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Essays on Institutional Investors, Portfolio Choice and Asset Prices

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"The important thing is not to stop questioning.
Curiosity has its own reason for existence."

— Albert Einstein

This thesis is the tangible output of a very important and rewarding chapter in my professional life. Looking back, at the start of the research master about five years ago, my understanding of economics and finance was limited. Despite the acquired quantitative skills during my bachelors and masters, I did not have a great sense of the bigger picture questions. Why is it so valuable to have all these quantitative tools for the real world? How can I apply the acquired quantitative skills to answer questions that we as a society care about? By now, I think its fair to say that I am capable of producing these questions. Next to the search for big picture questions, another important lesson I learned over the past years is that asking tough questions is so much easier than coming up with satisfactory solutions. Yet, trying to come up with good solutions is what I started to like a lot about research.

All these important lessons have shaped the person who I am today: curious, critical, and with a clear direction of my future career goals in mind. Of course, I would not have become this person without the support and guidance of many people. This is the opportunity to thank all of them.

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I am very much looking forward to finalizing the first version of our paper, and hopefully many more to come.

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Contents

Introduction

This dissertation is a collection of five independent chapters that aim to better understand the investment decisions of institutional investors. The share of institutional investors that holds and trades securities has substantially increased over the past decades. Since the eighties, the share of US equities held by institutional investors has grown by more than half, from 52 percent to approximately 80 percent (Stambaugh, 2014). This increase raises three important questions. First, what are the drivers behind the investment decisions of institutional investors? Second, how do their investment decisions subsequently affect asset prices? Third, and perhaps most importantly, how do their decisions affect the investors where we ultimately care about, namely, the households?

Regulation is one key channel that shapes the investment decisions of institutional investors (e.g. Ellul et al., 2011; Koijen and Yogo, 2015; Andonov et al., 2017). Understanding how regulation shapes investment decisions is important, because it allows us to better foresee how institutional investors will react to policy changes in the future. We can furthermore use this information to improve particular aspects of regulation, such as the design of risk-based capital requirements. For instance, if regulation creates incentives to take on additional risks, we could alter the regulation in such a way to reduce these incentives. Because regulation often creates similar incentives across institutional investors, simultaneous changes in asset demand can directly affect the prices of these assets. Therefore, in the first chapter, I study how regulation shapes investment decisions of pension funds and insurance companies, along with evidence how these decisions subsequently affect asset prices.

The investment decisions of institutional investors may also have real consequences for households. In the case of pension funds, the investment decisions have a direct impact on the retirement income of the beneficiaries. For instance, if a pension fund invests heavily in stocks, this may result in pension cuts during economic downturns. Hence, in the second chapter, I study determinants of pension funds' investment decisions, such as the liability structure and beliefs, and how their decisions ultimately affect the retirement income of the beneficiaries.

Another prominent trend in financial markets is the increased share of illiquid assets in institutional investors' portfolios. For instance, a report by Willis Towers Watson (2019) shows that pension funds have expanded their illiquid asset allocation by on average 20 percentage points over the past decades. The liquidity of a portfolio, i.e. the ease at which assets can be traded, is crucial because it determines the extent to which investors are able to fulfill their immediate, liquid obligations (e.g. Scholes, 2000; Duffie and Ziegler, 2003). As a result, investing in illiquid assets makes liquidity management highly complex. In the third chapter, I therefore analyse how investors should optimally invest in illiquid assets when faced with liquidity shocks, and the compensation investors require for holding these illiquid assets. In the fourth chapter, I study the actual investment decisions of pension funds towards illiquid assets and relate these decisions to both liquidity and capital requirements. To better understand institutional investors' own views about illiquid assets, the last chapter studies how pension funds deal with illiquid assets by means of a survey study. I will turn to a detailed summary of each of the chapters next.

In the first chapter, 'Long-term Investors and the Yield Curve', I show that pension funds and insurance companies (henceforth: P&Is) change their bond holdings following a shift in regulation and find that, at the same time, these changes substantially affected yields. In particular, I exploit a change in the regulatory discount curve at which liabilities are evaluated that made the long-end of the discount curve less dependent on market interest rates. Following the regulatory change, I show that P&Is decreased long-term bