.13%	0.00%	0.00%	10.00%	80.73%	8.46%	3.93%	21.34%	0.55%	0.29%	1.44%	46.79%	46.52%	5.00%
4	3.73%	0.60%	1.63%	0.00%	0.00%	0.00%	0.00%	10.00%	59.11%	29.26%	4.31%	21.35%	0.46%	5.16%	0.00%	89.84%	0.00%	5.00%
5	3.79%	1.00%	3.33%	0.00%	0.00%	0.00%	0.00%	10.00%	18.07%	68.60%	4.57%	21.50%	-0.94%	7.63%	0.00%	87.37%	0.00%	5.00%
6	3.87%	1.50%	4.53%	0.00%	0.00%	0.00%	0.00%	10.00%	0.00%	85.47%	4.84%	21.90%	-4.73%	13.08%	0.00%	81.92%	0.00%	5.00%
7	3.94%	2.00%	5.75%	0.00%	0.00%	0.00%	0.00%	10.00%	0.00%	84.25%	4.98%	22.20%	-7.62%	15.89%	0.00%	79.11%	0.00%	5.00%
8	4.20%	4.00%	9.24%	0.00%	0.00%	0.00%	0.00%	10.00%	0.00%	80.76%	5.09%	22.50%	-10.55%	18.26%	0.00%	76.74%	0.00%	5.00%
9	4.70%	8.00%	18.26%	0.00%	0.00%	0.00%	0.00%	10.00%	0.00%	71.74%	5.20%	22.80%	-13.52%	20.35%	0.00%	74.65%	0.00%	5.00%
10	4.95%	10.00%	22.74%	0.00%	0.00%	0.00%	0.00%	10.00%	0.00%	67.26%	5.26%	23.00%	-15.52%	21.64%	0.00%	73.36%	0.00%	5.00%
11	5.32%	13.00%	29.43%	0.00%	0.00%	0.00%	0.00%	10.00%	0.00%	60.57%	5.49%	23.80%	-23.70%	26.19%	0.00%	68.81%	0.00%	5.00%
12	5.90%	17.80%	40.00%	0.00%	0.00%	0.00%	0.00%	10.00%	31.43%	18.57%	5.68%	24.57%	-31.83%	30.00%	0.00%	65.00%	0.00%	5.00%

2.7.2.4. Retirement age of 65

There has been a lot of discussion in the literature about delaying retirement in China (James 2002; Queisser, Reilly, and Hu 2016; Imrohoroglu and Zhao 2018), and we examine the effects on the asset allocation of an immediate increase in the retirement age to 65 in 2016, which is the statutory or average retirement age in many developed countries, for all three groups of members. While members will contribute for longer, current assets will be unchanged. Increasing the retirement age affects the liabilities as it decreases the time spent in retirement, which alters the rate of change, volatility and total amount of the six liabilities. As members will contribute for longer, and receive a pension for a shorter period, the annuity factors in Equation (1) need to be adjusted. We assume that the annuity factors for male employees (139), female officials (170) and female blue- collar workers (195) are reduced by the same proportion as the reduction in their expected longevity at retirement. For example, in 2016, the average life expectancy of male members at the age of 60 is 14.8 years, and retirement at 65, not 60, implies a reduction in their period of receiving a pension of 33.78%. A summary of these changes is provided in Appendix 2.2. Delaying retirement to 65 increases the liabilities for active members by over 40%, mainly due to the reductions in the annuity factors. The liabilities for pensioners younger than 65 are not changed, as we treat retirement as irreversible.

In Figure 2.5, we compare the efficient frontiers of the ALM (post-2015 limits) and the current retirement ages, and with a retirement age of 65. Figure 2.5 shows that if the retirement age was increased to 65 in 2016, the ALM efficient frontier shifts a long way to the right of its original position. For little higher expected return, portfolios with retirement at 65 have much higher risk. This is because raising the retirement age increases the magnitude of the liabilities by over 40%, and their standard deviation by over 30%. Only portfolios 1–4 provide positive effectiveness, with the highest reduction of liability risk of 0.58%. The ALM efficient portfolios with a 65-year retirement age are presented in Table 2.6.

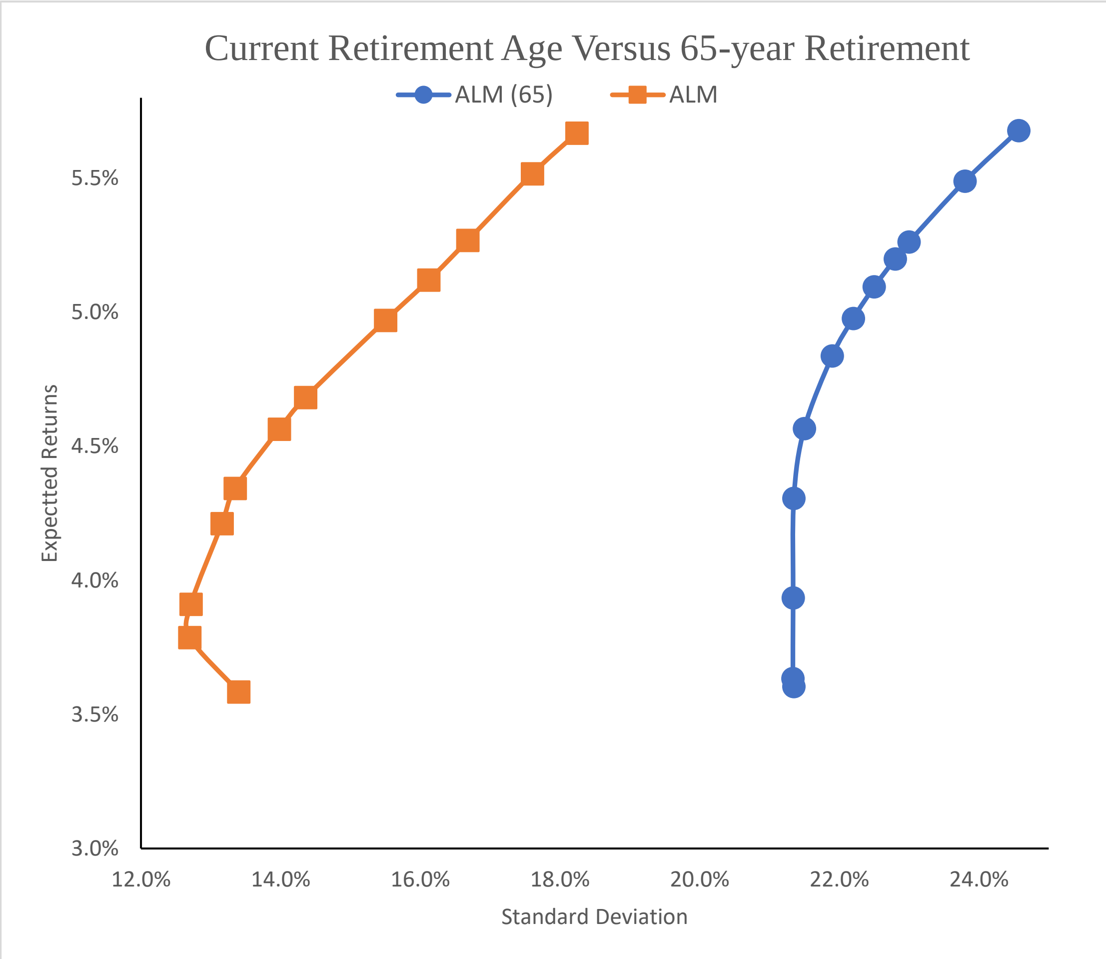

Figure 2.5: Asset–liability efficient frontiers with the current retirement ages and retirement at 65

With more pension contributions and smaller pension payments due to a modest reduction in the size of the annuity factors, and no more than a small increase in longevity induced by later retirement, delaying retirement will probably improve the sustainability of the PAYG system (pillar 1A) (Wang and Shan 2016). This will help postpone the time when the cash flow of pillar 1A becomes negative.

2.8. Conclusions

The Chinese pension system faces some very considerable challenges. The state scheme (pillar 1) dominates the pension system, and we study the individual accounts of pillar 1B of the state scheme, which is a funded cash balance scheme. We find that the total actuarial liabilities of pillar 1B are much larger than the accumulated balances in the individual accounts, and in 2016, it had a funding ratio of only 73.5%. This low funding ratio is forecast to get substantially worse, and improved investment performance is urgently needed. We use portfolio theory, both with and without the liabilities, to study the asset allocation of pillar 1B. To this end we divide the calculation of the actuarial liabilities into six different types – active members and pensioners, each in three groups (male employees, female officials in public institutions and female blue-collar workers).

Using the post-2015 limits on the investment of the pillar 1B funds, we demonstrate that the asset allocation of these funds should use an ALM, rather than the conventional assets-only portfolio model. We also show that the pre-2015 limits, which only allowed investment in government bonds and bank deposits, resulting in portfolios with very similar risk and return that lie at the bottom end of the post-2015 efficient frontier with low return and low risk. With the removal of all investment restrictions the efficient frontier mean-variance dominates the frontier when post-2015 limits apply, and this relaxation greatly expands the length of the efficient frontier by allowing investment in portfolios with much greater risk and return than is currently possible. Interestingly, these improvements are not due to allowing investment in foreign equities, but to relaxing the restrictions on domestic value stocks and domestic corporate bonds. Therefore, China should consider relaxing the restrictions on investment of pillar 1B funds in domestic assets as this both improves and expands the efficient frontier.

The investment track record of the NSSF in managing the Social Security Fund is superior to that of the provinces. This is due to some combination of great expertise, economies of scale, private information, investment in additional asset classes and the use of external fund managers (Shen et al. 2020). When managing pillar 1B funds the NSSF must observe the pillar 1B investment restrictions, rather than the Social Security Fund restrictions; and we find that this will further increase the investment performance of the NSSF when managing provincial pension funds. Moving funds to the NSSF will also limit the misuse of these funds by the provinces.

A common way of addressing pension underfunding is to increase the retirement age. If the Chinese retirement age is increased to 65, we find that the liabilities of active members will increase by over 40%. When we include these liabilities, compared to the ALM with current retirement ages, while the expected returns of asset–liability portfolios are largely unchanged, their risk increases considerably. As a result, an instantaneous increase in the retirement age to 65 is a challenging pension reform option for China because there is no accompanying increase in assets. However, if the increased retirement age were applied only to those currently of working age, they and the state would contribute for longer. The resulting increase in assets, coupled with the shorter period of retirement and appropriate annuity factors, should improve the scheme's funding ratio. To quantify the effects on the funding ratio over time requires a dynamic analysis of pillar 1B, and the problems of employing the elderly in China need further discussion.

This research has several implications for the reform of pillar 1B of the BPF. First, asset allocation using an ALM is preferable to an assets-only approach, if only because it reveals the correct risks and returns of the scheme and prevents fund managers and the government from thinking the current investment regulations are compatible with boosting the previous sluggish performance. Second, relaxing the restrictions on investment in domestic value stocks and corporate bonds would improve investment performance. Third, transferring provincial pension funds to the NSSF for investment should lead to better investment performance, and discourage empty accounts. Fourth, increasing the retirement age is an obvious policy to improve the pillar 1B funding ratio, although this change needs to be carefully designed. Finally, the official notional rate of return on individual accounts (pillar 1B) is uniformly set at 5% for 2014–2015 and 8.31% for 2016. Investment returns may be sufficient to meet a 5% notional rate per annum, but a notional rate of over 8% may be higher than can be achieved. This will lead to an increase in the liabilities, and a worse funding ratio. The choice of a reasonable notional rate, and the relationship between pillar 1B fund investment and notional rate need further investigation. We leave the analysis of this issue and raising the retirement age to future research.

2.9. Appendices

Appendix 2.1: Summary statistics of demographic data

Panel 1. Summary statistics of actuarial values for active members (2001-2016)

Values	Mean	S.D.	Quantiles 0%	25%	50%	75%	100%
Number of males (in million)	114.7	38.78	67.08	75.83	107.47	157.15	176.98
Number of female officers (in million)	19.4	8.44	11.29	12.47	15.09	25.74	37.27
Number of female workers (in million)	47.33	12.93	27.18	31.36	51.05	58.88	64.01
Average current age of males	38.84	0.78	37.32	38.36	39.03	39.47	40.01
Average current age of female officers	36.18	0.34	35.59	35.88	36.17	36.38	36.92
Average current age of female workers	37.61	1.65	35.03	36.33	37.55	38.94	40.41
Average service length of males	21.18	0.77	20	20.51	21.12	21.77	22.65
Average service length of female officers	18.59	0.52	17.72	18.19	18.67	18.92	19.68
Average service length of female workers	20.02	1.31	17.81	18.88	20.06	21.04	22.01
Life expectancy at retirement (males)	13.23	1.21	10.87	12.2	13.45	14.32	14.8
Life expectancy at retirement (female officers)	21.29	1.18	19.08	20.22	21.53	22.34	22.83
Life expectancy at retirement (female workers)	26.29	1.18	24.08	25.22	26.53	27.34	27.83
Average annual salary of males (¥)	35,958.31	19,804.00	11,557.17	16,988.64	32,582.29	54,640.40	71,889.29
Average annual salary of females (¥)	30,021.59	16,534.36	9,649.08	14,183.81	27,202.95	45,619.27	60,020.37

Panel 2. Summary statistics of actuarial values for pensioners (2001-2016)

Values	Mean	S.D.	Quantiles 0%	25%	50%	75%	100%
Number of males (in million)	38.13	13.91	20.99	25.40	34.78	52.27	64.26
Number of female officers (in million)	6.47	3.07	3.76	4.01	5.03	8.56	13.53
Number of female workers (in million)	15.70	4.59	8.51	10.50	16.52	19.58	23.24
Average current age of males	69.03	0.20	68.67	68.85	69.08	69.23	69.30
Average current age of female officers	66.16	0.30	65.76	65.88	66.09	66.50	66.62
Average current age of female workers	62.46	0.15	62.21	62.30	62.50	62.56	62.75
Average current life expectancy of males	4.20	1.29	2.01	3.07	4.18	5.48	6.04
Average current life expectancy of female officers	10.14	1.43	7.47	8.72	10.63	11.38	11.70
Average current life expectancy of female workers	13.83	1.18	11.32	12.93	14.12	14.78	15.30
Average annual pension benefits of males (¥)	17,088.60	8,318.33	7,324.67	9,109.29	15,587.30	24,378.91	33,543.66
Average annual pension benefits of females (¥)	14,267.27	6,944.97	6,115.37	7,605.35	13,013.83	20,353.95	28,005.60

Data sources: MOHRSS (2017a), National Bureau of Statistics of China (2018), World Bank (2018) and authors' own calculations.

Appendix 2.2: Changes in liabilities for active members with a single retirement age

	Current Retirement Age					65-year Retirement Age				
	Average Rate of Change	Average Volatility	Average Life Expectancy of Active Members	Annuity Factor	Forecast Amount (Billion, ¥, 2016)	Average Rate of Change	Average Volatility	Average Life Expectancy of Active Members	New Annuity Factor in 2016	Forecast Amount (Billion, ¥, 2016)
ALa1	25.39%	14.21%	13.23	139	1969	26.40%	15.56%	12.92	92.02	2290
ALa2	24.94%	18.40%	21.29	170	472	27.56%	22.95%	20.67	95.55	699
ALa3	17.11%	14.88%	26.29	195	743	22.13%	26.17%	25.35	89.91	1578

Data sources: Authors' calculations based on actuarial liability models and demographic assumptions.

3. Chapter Three: What determines the asset allocation of defined benefit pension funds?

3.1. Introduction

The asset allocation of defined benefit (DB) pension schemes is one of the most important decisions taken by such schemes. It has a major effect on their investment performance, which then affects the scheme's funding ratio and contribution rates. While they are separate legal entities, since the employer (sponsor) is responsible for any surplus or deficit on their DB scheme, it is now generally accepted that the assets and liabilities of DB pension schemes are effectively consolidated with those of their sponsor. Therefore, a DB scheme affects its corporate sponsor in many different ways, including leverage, mergers and acquisitions, dividends, capital expenditure, share price and credit rating[17].

DB pension scheme asset allocation has been the subject of a very active debate by trustees, actuaries, fiduciary managers, sponsors, fund managers, academics and regulators. A common solution, e.g. 60% equities and 40% bonds, does not prevail, and there is considerable variation in the asset allocations of UK DB pension schemes. This is the first study of the determinants of the equity-bond allocation of UK pension funds. The results for other countries do not necessarily apply to the UK due to institutional

[17] Leverage (Bartram 2016; Shivdasani and Stefanesu 2010), mergers and acquisitions (Cocco and Volpin 2013; Chang, Kang, and Zhang 2012; Meijdam 2012; Sudarsanam and Appadu 2015), dividends (Bunn and Trivedi 2005; Liu and Tonks 2010), capital expenditure (Bartram 2017; Campbell, Dhaliwal, and Schwartz 2012; Chaudhry, Yong, and Veld 2017; Dambra 2014; Kubick, Lockhart, and Robinson 2014; Phan and Hegde 2013; Rauh 2006), CAPM beta (Jin, Merton, and Bodie 2006), share price (Castro-Gonzalez 2012; Chen et al. 2014; Chen 2015; Feldstein and Mørck 1983; Feldstein and Seligman 1981; Franzoni 2009; Franzoni and Marin 2006a, 2006b; Liu and Tonks 2013; Nakajima and Sasaki 2010; Phan and Hegde 2013), and credit rating (Cardinale 2007; Carroll and Niehaus 1998; Gallagher and McKillop 2010a, 2010b; McKillop and Pogue 2009; Maher 1987, 1996; Martin and Henderson 1983; Wang, Wu, and Zhang 2013; Watson Wyatt 2005).

differences. The asset allocation decision is affected by UK pension legislation, the requirements of the Pension Regulator and UK institutions such as the Pension Protection Fund (Yuan and Lui 2016); as well as by the different circumstances of each scheme[18]. A better understanding of the determinants of asset allocation within the UK context will help both those making this decision, and those regulating and insuring pension schemes, as well as investors in DB scheme sponsors.

We study the determinants of the percentage of funds invested in equities by the DB pension schemes of FTSE 100 companies for the 2003–2019 period. We analyse the effects of ten explanatory variables on the equity allocation, while previous studies for other countries have used only a few explanatory variables. This is the first study of the effects of non-linear default risk, leverage, cash flow volatility, size of the sponsor (or scheme) and maturity on the asset allocation of UK schemes. In addition to the six explanatory variables that have been used in previous research on the asset allocation decision for various countries, we also include four new variables – scheme closure to new contributions, overseas pension assets, a time trend and equity returns exceeding bond returns. This is also the first study to measure the maturity of DB pension schemes using effective duration, which we argue is the best available measure of scheme maturity. We find that UK DB scheme asset allocations vary in response to eight factors in ways that are largely consistent with prior expectations. Our results indicate that the large variations in pension scheme asset allocation observed in practice are due to differences in the circumstances of both sponsors and schemes. There is no single

[18] There are no legal limits on the asset allocations of UK pension funds. However, the annual levy payable to the Pension Protection Fund rises with the riskiness of the asset allocation.

‘correct’ asset allocation where one size fits all, e.g. 60% equities and 40% bonds.

The rest of this chapter is structured as follows. Section 3.2 reviews the literature on the determinants of the pension fund asset allocation. Section 3.3 discusses the measurement of the maturity of pension scheme liabilities, and in section 3.4 we describe our empirical model. Sample selection, data sources and descriptive statistics are contained in section 3.5. Section 3.6 presents our empirical results, and section 3.7 concludes.

3.2. Literature Review

Theory indicates that three factors affect the asset allocation of DB pension schemes. The tax arbitrage strategies of Black (1980) and Tepper (1981) imply 100% investment in bonds, while the under-priced default insurance model of Sharpe (1976) leads to 100% investment in equities[19]. In the presence of risk sharing between the scheme’s sponsor and members the optimal asset allocation is indeterminate; depending on the risk sharing proportions and the sensitivity of total remuneration and the value of the sponsor’s pension call option to changes in asset volatility (Sutcliffe 2016, pp. 219–221). Pension schemes are usually affected by more than one of these three factors, making it difficult to predict the optimal asset allocation. The empirical evidence for the influence of these three factors is limited, and only tax arbitrage has been researched. Thomas (1988) and Frank (2002) found some modest US evidence in favour of the tax arbitrage strategy, while Bartram (2018) found no evidence for the tax arbitrage strategy

[19] The under-priced default insurance reflects the increase in risk as the scheme switches to risky investments, means that the employer and employees have an incentive to adopt a high equity allocation, since the costs of the scheme default become lower.

for the US. In the UK Boots moved to 100% bonds in 2000 (Ralfe, Speed, and Palin 2004) in accordance with tax arbitrage motive.

In addition to these three factors, a pension fund's asset allocation may be affected by the default risk of the sponsor, and this has been examined empirically by research on the opposing motives of risk management and risk shifting. Risk management implies a negative relationship between sponsor default risk and the equity proportion of the pension fund, while risk shifting implies a positive relationship (Rauh 2009). There have been many empirical studies of risk shifting versus risk management for the US, and to a lesser extent the UK. In these studies, most have used the scheme's funding ratio as a reverse proxy for default risk. For the US, the evidence is mixed, with an equal number of studies supporting the two alternative hypotheses[20], while the smaller number of studies for the UK mostly support risk shifting[21].

A further influence on a pension fund's asset allocation is the degree to which the asset allocation is re-balanced in response to price changes. Unless the asset allocation is fully rebalanced, a rise or fall in the equity market (relative to the other assets held by the fund) automatically changes the equity proportion of the pension fund. For the Netherlands, Bikker, Broeders, and De Dreu (2010) found that about 60% of such changes in asset proportions are not removed by re-balancing. Rauh (2009) showed that investment returns have a positive relationship with pension fund equity allocation, implying less than full re-balancing. High levels of leverage tend to increase the risk of

[20] Addoum, Van Binsbergen, and Brandt (2010), Amir and Benartzi (1999), An, Huang, and Zhang (2013), Anantharaman and Lee (2014), Atanasova and Gatev (2013), Bodie et al. (1985, 1987), Comprix and Muller (2006), Coronado, Liang, and Orszag (2006), Friedman (1983), Gallo and Lockwood (1995), Guan and Lui (2014), Mohan and Zhang (2014), Petersen (1996) and Rauh (2009).

[21] Guan and Lui (2014), LCP (2014), Li (2010), and McCarthy and Miles (2013).

default by the sponsor, and Davis and De Haan (2012) found that Dutch DB pension funds with a more highly levered sponsor have a lower equity allocation. Various studies have found that DB pension funds with a large sponsor also tend to have higher equity allocations (US – Amir and Benartzi 1999; Netherlands – Bikker et al. 2012; Netherlands – Davis and De Haan 2012; Switzerland – Gerber and Weber 2007; Kenya – Ngugi and Njuguna 2018; US – Rauh 2009). Another factor that has been found to influence asset allocations is the volatility of the sponsor's cash flows. Amir and Benartzi (1999) found that for US schemes the more volatile are the sponsor's cash flows, the lower is the equity allocation of its pension fund.

Finally, the structure of a scheme's liabilities may affect a pension fund's asset allocation. Previous studies for six countries (US, Canada, Netherlands, Finland, Switzerland and Belgium) of the effect of maturity (measured in various ways) on pension fund asset allocation support the view that, as a scheme becomes more mature, its equity allocation decreases[22].

Some DB schemes are immature with mostly young active members, while others are mature with few or no active members. Immature schemes have liabilities that will not become due for many years, and a strong positive cash flow due to large contributions and small pension payments. Mature schemes are in the opposite position, with most of their liabilities due for payment in the near future, and a negative cash flow due to small contributions and large pension payments. Immature schemes are

[22] US (Amir and Benartzi 1999; Friedman 1983; Lucas and Zeldes 2009; López-Villavicencio and Rigot 2013; Rauh 2009), US, Canada and Netherlands (Boon, Brière, and Rigot 2018), Canada (López-Villavicencio and Rigot 2013), Netherlands (Bikker et al. 2012), Finland (Alestalo and Puttonen 2006), Switzerland (Gerber and Weber 2007) and Belgium (Defau and De Moor 2018).

expected to favour equity investment, as they hope to benefit from the equity risk premium, and have the time to recover from a deficit by raising contribution rates and changing the benefits and retirement age. As they have little scope for raising contribution rates or changing the benefits and retirement age, mature schemes are expected to favour low-risk investments such as bonds. Bonds hedge the interest rate risk of the pension liabilities, are easy to liquidate to pay the pensions, and have low risk.

As well as cross-section differences in the liability structure of schemes, it has also been shifting over time. Over recent decades, the liability structure of DB schemes has been changing as many schemes have closed to new members or future accruals, to be replaced by defined contribution schemes. For example, in the UK, the proportion of DB schemes closed to future accruals in 2020 was 46% (Pension Protection Fund 2020). As a result, the average time lag before accrued benefits are paid has become shorter. However, increased longevity means that additional payments are required for pensioners at the end of their lives, which tends to lengthen the average time lag before payments are made. So, the net effect of scheme closure and increased longevity on the time lag before accrued benefits are paid is unclear. The measure of scheme maturity needs to allow for such effects.

3.3. Measuring maturity

There is no agreed way of measuring scheme maturity, and a large number of alternative definitions have been used in previous empirical studies. These include the ratio of the number of active members to pensioners (US, Canada – López-Villavicencio and Rigot

2013), the ratio of active members to total participants (Belgium – Defau and De Moor 2018; US – Lucas and Zeldes 2009; Netherlands, US, Canada – Boon, Brière, and Rigot 2018; US – Friedman 1983; US – Rauh 2009), the average age of all members and pensioners (Switzerland – Gerber and Weber 2007), the average age of active members (Netherlands – Bikker et al. 2012; Chandler 2017; Switzerland – Gerber and Weber 2007), the average age of the sponsor's employees (Finland – Alestalo and Puttonen 2006), the average age of pensioners (Canada – Chandler 2017), the proportion of liabilities represented by pensioners (Canada – Chandler 2017), and the log (Pension benefit obligation/Accrued benefit obligation) divided by the log(1+ Salary growth rate) (US – Amir and Benartzi 1999).

All these measures of maturity, apart from the last, simply group participants according to their age or membership status, which assumes that those of the same age or with the same membership status have the same effect on maturity. This ignores substantial differences in the magnitude of the benefits accrued by participants of the same age or membership status. Since scheme maturity influences a pension fund's asset allocation via its effect on when the scheme's liabilities fall due for payment, what is needed is a summary measure of the timing of future pension payments, irrespective of the age or membership status of participants. Macaulay duration provides such a measure (Macaulay 1938; Van Zijl 1990). Duration is expressed in years as it measures the weighted average number of years until pension payments are made, where the present values of these cash flows vary with the discount rate.

$$\text{Macaulay Duration} = \frac{1}{L_i}\sum_{t=1}^{n} t\frac{C_t}{(1+i)^t}$$

where C_t is the total of the DB pension payments expected to be made in time period t, i is the discount rate used to calculate the present value of the DB pension liabilities, L_i is the DB pension liability when the discount rate is i, and n is the total number of time periods.

Macaulay's duration depends on several assumptions. First, a single interest rate is applied to discount all the cash flows, i.e. the yield curve is flat. Second, there are only parallel shifts in the yield curve. Finally, the cash flows are independent of changes in the yield curve. To avoid making these assumptions McCaulay (2013) suggested using effective duration to measure the duration of pension liabilities. The value of effective duration is usually reasonably similar to the Macaulay duration, with a smaller effective duration indicating a more mature pension scheme, i.e. pension payments are weighted more towards the present, than to some distant horizon. The information in UK annual reports does not permit the calculation of Macaulay's duration (or modified duration), only effective duration. So, we measure the maturity of pension schemes in years using effective duration, which is defined as:

$$\text{Pension Effective Duration} = \frac{L_{i-x} - L_{i+x}}{2L_i x}$$

where x is the change in the discount rate, and L_{i-x} and L_{i+x} are the DB pension liabilities when the discount rate is $i \pm x$.

3.4. Empirical Model

To investigate the determinants of the asset allocation of pension funds we estimate the model:

$$Equity_{it} = \alpha + \beta_1 ED_{it} + \beta_2 FR_{it} + \beta_3 FR_{it}^2 + \beta_4 LEV_{it} + \beta_5 SDCF_{it} + \beta_6 Size_{it} + \beta_7 Close_{it} + \beta_8 EHB_t + \beta_9 Overseas_{it} + \beta_{10} T_t + \varepsilon_{it}$$

The dependent variable ($Equity_{it}$) is the percentage of the pension fund's equity assets, as a proportion of the total pension assets of firm i at the end of financial year t. ED_{it} is the effective duration of firm i's pension liabilities (years) at the end of financial year t. We expect a positive relation between the effective duration of pension liabilities and the equity allocation. In other words, more immature (or younger) schemes are expected to have higher equity allocations.

Bader (1991) argues that pension schemes with substantial over or underfunding should invest mainly in fixed-income securities, whereas fully funded schemes should allocate more to equities. This implies an upside-down *U*-shaped relationship between the funding ratio and equity allocation. Using UK data Li (2010) found empirical support for this view, which involves both risk sharing and risk management. To allow for a non-linear relationship between the funding ratio and equity allocation we include the funding ratio squared (FR_{it}^2), as well as the funding ratio (FR_{it}). FR_{it} is the total market value of pension assets divided by the DB pension liabilities (%) for firm i at the end of financial year t. Whether the funding ratio has a positive, negative or non-monotonic effect on the equity allocation is an empirical question.

Higher levels of leverage increase the risk of default, and Amir *et al.* (2010) argue that companies close to violating debt covenants are particularly at risk. To capture the effect of debt, we include the financial leverage ratio (LEV_{it}) in our model. LEV_{it} is measured as long-term debt divided by the sum of long-term debt and the market value of the sponsor's equity (%) for firm i at the end of year t. A higher level of leverage increases the sponsor's default risk, and we expect this to result in a lower allocation of pension assets to equities.

Sponsors usually make pension fund contributions using their net cash inflows from operations. If these cash flows fluctuate this increases the risk that the sponsor will have difficulty in making their pension contributions; and this risk is increased if the size of the required contributions also fluctuates. To reduce this risk sponsors with fluctuating net cash inflows from operations may tend to invest their pension fund in low-risk assets. $SDCF_{it}$ is the volatility of cash flows from operating activities, measured as the standard deviation of operating cash flows over the current and previous four years, deflated by the book value of common equity for firm i at the end of financial year t. We expect this variable to have a negative effect on the equity allocation.

Larger companies tend to have lower risk and better access to investment expertise, and so are willing to hold more risky assets in their pension fund (De Dreu and Bikker, 2012). To control for this effect, we include company size ($Size_{it}$), which we measure as the natural logarithm of the DB pension sponsor's market capitalization (£ million) for company i at the end of year t. We also use an alternative measure of $Size_{it}$, which is the natural logarithm of total DB pension assets (£ million) of company i at the end of year t (Gorter and Bikker, J.A. 2013). We expect size to have a positive effect on the equity allocation.

Over the past two decades many UK companies have closed their DB pension schemes to future accruals (hard closed), and these schemes are now in 'run-off'. Since these schemes have no contributions, they will probably invest in low-risk assets (Butt 2011). We use the (1–0) dummy variable $Close_{it}$ to capture the effect of hard closure on the pension fund's asset allocation. $Close_{it}$ equals one when the sponsor's principal DB scheme is hard closed for firm i at the end of financial year t, and zero otherwise. We expect a negative effect of this dummy variable on equity allocations.

When equity markets have a higher average total return than bond markets, this will not only increase the proportion of pension assets in equities but also encourage DB schemes to invest more in equities. Therefore, we include a (1–0) dummy variable EHB_{it}, which is one when the total return on the equity index is higher than the total return on the bond index in year t, and zero otherwise. We expect the relation between this dummy variable and equity allocations to be positive.

Some companies in the FTSE 100 are multinational businesses with DB pension schemes in other countries. These companies are concentrated in industries such as basic materials and oil and gas with major operations in developing countries, and this may mean they have younger members. Because overseas schemes are subject to different regulations, we include another (1–0) dummy variable ($Oversea_{it}$) to capture this effect. It is equal to one if company i has more than 20% of its pension assets in overseas schemes at the end of fiscal year t, and zero otherwise. The sign on this variable is difficult to predict.

In the 1950s UK pension funds began a trend towards increasing their investment in equities (the cult of the equity), which culminated in the 1990s with very high average equity allocations (Sutcliffe 2005). As Figure 3.2 shows, this century there has been a steady downward trend in the average equity allocation. So, we include a time trend (T), with the expectation that it will have a negative coefficient.

Since all the firms in our data are FTSE 100 companies, the tax arbitrage motive probably applies to all, or most, of them; implying a general motive to invest the pension fund in 100% bonds. All these firms are also subject to the Pension Protection Fund[23] which aims to price its insurance fairly, and this implies 100% of the pension fund in equities. The presence of risk sharing between the sponsor and members, and its likely effect on the pension fund's asset allocation are hard to determine; and could lead to more or less investment in equities. These three factors are not included in our empirical model as there is minimal, or no, within sample variation in the first two factors, and no data on the third factor.

3.5. Data

Our sample consists of annual data on 125 of the past and present FTSE 100 constituents that have, or had, DB pension schemes over the 2003–2019 period. The information to compute the effective duration was collected manually from the sensitivity analysis section of each company's annual reports. The dates of the closure of DB schemes to future accruals, and the proportions of pension assets in overseas schemes were also obtained from the annual reports. The funding ratios, percentage of pension asset allocations, sponsors' market capitalization and other financial data for

[23] The Pension Protection Fund began operating in 2004, and so does not apply in 2003.

the sample companies were downloaded from Bloomberg. Market capitalizations denoted in foreign currency were converted to pound sterling using official exchange rates from World Bank Open Data[24]. The annual returns for the equity and bond indices were downloaded from DataStream[25]. After removing observations with missing values, the sample contains 1,304 company-year observations.

Table 3.1: Descriptive statistics for FTSE 100 companies from 2003 to 2019

Variable	FTSE 100 Sample		
	Mean	Median	STD
Equity	35.23	34.16	18.40
ED	18.00	17.89	3.13
FR	91.88	92.65	17.96
FR^2	8757.21	8572.89	3258.79
LEV	16.38	13.47	13.76
SDCF	0.12	0.06	1.33
Size (SMC)	9.49	9.08	1.75
Size (PA)	7.19	7.29	1.89
Close	0.22	0	0.42
EHB	0.64	1	0.48
Overseas	0.31	0	0.46
T	11.04	11	3.61

Notes: *Equity* is the percentage of the pension fund's equity assets, as a proportion of the total pension assets. *ED* is the effective duration of firm's pension liabilities (years). *FR* is the total market value of pension assets divided by the DB pension liabilities (%), and FR^2 is the funding ratio squared to allow for the non-linear relation between the funding ratio and equity allocation. *LEV* represents the leverage which is measured as long-term debt divided by the sum of long-term debt and the market value of the sponsor's equity (%). *SDCF* is the volatility of cash flows from operating activities, measured as the standard deviation of operating cash flows over the current and previous four years, deflated by the book value of common equity. *Size (SMC)* is the natural logarithm of the

[24] Official exchange rate is the local currency units relative to the US dollar calculated and based on monthly averages supplied by the World Bank:
databank.worldbank.org/reports.aspx?source = 2&series = PA.NUS.FCRF&country =

[25] We use the FTSE All-World Index as the equity index, and the J.P. Morgan Global Aggregate Bond Index as the bond index.

sponsor's market capitalization (£ million), and *Size (PA)* is the natural logarithm of pension scheme assets (£ million). *Close* equals one when the sponsor's principal DB scheme is hard closed, and zero otherwise. *EHB* is one when the total return on the equity index is higher than the total return on the bond index, and zero otherwise. *Overseas* is equal to one if a company has more than 20% of its pension assets in overseas schemes, and zero otherwise. *T* is a time trend (1, 2, 3, 4, ...) starting in 2007 to pick up the time effect of the credit crunch, with prior years assigned a value of zero.

Descriptive statistics for our data are presented in Table 3.1. During the sample period companies allocated an average of 35.23% of their total pension assets to equities. The average effective duration (*ED*) for the sample is 18 years, which is close to the median. The average funding ratio (*FR*) is 91.88%, which means the sample is moderately underfunded. We use the natural logarithm of each DB pension sponsor's market capitalization to represent the *Size (SMC)*; but we also consider the natural logarithm of DB pension assets, *Size (PA)*, as an alternative measure of size. Finally, for our three dummy variables, 22% of the sample pension schemes are closed to future accruals. Over the sample period 64% of the time the equity index generated higher total returns than the bond index, and 31% of the sponsors had overseas DB schemes which accounted for over 20% of their total pension assets.

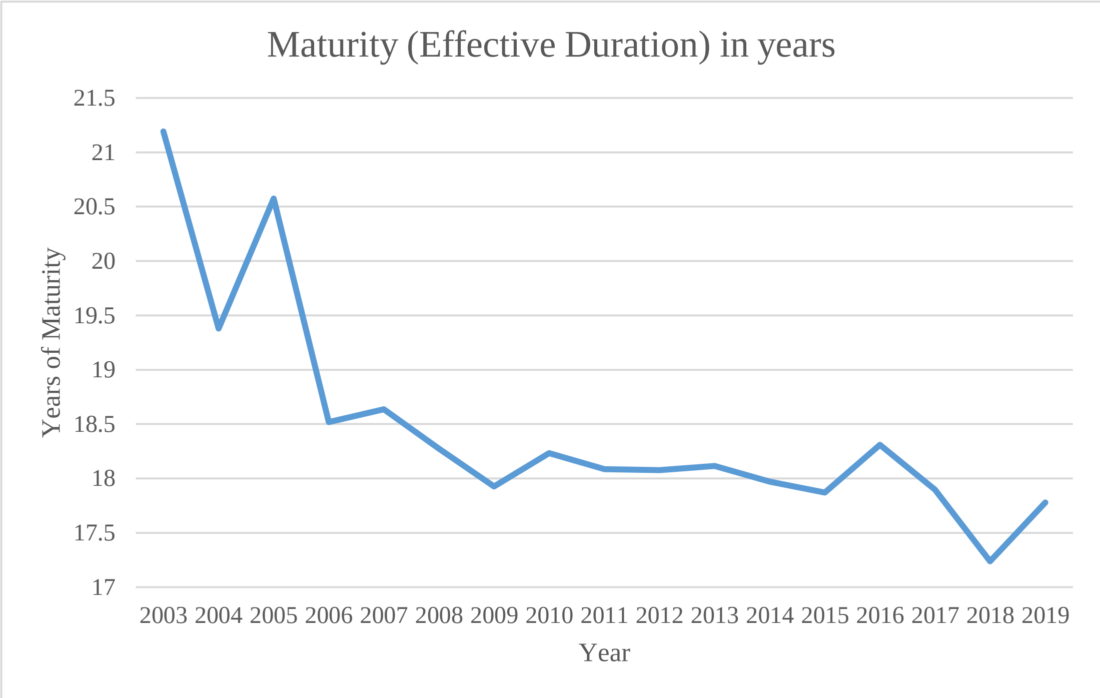

Figure 3.1: Trend in the average maturity (effective duration) of UK pension funds - 2003-2019

From Figure 3.1, we can see a clear downward trend in the average maturity of pension liabilities per year for our sample companies, dropping from 21.2 years in 2003 to 17.8 years in 2019. This is probably due to the continuing closure of DB schemes to new members or future accruals. In 2006 43% of UK DB schemes were open to new members, but by 2020 this had dropped to 11% (Pension Protection Fund 2020). Figure 3.2 shows that there is a clear and relatively smooth down-ward trend in the average equity allocation in our sample, decreasing from 65.17% in 2003 to 21.40% in 2019. Table 3.2 has the correlations between the variables in our model. There are only two correlations above 0.5, so multicollinearity does not appear to be a problem.

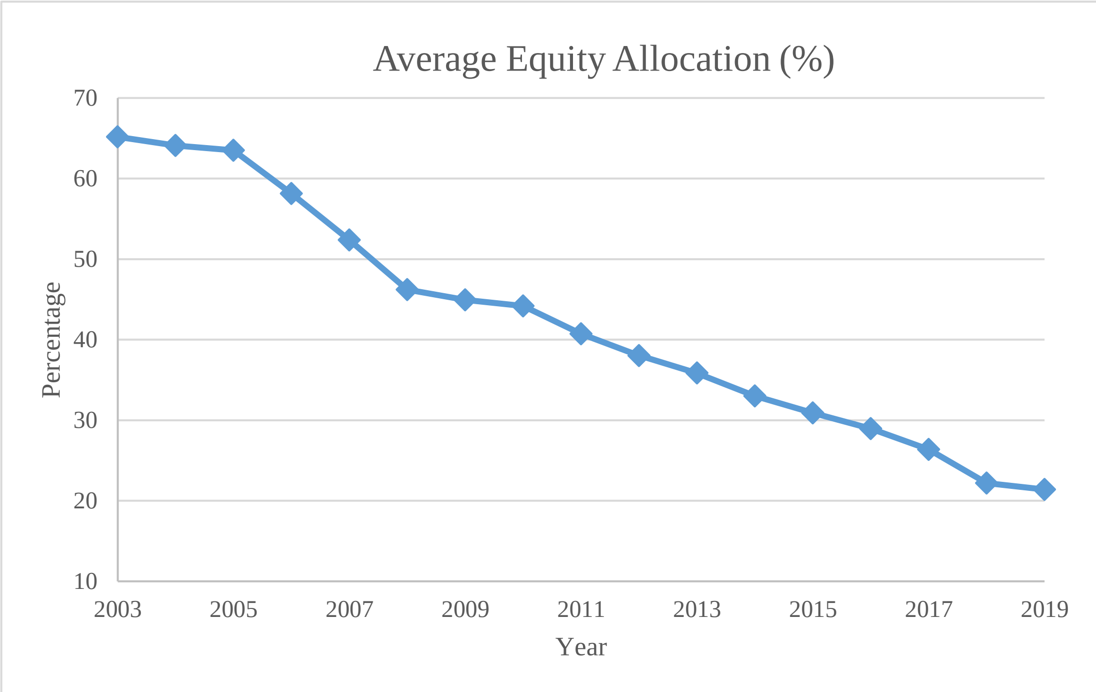

Figure 3.2: The average equity allocation of FTSE 100 pension funds - 2003-2019

3.6. Empirical results

We use linear regression with heteroscedastic panel corrected standard errors (PCSE), where we cluster the standard errors at the level of the sponsor company, since the sample is an unbalanced panel and contains possible heteroscedasticity and serial correlation in the errors. The initial number of observations is 1,304, but after removing observations with missing values and outliers with extremely large or small values, the number of observations decreases to 1,268. The Jarque-Bera test (2.143, $\chi 2 = 0.3426$) shows that the regression residuals are normally distributed, and so the significance tests on the coefficients are reliable.

Since the coefficient on ED is positive and highly significant, the results in model (1) of Table 3.3 support our hypothesis that FTSE 100 companies with less mature pension schemes allocate more assets to equities. The coefficient means the equity allocation is increased by 1.232% when the effective duration (ED) of DB pension liabilities is increased by one year. The positive coefficient on the funding ratio (*FR*) of pension schemes shows that every 1% increase in the funding ratio leads to a 0.431% increase in the equity allocation. This supports the risk management hypothesis. The negative coefficient of -0.004 on FR^2 indicates that, for funding ratios of less than 54%, increases in *FR* have a net positive effect on the equity allocation, but at a decreasing rate. However, for funding ratios above 54%, the equity allocation decreases, giving an inverted U-shaped relationship. As only 2.84% of the funding ratios of our sample of 1,304 observations are below 54%, the empirical reality for the UK is risk shifting.

As expected, pension funds with more highly levered sponsors (*LEV*) have lower equity allocations, with a 1% higher financial leverage leading to equity allocations that are 0.089% lower. The negative coefficient on *Size (SMC)* (-1.178) indicates that the schemes of larger companies have lower equity allocations. This conflicts with our expectation, and may be because larger schemes have responded more strongly to the general trend for de-risking. Companies with pension schemes closed to future accruals (*Close*) have equity allocations 3.413% lower than otherwise, which accords with our expectations. Those companies with more than 20% of their pension assets in foreign schemes (*Overseas*) have equity allocations that are 4.900% higher. The highly significant time trend (*T*) shows there is a strong de-risking trend. Finally, the coefficients on *SDCF* and *EHB* are insignificant, indicating that changes in the volatility of operational cash flows do not cause UK listed companies to hold less equities in their pension funds; and higher annualized total returns for the equity index have no effect on the equity allocation.

Model (2) of Table 3.3 measures size using total pension assets *Size (PA)*, and leads to the same main conclusions as model (1). The differences are that *LEV* is no longer significant, *Overseas* has a smaller coefficient, and *Size* has a larger coefficient.

Table 3.2: Correlation matrix for the variables of the companies studied - 2003-2019

	Equity	ED	FR	FR^2	LEV	SDCF	Size (SMC)	Size (PA)	Close	EHB	Overseas	T
Equity	1											
ED	0.173	1										
FR	-0.285	0.154	1									
FR^2	-0.338	0.163	0.954	1								
LEV	0.067	-0.012	-0.086	-0.099	1							
SDCF	-0.006	0.016	0.018	0.023	0.006	1						
Size (SMC)	-0.135	-0.167	0.128	0.109	-0.294	0.056	1					
Size (PA)	-0.157	-0.199	0.319	0.243	0.014	0.027	0.570	1				
Close	-0.252	-0.015	0.174	0.170	-0.166	0.022	-0.077	-0.060	1			
EHB	0.077	0.003	0.024	0.010	-0.010	-0.033	0.015	0.020	-0.055	1		
Overseas	0.112	-0.294	-0.312	-0.290	0.107	-0.077	0.257	0.007	-0.218	0.018	1	
T	-0.521	-0.068	0.167	0.199	-0.094	-0.016	0.031	0.006	0.377	-0.165	-0.053	1

Notes: *Equity* is the percentage of the pension fund's equity assets, as a proportion of the total pension assets. *ED* is the effective duration of firm's pension liabilities (years). *FR* is the total market value of pension assets divided by the DB pension liabilities (%), and FR^2 is the funding ratio squared to allow for the non-linear relation between the funding ratio and equity allocation. *LEV* represents the leverage which is measured as long-term debt divided by the sum of long-term debt and the market value of the sponsor's equity (%). *SDCF* is the volatility of cash flows from operating activities, measured as the standard deviation of operating cash flows over the current and previous four years, deflated by the book value of common equity. *Size (SMC)* is the natural logarithm of the sponsor's market capitalization (£ million), and *Size (PA)* is the natural logarithm of pension scheme assets. *Close* equals one when the sponsor's principal DB scheme is hard closed, and zero otherwise. *EHB* is one when the total return on the equity index is higher than the total return on the bond index, and zero otherwise. *Overseas* is equal to one if a company has more than 20% of its pension assets in overseas schemes, and zero otherwise. *T* is a time trend (1, 2, 3, 4, ...) starting in 2007 to pick up the time effect of the credit crunch, with prior years assigned a value of zero.

Table 3.3: The equity allocation of DB pension funds

Variable	Expected Sign	(1)	(2)
ED	+	1.232***	1.211***
		(9.55)	(8.89)
FR	?	0.431***	0.452***
		(4.94)	(4.57)
FR^2	?	-0.004***	-0.004***
		(-7.31)	(-6.76)
LEV	-	-0.089***	-0.035
		(-3.29)	(-1.36)
SDCF	-	0.020	-0.053
		(0.05)	(-0.14)
Size	+	-1.178***	-0.746***
		(-4.98)	(-2.75)
Close	-	-3.413***	-3.131***
		(-3.16)	(-2.84)
EHB	+	0.238	0.348
		(0.29)	(0.42)
Overseas	?	4.900***	3.435***
		(5.88)	(4.09)
T	-	-2.097***	-2.076***
		(-17.67)	(-17.33)
Constant	+	38.713***	31.838***
		(7.89)	(6.54)
Observations		1268	1287
Number of companies		125	125
Adj. R^2		0.4155	0.3972

Notes: This table shows the regression results of heteroskedastic panel corrected standard errors (clustering the standard errors at the level of a sponsor firm) for a sample of FTSE 100 companies with DB pension schemes. The dependent variable is *Equity*, it represents the percentage of the pension fund's equity assets, as a proportion of the total pension assets. *ED* is the effective duration of firm's pension liabilities (years). *FR* is the total market value of pension assets divided by the DB pension liabilities (%), and FR^2 is the funding ratio squared to allow for the non-linear relation between the funding ratio and equity allocation. *LEV* represents the leverage which is measured as long-term debt divided by the sum of long-term debt and the market value of the sponsor's equity (%). *SDCF* is the volatility of cash flows from operating activities, measured as the standard deviation of operating cash flows over the current and previous four years, deflated by the book value of common equity. *Size (SMC)* is the natural logarithm of the sponsor's market capitalization (£ million), and *Size (PA)* is the natural logarithm of pension scheme assets (£ million). *Close* equals one when the sponsor's principal DB scheme is hard closed, and zero otherwise. *EHB* is one when the total return on the equity index is higher than the total return on the bond index, and zero otherwise. *Overseas* is equal to one if a company has more than 20% of its pension assets in overseas schemes, and zero otherwise. *T* is a time trend (1, 2, 3, 4, ...) starting in 2007 to pick up the time effect of the credit crunch, with prior years assigned a value of zero. Column (1) provides coefficients and z-statistics (in parentheses) when *Size* is denoted by the natural logarithm of the sponsor's market capitalization. Column (2) provides coefficients and *z*-statistics (in parentheses) when *Size* is denoted by the natural logarithm of total pension assets. ***, ** and * indicate the significance levels 1%, 5% and 10%, respectively.

To further measure the importance of each explanatory variable on the equity allocation, we use sensitivity analysis to quantify the effect of a one standard deviation change in the value of each significant non-dummy explanatory variable on the predicted average equity allocation, with all other explanatory variables set to their average values. These sensitivities depend on both the variability of each variable and its regression coefficients. Since the two *Size* variables are natural logs, their effect on the dependent variable is non-linear. So, we first use the original values of *Size (SMC)* and *Size (PA)* to compute their means and standard deviations, and then employ the natural logs of the increased and decreased *Size* values in the empirical equation. The effect of changes in the funding ratio are also non-linear as *FR* involves a squared term. The sensitivity results for models 1 and 2 in Table 3.3 are in Table 3.4.

Table 3.4: Sensitivity analysis of significant explanatory variables

Significant Explanatory Variable (One Std. Dev. Increase or Decrease)*	Model 1 - % Change in *Equity*	Model 2 - % Change in *Equity*
ED	12.10%	12.06%
FR	-21.19% & 13.09%	-20.29% & 12.07%
LEV	-3.84%	-----
Size	-0.65% & 0.92%	-0.42% & 1.33%
T	23.76%	23.85%

Notes: This table is calculated on the basis of the descriptive statistics from Table 3.1, and the regression coefficients from Table 3.3. All the variables have been explained in Table 3.3. The predicted values of *Equity* using the average values of the explanatory variables are 31.86% for model 1, and 31.42% for model 2.

* The effects of a decrease of one standard deviation are the same as those for a decrease, except for the funding ratio and the size variable, where we report the effect of both an increase and a decrease in their standard deviation.

Table 3.4 shows that the sensitivity of the equity allocation to one standard deviation changes in *ED*, *FR*, *Size* and *T* are broadly similar for models (1) and (2). The dependent variable is most sensitive to variations in *T* (24%), closely followed by variations in *FR* (-21% for an increase and 13% for a decrease of one standard deviation). Variations in *ED* have half the effect (12%) of *T* and *FR* on the equity allocation. Variations in *LEV* have a much smaller effect (4%), and *Size* has an even smaller effect (below 1%). Changes in the dummy variables *Close* and *Overseas* change the equity allocation by between 3% and 5%.

As a robustness check, we apply fixed effects and random effects panel regressions for both the *Size (SMC)* and *Size (PA)* models, with a Hausman test to select between fixed and random effects. We also apply robust standard errors to address heteroscedasticity and autocorrelation in the errors. The panel data results of these regressions are presented in Table 3.5.

Columns (1) and (2) in Table 3.5 show the fixed and random effects models with robust standard errors when size is denoted by the natural logarithm of sponsor's market capitalization, i.e. *Size (SMC)*. The Hausman test statistic of 0.0064 means the fixed effects model (1) is superior to the random effects model (2). Column (1) confirms that for the fixed effects model *ED* has a positive effect on Equity; and *FR2*, *Close* and *T* have a negative effect on Equity. Columns (3) and (4) has the results for the fixed and random effects models with robust standard errors, where size is now denoted by the natural logarithm of total pension assets, i.e. *Size (PA)*. The Hausman test statistic of 0.0000 favours the fixed effects model in column (3), rather than the random effects model in column (4); and the results in column (3) confirm those in column (1) of Table 3.5.

Table 3.5: Robustness test for the equity allocation of DB pension funds

Variable	(1)	(2)	(3)	(4)
ED	0.417**	0.576***	0.434***	0.592***
	(0.181)	(0.165)	(0.181)	(0.166)
FR	0.038	0.083	0.012	0094
	(0.092)	(0.084)	(0.094)	(0.086)
FR^2	-0.001**	-0.001***	-0.001*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
LEV	-0.073	-0.094**	-0.024	-0.021
	(0.046)	(0.041)	(0.039)	(0.037)
SDCF	-0.066	-0.049	-0.013	-0.023
	(0.182)	(0.182)	(0.186)	(0.186)
Size	0.265	-0.558	1.655	-0.436
	(0.661)	(0.500)	(1.021)	(0.533)
Close	-2.547***	-2.762***	-2.893***	-2.987***
	(0.967)	(0.934)	(0.984)	(0.957)
EHB	0.510	0.511	0.571	0.588
	(0.496)	(0.495)	(0.502)	(0.503)
Overseas	2.863	2.679	2.310	2.072
	(2.192)	(1.733)	(2.153)	(1.701)
T	-2.452***	-2.371***	-2.497***	-2.327***
	(0.092)	(0.087)	(0.109)	(0.089)
Constant	57.134***	60.915***	47.650***	54.855***
	(9.328)	(7.583)	(8.240)	(6.265)
Observations	1268	1268	1287	1287
Number of companies	125	125	125	125
Robust standard errors	Yes	Yes	Yes	Yes
Fixed effects in company	Yes	No	Yes	No
Random effects	No	Yes	No	Yes
R^2 overall	0.3607	0.3891	0.2882	0.3685
Hausman test	0.0064		0.0000	

Notes*:* This table shows the regression results of the fixed and random effects with robust standard errors. All the variables have been explained in Table 3.3. Columns (1) and (2) provide coefficients and robust standard errors (in parentheses) when *Size* is denoted by the natural logarithm of the sponsor's market capitalization. Columns (3) and (4) provide coefficients and robust standard errors (in parentheses) when *Size* is denoted by the natural logarithm of total pension assets. ***, ** and * indicate the significance levels 1%, 5% and 10%, respectively.

Overall, the results of these four regressions (columns 1 and 2 in Table 3.3, and 1 and 3 in Table 3.5) support a positive effect of *ED* on *Equity*; and negative effects for

FR^2, *Close* and *T.* There is also evidence from columns (1) and (2) in Table 3.3 that *FR* and *Overseas* have a positive effect on *Equity,* and *LEV* and *Size* have a negative effect. Apart from *Size*, the signs of the eight significant variables are in accord with our prior expectations.

3.7. Conclusions

We use a sample of 125 UK-listed companies who were constituents of the FTSE 100 index over the 2003-2019 period to study the factors affecting their pension fund asset allocation. This is a very important decision for pension schemes and their sponsors that has a major effect on their funding ratios and contribution rates. We use ten explanatory variables, including the first use of effective duration to measure maturity, as well as being the first to include scheme closure, the long-term downward trend, the presence of overseas scheme assets and excess equity returns in the analysis.

Our panel regressions indicate a positive relation between the effective duration of pension liabilities, and the proportion of the pension fund invested in equities. In other words, UK companies with less mature pension schemes tend to increase the investment of their DB pension fund in equities. There is also evidence for a small non-linear negative effect of the funding ratio on the equity allocation, consistent with risk shifting; and strong evidence of a de-risking time trend. We also find that firms with a hard closed pension scheme also have lower equity allocations.

There is weaker evidence that the equity allocation is higher for firms with more than 20% of their pension assets in overseas schemes, and that the funding ratio has a positive effect of the equity allocation. When combined with the negative effect of the squared funding ratio, the result is that the funding ratio has an inverted *U*-shaped effect on the equity allocation, as proposed by Bader (1991) and Li (2010). Some evidence is also available that firms with a higher leverage have a lower equity proportion. Contrary to expectations, sponsor or scheme size has a negative effect on the equity proportion, which suggests that larger schemes have responded more strongly to the general de-risking trend. The volatility of cash flows from operations and the return on the equity index exceeding that on bond index do not have a significant effect on the equity allocation. Our sensitivity analysis finds that variations in scheme maturity and the funding ratio, along with the time trend, have the largest effect on the equity allocation. The leverage of the sponsor, size of the sponsor/scheme, hard closure of the scheme, and a sponsor with more than 20% of its pension assets in overseas schemes have smaller effects on the equity allocation.

Our results indicate that the DB pension schemes of large UK firms have adjusted their equity allocation in a way that is consistent with our prior expectations; and provide some justification for the wide range of scheme specific asset allocations that occur in practice. They may also assist trustees and scheme sponsors in setting an asset allocation that is appropriate for their particular circumstances. The downward time trend in maturity (see Figure 3.1), and the downward time trend in the equity allocation (see Figure 3.2), will lead to even more investment in low-risk assets in the future. The continuing closure of DB schemes will also cause a further decrease in their average equity allocation.

Our analysis of 125 FTSE 100 companies using nine scheme-specific variables and one economic variable has explained about 40% of the variation in asset allocation. It could be extended to the constituents of the FTSE 350, and by the inclusion of additional control variables to explain more of the variation in the dependent variable. For example, acquisitions, mergers, and buy-ins could be examined. Finally, since pension scheme regulations differ between countries, an analysis of DB pension scheme asset allocation in developing countries would be interesting.

4. Chapter Four: Why are pension schemes frozen?

4.1. Introduction

There are two main types of occupational pension scheme - defined benefit (DB) and defined contribution (DC). Employers sponsoring a DB scheme promise to pay members a pension for the rest of their lives (effectively a lifetime annuity) based on each member's final or average salary. This pension promise is independent of the risks arising from investment returns, interest rates, longevity, salary levels, inflation rates and regulations. All these risks are assumed by the employer, and only employer default risk is borne by the members. In contrast, DC schemes do not create any risks for the employer, as they just pay a proportion of each member's salary into that member's pension pot, with all the risks falling on the members.

DB deficits are the responsibility of the employer, and in recent decades these risks have caused some very large deficits. For example, in August 2016 the Pension Protection Fund 7800 index showed an aggregate deficit of £459.4 billion for UK DB schemes, giving an average funding ratio (assets/liabilities) of only 76.1%. The major causes of these deficits have been poor investment performance, increased longevity, very low interest rates, new regulations imposing additional costs on DB schemes, and changes in actuarial and accounting practice which increased both the magnitude and volatility of the reported liabilities.

These large deficits, and the risks of even larger deficits, have had a range of adverse consequences for DB employers. Underfunded DB schemes require higher employer contributions, which has often led to company resources being diverted from discretionary expenditure such as investment, dividends, marketing, training etc[26]. Deficits have been tackled by asset-backed funding, and/or the contribution of contingent assets by employers. Higher pension contributions and changes in accounting and actuarial practice have created lower and more volatile employer accounting profits, a reduction in the employer's credit rating leading to an increase in their cost of capital; and a drop in their share price[27]. As a DB scheme's size increases relative to the employer, its adverse effects on the employer also increase. In some cases, the DB scheme is many times larger than the employer, e.g., in 2003 British Airways two pension schemes were nine times bigger than the company market capitalization, and in 2019 the 600 Group's pension liabilities were 13.4 times bigger than its market capitalization.

Previous research on scheme closures has used US data. Since there are substantial differences in the DB pension regulatory and institutional environment between countries, the US results may not be generalizable to other countries. This is only the second non-US study of the reasons for the closure decision, and the first study of this issue in the UK with 13 explanatory variables. To prevent confounding the effects of a freeze with the causes of a freeze, this is the first empirical analysis to remove all post-freeze observations, and then re-estimate the sensitivity of the model with modified dependent variables (all post-freeze dummies equal to one or all post-freeze dummies equal to zero). We find that five variables have a significant effect on the probability of

[26] Bartram (2017), Bunn and Trivedi (2005), Campbell, et al., (2012), Liu and Tonks (2013), Rauh (2006).
[27] Campbell, et. al, (2012), Cardinale (2007), Carroll and Niehaus (1998), Franzoni (2009), Gallagher and McKillop (2010a, 2010b), Maher (1987, 1996), Wang and Zhang (2014), Watson Wyatt (2005).

making a hard freeze decision – size of the employer, operating cash flow of the employer, unionization rate of the employer's workforce, whether the scheme has been previously soft frozen and the change in employer's sales revenue. These findings are broadly in line with expectations based on the US evidence. There is little evidence that schemes are hard frozen in response to financial pressure on the employer in the UK. Our robustness checks further confirm these significant effects. The results suggest that a hard freeze is followed by an increase in the funding ratio and R&D expenditure; and an increase in leverage, which reduces the probability of a hard freeze. In addition, the freeze may also have led to some movement in the post-freeze values of these variables back towards their pre-freeze values.

This chapter is structured as follows: section 4.2 reviews the intentions and methods of the employers to remove or reduce pension costs and associated risk, and the possible effects on these employers. Next, we review the empirical evidence on the causes of freezes in section 4.3. Data and descriptive statistics are provided in section 4.4. Section 4.5 shows the empirical model for estimating the causes of freeze decisions. Section 4.6 explains the empirical results. Robustness checks are illustrated in section 4.7 and conclusions in section 4.8.

4.2. Removing or reducing pension costs and risk

For an employer who wishes to escape from the costs and risks of a DB scheme, there are a number of choices. One possibility is to wind-up (or terminate) the scheme, which will involve a full buy-out of the entire scheme with an insurance company. In the UK, a wind-up triggers a legal requirement for the employer to immediately fully fund the scheme, which may be impossible. Superfunds have recently emerged in the UK as a cheaper alternative to full buyouts. The superfund becomes the scheme sponsor, which frees the employer from any future costs and risks. But a superfund may require a large initial payment from the employer to compensate them for taking on these costs and risks. Employers can buy-out the liabilities of a particular group of scheme participants (usually pensioners), but this generally requires a substantial initial payment, and leaves the costs and risks of the remaining participants with the employer. Buy-ins and longevity swaps insure some of the risks of a specified group of scheme participants, with the scheme continuing in operation. The employer makes payments to the insurance company to insure the specified costs and risks, but ultimate responsibility for all scheme costs remains with the employer. These ways of dealing with the costs and risks of a DB scheme either involve a large up-front payment; or making regular payments to insure some of the risks and leaving the final liability for the scheme with the employer.

Employers want a way of reducing or eliminating their exposure to a DB scheme's costs and risks, but without having to make a large up-front payment, or having to make a series of insurance or swap payments and freezing (or closing) a scheme is an alternative which meets these two conditions. DB schemes can be frozen (or closed) in two main ways[28]. A soft freeze occurs when no-one can join the scheme, but existing active members can continue making contributions and accruing benefits. A hard freeze is when no-one can join the scheme, and active members cannot make any further

[28] Partial freezes, where the pensions of only some scheme members are frozen are uncommon in the UK, while US partial freezes have not been analysed by previous researchers.

contributions or accrue new benefits. A soft or hard freeze puts the scheme into 'run-off', and it will automatically close when all current members and pensioners have died. Freezing DB schemes has been widely adopted in both the US and UK. From about 1990 onwards UK companies have been freezing their DB schemes in increasing numbers and replacing them with defined contribution (DC) schemes (see Table 4.1). In 2006 the proportion of open DB schemes was 66%, but by 2020 this had dropped to 24%. Not only do DC schemes involve no risk for the employer, but they usually have much lower employer contribution rates than DB schemes. In the US, a freeze also has the benefit that the scheme immediately switches from valuing its liabilities at the pension benefit obligation (PBO), to using the accumulated benefit obligation (ABO), which will be considerably smaller (Begley, et. al, 2015; Atanasova and Hrazdil, 2010). During run-off, the scheme matures, and its assets and liabilities decline. This reduces the costs and risks to which the employer is exposed, which gradually decline towards zero. This risk reduction is faster for hard frozen schemes, as no additional benefits can be accrued.

The proportions of US DB schemes that were frozen are listed in Table 4.2. This shows that over the 2003-2013 period there was a rapid increase in the proportion of US schemes that were hard frozen, and that in contrast to the UK, in 2013 hard frozen schemes were much more common in the US than soft frozen schemes.

Table 4.1: Proportions of open, soft frozen and hard frozen DB schemes (Pension Protection Fund, 2020)

Year	Open	Soft Frozen	Hard Frozen
2006	66%	32%	2%
2007	50%	46%	3%
2008	44%	52%	4%

2009	37%	59%	4%
2010	34%	60%	5%
2011	31%	62%	6%
2012	28%	64%	8%
2013	23%	65%	12%
2014	22%	62%	15%
2015	22%	62%	16%
2016	19%	60%	20%
2017	21%	55%	24%
2018	21%	53%	25%
2019	21%	52%	27%
2020	24%	45%	30%

Table 4.2: Proportions of US DB schemes that were open, soft and hard frozen (PBGC, 2008,2013)

Year	Open	Soft Frozen	Hard Frozen
2003	-	-	9%
2004	-	-	12%
2005	-	-	14%
2013	64%	5%	31%

There are some negative effects associated with freezing a scheme. First, if a scheme is closed to new members the average age of active members tends to increase. If, as is very common, the scheme has age-independent contribution and accrual rates, the inter-generational cross-subsidy from young to old active members decreases. This causes the scheme's funding ratio to drop over time (Campbell, et. al, 2006). Second, frozen schemes, particularly hard frozen schemes, will probably have a negative cash flow, and need to hold some highly liquid investments in order to make the pension payments. These assets will generally have a lower expected return than less liquid assets. Third, since there are fewer active members of soft frozen schemes, and no active members of hard frozen schemes, deficits are difficult or impossible to rectify by raising the contribution rate. Therefore, to reduce under-funding risk, the pension fund will probably reduce its allocation to risk bearing assets, which will reduce the fund's expected return (Butt, 2011; Biggs, 2015). Frozen DB schemes in run-off may also seek to hedge their risks. Finally, as a scheme's assets and liabilities shrink, its economies of scale in both administration and investment will reduce, increasing the average cost per participant.

Choy, et. al, (2014) and Silverstein (2021) propose that a freeze has two offsetting effects on the employer's risk - a direct effect and an indirect effect. The direct effect is a reduction in risk because a hard freeze stops the accrual of any additional liabilities, and over time the assets and liabilities decrease to zero as participants die. The indirect effect is an increase in risk because a freeze causes a change in the risk preferences of the employer's senior management. In the US, the senior managers will usually be members of a supplemental executive retirement plan (SERP), as well as being members of the employer's DB scheme. SERPs provide additional and often substantial pension provision; but according to US law must be unfunded and unsecured, and so expose senior executives to employer bankruptcy risk with the priority of unsecured creditors. Therefore, SERPs create inside debt that aligns the interests of senior executives with those of the employer's debt holders, making them more risk averse than otherwise (Sundaram and Yermack, 2007). A hard freeze of a company's DB scheme typically leads to the SERP also being hard frozen (Choy, et. al, 2014; Begley, et. al, 2015), which gradually reduces the alignment of senior management with the employer's debt holders and increases their willingness for the employer to take on risk. Since SERPs are an important part of the rewards of senior executives of large US companies, they have been used by Choy, et. al, (2014) and Silverstein (2021) to explain the increase in risk following a freeze. In the UK senior executives' pensions schemes are funded, and so this effect does not apply.

A freeze leads to a sharp drop in employer contributions, as their DC contributions are much smaller than their DB contributions. Since pension contributions are tax deductible, this reduction in pension contributions is split between an increase in the employer's tax bill and in their net profits. The employer may respond in a variety of ways. They may use the increase in net profit to create new tax deductions such as higher investment, which lowers net profits to their previous level, except for any extra profit generated by the additional investment. The employer may also respond by issuing debt with tax deductible interest payments that return net profits to their previous level, except for any increase in net profits generated by using the proceeds for investment. The employer might also use the increase in net profits in ways that are not tax deductible, such as increasing dividends, or creating a cash reserve to cover possible losses on new risky ventures. Therefore, freezing a DB scheme can lead to some mixture of higher net profits, higher investment, higher leverage, higher dividends, and a larger capital reserve for risky projects. These changes will then have further repercussions for the employer. For example, higher leverage will tend to increase the employer's equity risk and cost of capital, and lower their credit rating. A larger capital reserve, coupled with more money for investment, may encourage investment in riskier activities, e.g., R&D. In summary, the effects of freezing a scheme on the employer are an empirical question.

4.3. Empirical evidence on the causes of the freezes

Previous research, all of US DB schemes, has found that the probability of a freeze is affected by a wide range of variables[29]. They find it is a positive function of the probability of employer bankruptcy, employer credit risk, a loss making employer, the scheme's level of annual benefit accrual, the PBO minus the ABO, the ratio of (pensioners/total participants), scheme assets are less than the PBO, the proportion of independent directors of the employer, the introduction of accounting standard SFAS 158, the number of schemes sponsored by the company, the employer's age, the percentage of other companies in the same industry that have DC schemes, an increase in disclosure requirements, and after an increase in the employer's sales. The probability of a freeze is decreased by scheme size, the ABO, the ratio of (actives/total employees), the unemployment rate, the unionization of the employer's workforce, CEO accumulated pension benefits, and the employer's size, fixed assets, intangible assets, debt/equity ratio, (operating income/total assets) ratio, the employer's interest coverage, the length of tenure of the employer's CEO, and after an increase in dividends paid by the employer. Previous studies have reached opposite conclusions on whether a higher funding ratio increases or decreases the probability of a freeze. There has been a recent study (Li, Liu and Newton, 2021) of the reasons for freezing UK DB schemes, and their conclusions are different from those of the US studies. They find that the probability of a hard freeze is a positive function of employer and scheme assets, and the funding ratio; and is decreased by the employer's leverage and the annual level of

[29] Atanasova and Hrazdil, 2010; Beaudoin, et. al, 2010; Begley, et. al, 2015; Choy, et. al, 2014; Comprix and Muller, 2011; Hwang and Hong, 2021; Kim, et. al, 2015; Munnell and Soto, 2007; Rauh, et. al, 2020; Silverstein, 2021; Vafeas and Vlittis, 2018; Yu, 2016.

benefit accrual. This suggests there are important differences between the freeze decision in the US and UK.

The decision to freeze a DB scheme and replace it with a DC scheme appears to be governed by a wide range of factors, which does not permit the simple conclusion that employers in a weak financial position with poorly funded schemes are more likely to freeze their DB schemes to reduce their costs and risk. While Begley, et. al, (2015), Munnell and Soto (2007), Rauh, et. al, (2020) and Silverstein (2021) find the funding ratio lowers the probability of a freeze; Atanasova and Hrazdil (2010) and Choy, et. al, (2014) find the opposite result. All these studies are of the US, and we investigate this question for a different country and set of regulatory and institutional arrangements.

4.4. Data and descriptive statistics

Our annual data is for 2003-2019, and our sample is 125 companies with a DB pension scheme that were members of the FTSE 100 at some point between 2003 to 2019. The hard and soft freeze dates and the change of CEO were collected manually from annual reports and company announcements, and on average there are eight years between a soft freeze, and a subsequent hard freeze. No UK scheme has been unfrozen. Annual trade union membership, as a proportion of employees by industry, was downloaded from Trade Union Membership 2019[30]. We use the effective duration of DB pension liabilities as a proxy for the maturity of DB schemes and, following Zhao and Sutcliffe (2021), measure it as:

$$\text{Pension Effective Duration} = \frac{L_{i-x} - L_{i+x}}{2L_i x}$$

[30] Department of Business, Energy & Industrial Strategy: https://www.gov.uk/government/statistics/trade-union-statistics-2019

where x is the change in the discount rate, and $L_{i\text{-}x}$ and L_{i+x} are the DB pension liabilities when the discount rate is $i \pm x$. We hand collected the data to compute the effective duration from the sensitivity analysis section of each company's annual reports. The funding ratio of DB schemes, company market capitalization, operating cash flow, net income and other financial data were extracted from Bloomberg. Market capitalizations in a foreign currency were converted to pound sterling using official exchange rates from World Bank Open Data[31].

Figure 4.1 plots the proportion each year of companies in our sample with a hard frozen scheme. There is a clear upward trend, increasing from 2% in 2003 to 60% in 2019. Figure 1 also shows the number of schemes in our sample that were newly hard frozen each year. In 2011 the number of employers who hard froze their DB scheme jumped to a higher annual rate (between 8 and 12) that was maintained for the next seven years. Figure 4.2 has the distribution of hard freezes in our sample by industrial sector. It shows that most hard freezes are in consumer services (22 companies), financials (19 companies) and industrials (11 companies); and two thirds of our sample is from these three industries.

Table 4.3 contains descriptive statistics of our 13 explanatory variables for all company-year observations. It splits the observations between employers who hard froze their DB scheme, and whose who did not. The mean of the 1,324 *Freeze* dummy variables is 0.222 (it means around 22% company-year observations in our sample have frozen DB schemes), with a standard deviation of 0.416, a median of zero after

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[31] World Bank: databank.worldbank.org/reports.aspx?source = 2&series =PA.NUS.FCRF&country =

removing observations with missing data. Using both parametric and non-parametric tests, employers with hard frozen schemes have higher funding ratios, smaller market capitalizations, lower operating cash flows, lower employee unionization, are more likely to have previously been soft frozen, have lower leverage, higher rates of sales growth and higher increases in R&D expenditure. These univariate results are in line with those of previous empirical studies of the US. Table 4.4 has the correlation coefficients between the 14 variables in our regression model. There is no correlation above 0.33, and so multicollinearity is not a problem.

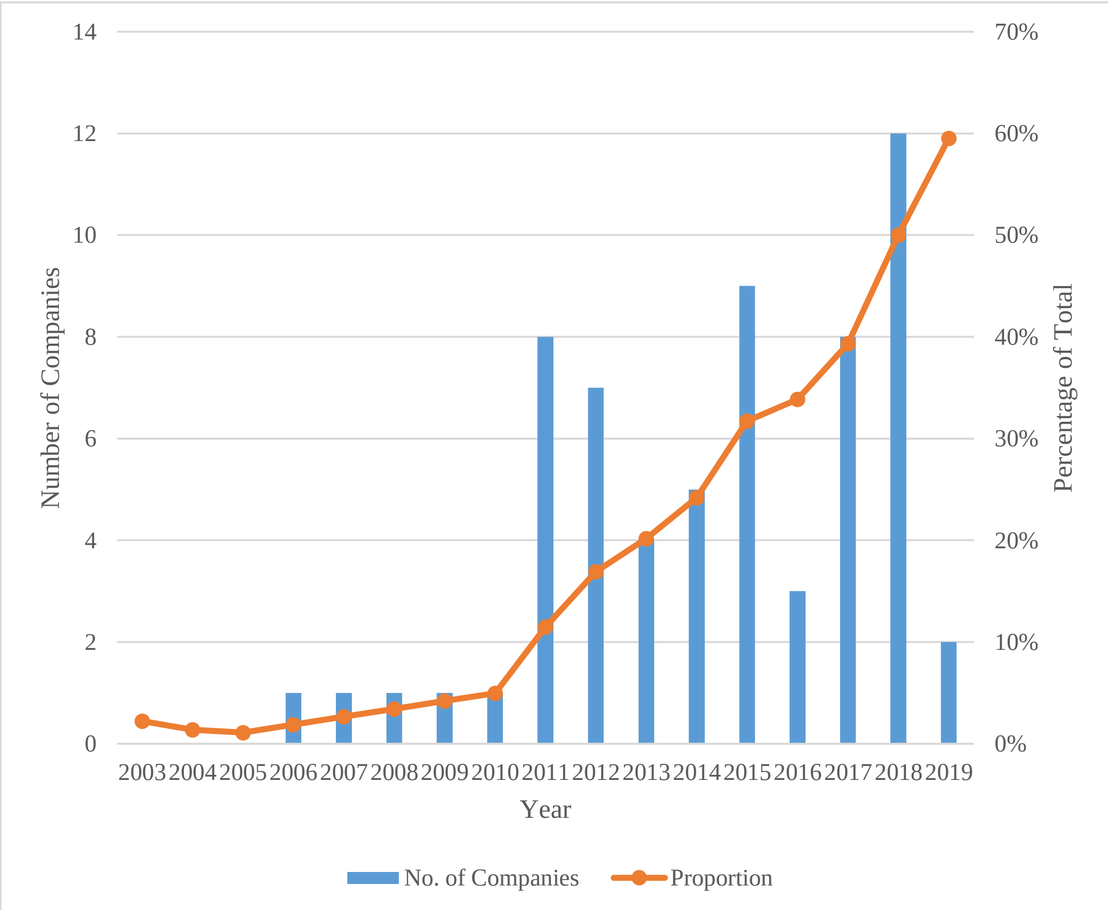

Figure 4.1: Distribution of DB scheme hard freezes[32]

[32] Only 42 companies in our sample include data for 2019.

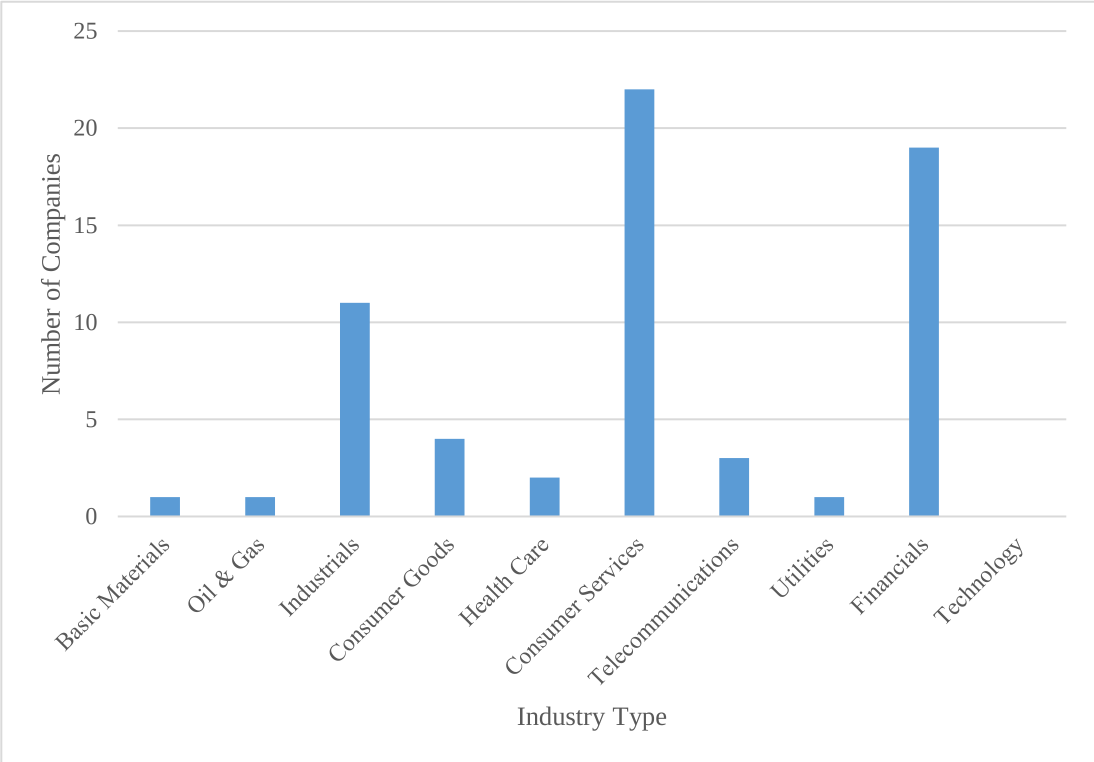

Figure 4.2: UK hard-frozen DB schemes by industry, 2003 to 2019

Table 4.3: Descriptive statistics

	Non-Freeze				Freeze				Test statistics	
Variables	N	Mean	Std Dev	Median	N	Mean	Std Dev	Median	t-Statistic	Wilcoxon z-statistic
FR	1,509	87.836	17.738	89.309	321	97.213	17.643	97.661	-8.608***	-9.641***
Size	1,465	9.365	1.788	9.033	321	9.169	1.528	8.786	1.818**	1.968**
OCF	1,496	0.089	0.090	0.083	320	0.070	0.104	0.052	3.342***	6.721***
Loss	1,497	0.106	0.307	0.000	320	0.106	0.309	0.000	-0.037	-0.037
ED	1,030	18.052	3.207	17.811	294	17.907	2.911	18.000	0.697	-0.003
Union	1,512	19.095	10.219	17.300	321	13.361	6.027	12.900	9.699***	9.118***
ΔCEO	1,515	0.159	0.526	0.000	321	0.131	0.338	0.000	0.922	0.591
SFreeze	1,493	0.568	0.496	1.000	321	0.975	0.156	1.000	-14.561***	-13.782***
LEV	1,477	0.166	0.135	0.144	321	0.129	0.117	0.099	4.549***	6.286***
ΔSales	1,481	0.077	0.572	0.048	320	1.926	33.022	0.039	-2.155**	2.148**
ΔDIV	1,481	0.044	6.573	0.003	320	-0.066	4.128	0.000	0.288	-0.314
ΔR&D	1,480	0.032	0.485	0.000	320	0.004	0.184	0.000	-1.298*	-1.175
ΔCAPEX	1,481	-0.083	1.917	-0.023	320	-0.025	1.272	0.000	-0.510	-0.800

This table provides the summary statistics for our company-year observations used in the analysis of freeze determinants. The comparison between freeze companies and non-freeze companies are based on data from 2000 to 2019. *FR* is the funding ratio of the DB scheme, which is calculated as the market value of pension assets divided by the total pension liability. *Size* is the natural logarithm of the employer's market capitalization (£ million). *OCF* is the employer's operating cash flow, deflated by its total assets. *Loss* is a dummy variable equal to one if the employer reported a negative net income in the previous fiscal year, and zero otherwise. *ED* is the effective duration of employer's total pension liability (years) at the end of each financial year. *Union* is the industry-average percentage the employer's labour force that is unionized at the end of each year. Δ*CEO* is an indicator variable equal to one if there is a change of CEO, and zero otherwise. *SFreeze* is an indicator variable equal to one if the employer has soft frozen (closed to new entrants) previously. *LEV* is the leverage ratio which is measured as long-term debt divided by the sum of long-term debt and the market value of the sponsor's equity (%) in the previous fiscal year. Δ*Sales* is $(S_{t-1}-S_{t-2})/S_{t-2}$, where S_t is total sales revenue in year *t*. Δ*DIV* is the change of dividend pay-out ratio (calculated as dividends paid over net income) in the previous year. Δ*R&D* is the change in the ratio of R&D expenses to total assets in the previous year. Δ*CAPEX* represents the change in the ratio of capital expenditure to total assets in the previous year. Tests of significant differences between the two groups use both parametric (t-statistics for means) and nonparametric (Wilcoxon z-statistics for the median) statistics. ***, **, or * denotes statistical significance at the 1%, 5%, or 10% level, respectively.

Table 4.4: Correlation matrix for the variables in the hard freeze determinants model

	Freeze	FR	Size	OCF	Loss	ED	Union	CEO	SFreeze	ΔSales	ΔDIV	LEV	ΔR&D	ΔCAPEX
Freeze	1													
FR	0.1974***	1												
Size	-0.0430*	0.1479***	1											
OCF	-0.0782***	-0.0907***	-0.1466***	1										
Loss	0.0009	-0.0238	0.0093	-0.1004***	1									
ED	-0.0192	0.1513***	-0.1607***	0.0617**	-0.0034	1								
Union	-0.2211***	0.0414*	0.0313	-0.0043	0.0165	0.0123	1							
ΔCEO	-0.0215	-0.0225	0.0131	0.0025	0.0804***	0.0022	-0.0261	1						
SFreeze	0.3237***	0.1289***	-0.0109	0.0059	-0.0106	-0.0551**	-0.3183***	0.0309	1					
ΔSales	0.0507**	-0.0204	-0.0282	-0.0354	-0.0088	0.0238	-0.0121	0.0394*	0.0149	1				
ΔDIV	-0.0068	0.0015	-0.0075	0.0046	0.1010***	-0.0024	0.0005	0.0946***	-0.0018	-0.0006	1			
LEV	-0.1208***	-0.0560**	-0.2227***	-0.1193***	0.1568***	-0.0238	0.1087***	0.0175	-0.1397***	-0.0315	-0.0023	1		
ΔR&D	0.0306	0.0624***	-0.0288	-0.0057	0.0238	-0.0211	0.0159	-0.0069	0.0205	0.0007	-0.0968***	-0.0728***	1	
ΔCAPEX	0.0120	0.0019	-0.0038	0.0047	-0.0402*	0.0088	0.0206	0.0049	0.0011	0.0456*	-0.0101	-0.0169	0.0125	1

Notes: all the variables have been previously explained in Table 4.3. ***, **, or * denotes statistical significance at the 1%, 5%, or 10% level, respectively.

4.5. Empirical analysis of the freeze decision

Some previous researchers have set the 0-1 dependent variable (*Freeze*) to one in the year of the freeze and in all subsequent years for which the scheme remains frozen. Other researchers appear to have set the freeze variable to one in the freeze year and included post-freeze observations with a zero-freeze dependent variable, presumably because there was no freeze decision in these post-freeze years. Most researchers are unclear on their definition of the freeze variable. The probability of deciding to freeze a scheme can only be determined by variables known before the freeze decision is made, not what happens afterwards. The evidence cited above shows that freezing a scheme is associated with changes in many aspects of the employer, and so the values of the explanatory variables after a freeze may well be different from those that led to the freeze decision. Regression coefficients estimated with the freeze variable set to one in the year of the freeze and in subsequent years measure the difference between employers with frozen and non-frozen schemes. Regressions where the freeze variable is one in the freeze year and zero in post-freeze years conflate observations where the scheme is unfrozen, with those where it has previously been frozen. While the values of the explanatory variables will change after a freeze decision, they are likely to be fairly similar to those that led to the freeze decision, and different from their pre-freeze values. Therefore, the estimated coefficients of such regressions are biased. To prevent confounding the effects of a freeze with the causes of a freeze, we removed the post-freeze observations from the panel regression. In Section 4.7 we investigate the sensitivity of our conclusions to the definition of the freeze variable.

To understand the reasons for freezing a DB scheme, we regress the hard freeze dummy on 13 explanatory variables, ten of which have previously been found to have a significant effect by US researchers. Based on the empirical results for the US, we expect the regression coefficients of these variables to have the following signs: *FR* - mixed previous results; *Size* - negative; *OCF* - negative; *Loss* - positive; *ED* - positive; *Union* - negative; *LEV* - negative; *SFreeze* - no previous results; *ΔCEO* - positive; *ΔSales* - positive; *ΔDIV* - negative; *ΔR&D* - no previous results; *ΔCAPEX* - no previous results. We lagged the explanatory variables by one year, as their values need to be known by the employer at the time of the freeze decision. To control for economic and legislative changes, we include year-fixed effects, and because the dependent variable is binary, we use probit regression. Our regression model is:

$$Freeze_t = \alpha + \beta_1 FR_{t-1} + \beta_2 Size_{t-1} + \beta_3 OCF_{t-1} + \beta_4 Loss_{t-1} + \beta_5 ED_{t-1} + \beta_6 Union_{t-1} + \beta_7 LEV_{t-1}$$

$$+ \beta_8 SFreeze_{t-1} + \beta_9 \Delta CEO_{t-1} + \beta_{10} \Delta Sales_{t-1} + \beta_{11} \Delta DIV_{t-1} + \beta_{12} \Delta R\&D_{t-1} + \beta_{13} \Delta CAPEX_{t-1} + \mathcal{E}$$

where *Freeze* is a dummy variable equal to one in the year when the employer's DB scheme is hard frozen, and zero before the hard freeze year. Observations after the freeze year are dropped. *FR* is the funding ratio of the DB scheme, calculated as the market value of pension assets divided by the total pension liability. *Size* is the natural logarithm of the employer's market capitalization (£ million). *OCF* is the employer's operating cash flow, over its total assets. *Loss* is a dummy variable equal to one if the employer reported a negative net income, and zero otherwise. *ED* is the effective duration of employer's total pension liability (years) at the end of each financial year. *Union* is the percentage the employer's labour force that is unionized at the end of each year. *LEV* is the leverage ratio (%), computed as long-term debt divided by total assets. *SFreeze* is that the scheme has previously been soft frozen. *ΔCEO* is an indicator variable equal to one if there is a change of CEO, and zero otherwise. *ΔSales* is $(S_{t-1}-S_{t-2})/S_{t-2}$, where S_t is total sales revenue in year *t*. *ΔDIV* is the change of dividend pay-out ratio (calculated as dividends paid over net income). *ΔR&D* is the ratio of the change in R&D expenses to total assets. *ΔCAPEX* represents the change in the ratio of capital expenditure to total assets.

4.6. Results

Table 4.5 shows the regression results for in our empirical model and the causes of a hard freeze. All the explanatory variables are lagged by one year to allow time for the employer to react. In line with expectations based on the US evidence, we find that large employers with a small operating cash flow and a highly unionized workforce are less likely to hard freeze their scheme; while those who have previously soft frozen their scheme and whose sales revenue has increased are more likely to freeze their scheme. The funding ratio, a loss-making employer, a more mature scheme, employer leverage, and a change of CEO, dividends, R&D and CAPEX have no effect. These results indicate that the reasons for hard freezes are broadly similar in the US and UK. They also show that hard freezes are not motivated solely by financial pressures. A low funding ratio, loss making employer, highly levered employer, mature scheme, and decreases in discretionary expenditure (dividends, R&D, CAPEX) have no effect on the freeze decision. If financial pressure is one of the important motivations for hard freezes, some or all of these variables should be significant.

Table 4.5: Causes of a hard freeze decision

	Coefficients	Std. Error
Funding Ratio (*FR*)	-0.000	0.004
Size of Employer (*Size*)	-0.123**	0.052
Operating Cash Flow (*OCF*)	-4.881***	1.665
Employer Loss (*Loss*)	0.113	0.237
Effective Duration (*ED*)	0.007	0.027
Unionized % (*Union*)	-0.020**	0.010
Leverage Ratio (*LEV*)	-0.464	0.710
Change in CEO (*ΔCEO*)	-0.043	0.205
Previous Soft Freeze (*SFeeze*)	0.700***	0.202
Change in Sales (*ΔSales*)	0.005***	0.001
Change in Dividends (*ΔDIV*)	-0.022	0.014
Change in R&D (*ΔR&D*)	0.102	0.068
Change in CAPEX (*ΔCAPEX*)	-0.022	0.060
Constant	0.268	1.071
Observations	1061	
Log pseudo likelihood	-174.469	
Pseudo R squared	0.154	

Notes: the dependent variable is *Freeze*, which is a dummy variable equal to one in the year when the employer's DB scheme is hard frozen, and zero before the hard freeze year. Observations after the freeze year are dropped. For details of the explanatory variables see Table 4.3. This regression includes year-fixed effects. We use probit regression, with robust standard errors clustered at the firm level in parentheses. ***, **, or * denotes statistical significance of each correlation coefficients at the 1%, 5%, or 10% level, respectively.

In addition, the variables that are significant do not support a financial pressure motivation. The significant negative effects of a unionized workforce and a large employer are independent of the financial status of the employer. A previous soft freeze may not have been due to financial pressure, and since schemes are soft frozen on average eight years before a hard freeze, the financial status of the employer may have changed since the soft freeze decision. The significant positive sign for a rise in sales implies a reduction in financial pressure, but this increases the probability of a hard freeze. A rise in the employer's operating cash flow suggests a reduction in financial pressure, and the significant negative sign reduces the probability of a hard freeze, and so is the only significant variable that is consistent with a financial pressure motive. Therefore, there is little evidence that schemes are hard frozen in response to financial pressure on the employer.

4.7. Robustness checks

To investigate the sensitivity of our conclusions to the exclusion of post-freeze observations in Table 4.5, we re-estimated the empirical model with a modified dependent variable. First, we set the freeze variable to one in both the year of the freeze and in all subsequent years (denoted *Freeze1*); and then to one in the freeze year and zero in all post-freeze years (denoted *Freeze0*). In the first case changes in the estimated coefficients and standard errors are due to post-freeze changes in the explanatory variables. In the second case changes in the regression results are due to the explanatory variables not instantly reverting to their pre-freeze levels.

The results for *Freeze1* appear in Table 4.6. These confirm the results for *Freeze* in Table 4.5 that the size of the employer, operating cash flow and unionization have a negative effect on the hard freeze probability, and a previous soft freeze has a positive effect. A change in sales is no longer significant, while the funding ratio and a change in R&D now have a significant positive effect on the probability of a hard freeze, and a change in leverage has a negative effect. These changes are due to the inclusion of the post-freeze observations as causes of the hard freeze decision. They suggest that a hard freeze is followed by an increase in the funding ratio and R&D expenditure; and an increase in leverage.

Table 4.6: Causes of a hard freeze with post-freeze dummies equal to one or zero

Dependent Variable	Freeze1		Freeze0	
Explanatory Variables	Coefficients	Std. Error	Coefficients	Std. Error
Funding Ratio (*FR*)	0.007**	0.003	-0.000	0.003
Size of Employer (*Size*)	-0.181**	0.081	-0.068*	0.039
Operating Cash Flow (*OCF*)	-2.406*	1.437	-2.765**	1.177
Employer Loss (*Loss*)	0.227	0.191	0.049	0.211
Effective Duration (*ED*)	-0.006	0.037	0.010	0.019
Unionized % (*Union*)	-0.026*	0.014	-0.013	0.008
Leverage Ratio (*LEV*)	-2.710*	1.405	0.196	0.467
Change in CEO (*ΔCEO*)	-0.091	0.126	-0.042	0.200
Previous Soft Freeze (*SFeeze*)	1.398***	0.260	0.462**	0.185
Change in Sales (*ΔSales*)	0.040	0.040	0.006***	0.001
Change in Dividends (*ΔDIV*)	-0.007	0.005	-0.020	0.016
Change in R&D (*ΔR&D*)	0.146*	0.085	0.092	0.078
Change in CAPEX (*ΔCAPEX*)	0.028	0.024	-0.022	0.053
Constant	0.086	1.231	-1.320*	0.754
Observations	1171		1171	
Log pseudo likelihood	-394.495		-157.777	
Pseudo R squared	0.297		0.090	

Notes: the dependent variable is *Freeze1*, which is a dummy variable equal to one in the year when the employer's DB scheme is hard frozen, and zero before the hard freeze year. Observations after the freeze year are included with *Freeze1* set to one. The dependent variable is *Freeze0*, which is a dummy variable equal to one in the year when the employer's DB scheme is hard frozen, and zero before the hard freeze year. For details of the explanatory variables see Table 4.3. This regression includes year- fixed effects. We use probit regression, with robust standard errors clustered at the firm level in parentheses. ***, **, or * denotes statistical significance of each correlation coefficients at the 1%, 5%, or 10% level, respectively.

Table 4.6 also has the regression results for *Freeze0*. As in Table 4.5, employer size, operating cash flow and unionization have a negative effect on the probability of a hard freeze; and a rise in sales and a previous soft freeze have a positive effect. The significant variables are the same as in Table 4.5, and therefore these results are consistent with the conclusions from Table 4.5. However, these variables now have smaller coefficients, and are less significant than in Table 4.5, which suggests the freeze may have led to some movement in their post-freeze values back towards their pre-freeze values, i.e., a reduction in their operating cash flow, less unionization, lower market capitalization, smaller increases in sales and fewer previous soft freezes for schemes that are hard frozen.

4.8. Conclusions

We use a sample of 125 UK-listed companies with a DB pension scheme who were constituents of the FTSE 100 index over the 2003-2019 period to study the determinants affecting the probability of their hard freeze decision. This is a crucial decision for pension schemes and their sponsors that has a major effect on their resource allocation and associated risks. We use 13 one-year lagged explanatory variables to estimate the probability of a hard freeze decision in this second non-US study.

To prevent confounding the effects of a freeze with the causes of a freeze, we removed the post-freeze observations from the probit panel regression. We find that large employers with a small operating cash flow and a highly unionized workforce are less likely to hard freeze their scheme; while those who have previously soft frozen their scheme and whose sales revenue has increased are more likely to freeze their scheme. Other explanatory variables have no effect. These results indicate that the reasons for hard freezes in the UK are broadly in line with US findings and we find little evidence that schemes are hard frozen in response to financial pressure on the scheme sponsor.

To investigate the sensitivity of our conclusions to the exclusion of post-freeze observations, we re-estimated the empirical model with a modified dependent variable for the robustness checks. First, we set the freeze variable to one in both the year of the freeze and in all subsequent years (denoted *Freeze1*). The results broadly confirm the previous empirical analysis, and suggest that a hard freeze is followed by an increase in the funding ratio and R&D expenditure; and an increase in leverage. And then we set the freeze variable to one in the freeze year and zero in all post-freeze years (denoted *Freeze0*). The results further confirm the conclusions from table 4.5, but the smaller coefficients and lower significance levels of these variables suggest the freeze may have led to some movement in their post-freeze values back towards their pre-freeze values, i.e., a reduction in their operating cash flow, less unionization, lower market capitalization, smaller increases in sales and fewer previous soft freezes for schemes that are hard frozen.

Our empirical analysis of 125 FTSE 100 companies using ten employer-specific variables and three scheme-specific variables has explained 30% of the variation in the probability of the hard freeze decision. It could be extended to cover the FTSE-350, and by the inclusion of extra lagged explanatory variables to explain more of the variation in the probability of the hard freeze decision, such as pension scheme sizes, mergers and acquisitions. Moreover, since different countries have different economic and legislative environments, further analysis of reasons for hard freezes in other developed and emerging economies would be worth exploring.

Last, another related and interesting area of research lies in the effects of scheme closure decisions on employer risks. One may attempt to estimate the effects on, for example, total risk, systematic risk, unsystematic risk, credit risk and bond risk.

5. Chapter Five: Conclusions

5.1. Summary of main findings

The thesis contributes to the literature of DB pension schemes regarding the ALM application to the Chinese BPF pillar 1B, empirical analysis of the factors that determine the equity asset allocation and the reasons for making a hard freeze decision for UK DB pension schemes. It thus supplies guidance on making investment regulations and portfolio allocations of DB schemes for the corresponding authorities, and assists trustees and scheme sponsors in setting an asset allocation and making a hard freeze decision that is appropriate for their particular circumstances.

In Chapter Two, we use portfolio theory, both with and without the liabilities, to study the asset allocation of the Chinese pillar 1B. To this end we divide the calculation of the actuarial liabilities into six different types – active members and pensioners, each in three groups (male employees, female officials in public institutions and female blue-collar workers). We compare the efficient frontiers of the pillar 1B assets under five different investment constraints: 1) post-2015 limits; 2) pre-2015 limits; 3) instantaneous raising retirement age to 65; 4) NSSF limits; and 5) no limits. We find that the asset allocation of pillar 1B funds should use an ALM, rather than the conventional assets-only portfolio model, if only because it reveals the correct risks and returns of the scheme. Removing the limits on investment in domestic assets (but not foreign assets) would be beneficial, as would transferring the assets to the NSSF and raising the retirement age to 65. Finally, investment returns may be sufficient to meet a 5% notional rate per annum, but an official notional rate of over 8% may be higher than can be achieved, and will increase total pension liabilities and worsen the funding ratio.

In Chapter Three, we use a sample of 125 UK-listed companies who were constituents of the FTSE 100 index over the 2003-2019 period to study the factors affecting their pension fund asset allocation, with the first use of effective duration to proxy the maturity of DB schemes. We find that UK companies with less mature (younger) pension scheme participants tend to increase the investment of their DB pension fund in equities. There is also evidence for an inverted U-shaped effect of the funding ratio on the equity allocation, consistent with risk shifting; and strong evidence of a de-risking time trend. Some evidence is also available that firms with a higher leverage have a lower equity proportion, and hard frozen pension scheme also have lower equity allocations. Contrary to expectations, sponsor or scheme size has a negative effect on the equity proportion, which suggests that larger schemes have responded more strongly to the general de-risking trend. The sensitivity analysis further reveals that variations in scheme maturity and the funding ratio, along with the time trend, have the largest effect on the equity allocation.

In Chapter Four, we use and expand a sample of 125 UK-listed companies (from Chapter Three) with a DB pension scheme who were members of the FTSE 100 index over the 2003-2019 period to study the reasons affecting the probability of their hard freeze decision. This is the first non-US research with 13 one-year lagged explanatory variables. We first remove the post-freeze observations from the regression to avoid confusing the effects of a freeze with the causes of a freeze. The results demonstrate that large employers with a small operating cash flow and a highly unionized workforce are less likely to hard freeze their scheme; while those who have previously soft frozen their scheme and whose sales revenue has increased are more likely to freeze their scheme. These significant variables do not support a financial pressure motivation. Thus, in the UK, there is little evidence that DB schemes are hard frozen in response to financial pressure on the scheme sponsor. To investigate the sensitivity of our conclusions to the exclusion of post-freeze observations, we then rerun the empirical analysis with a modified dependent variable (*Freeze1* or *Freeze0*) for the robustness checks. The results not only further confirm the findings of the exclusion of post-freeze observations, but also suggest that a hard freeze is followed by an increase in the funding ratio and R&D expenditure; and an increase in leverage, as a freeze may have led to some movement in their post-freeze values of these variables back towards their pre-freeze values.

5.2. Future research directions

Even though we believe this thesis makes contributions to the literature on Chinese and UK DB pension schemes, there are still aspects of our research that need to be extended to help to deepen and expand our understanding and knowledge of DB pension schemes. We outline several future research directions based on the findings of this thesis as follows.

5.2.1. The Chinese BPF

Chapter two contributes to the application of ALMs in the Chinese BPF pillar 1B under different investment constraints. Raising the retirement age is a direct remedy for pension underfunding, which has been used or planned by pension schemes in many other countries, including China. We find that raising the retirement age instantaneously to 65 for all urban employees is a challenging pension reform option for China. But a phased change should improve the funding ratio due to an increase in assets, a shorter period of retirement and appropriate annuity factors. How to gradually postpone the retirement age, and what are the appropriate retirement ages for both male and female employees are questions worth exploring by future research in actuarial studies and policy making.

Our hypothetical analysis also demonstrates that investment returns under current regulations may be sufficient to meet a 5% notional rate per annum, but a notional rate of over 8% may be higher than can be achieved. This will lead to an increase in the liabilities, and a worse funding ratio. So, the choice of a reasonable and sufficient notional rate of individual accounts, and the relationship between pillar 1B fund investment and the notional rate need further attention by the authorities.

5.2.2. Equity allocations of DB pension schemes

Chapter three indicates that maturity of the scheme, the size of sponsor, company leverage ratio, whether the scheme is closed to future contributions, has significant overseas assets, and a time trend have a significant effect on the equity allocation of UK DB schemes. Since this study uses a sample of 125 UK-listed companies that were members of FTSE 100, further research could try a larger sample (e.g. FTSE-350 companies) with the inclusion of additional macroeconomic and financial control variables (e.g. GDP per capita, unemployment rate and monetary growth) to explain more variation in the equity allocation. Due to the different economic environments and pension regulations, changes in legislation (such as FRS 17) can also be included as control variables, and comparative research between developed and emerging countries would be interesting.

5.2.3. Reasons for a hard freeze decision

Chapter four investigates the reasons for a hard freeze decision. The results show that large employers with a small operating cash flow and a highly unionized workforce are less likely to hard freeze their scheme; while previously soft frozen schemes and those with an increased sales revenue have a higher probability of making a hard freeze decision. Similarly, a larger sample of FTSE-350 level companies (or companies in different developed and emerging countries) could be examined with extra explanatory variables, such as aforementioned macroeconomic factors and behavioural factors (e.g. 'institutional isomorphism'[33]), to capture more variations in the probability of scheme hard freeze decisions in the future research. It would be interesting to research the effects of a hard freeze on different measures of UK employer risk. The comparative research between developed and emerging countries would be interesting as well.

[33] DiMaggio and Powell, 1983.

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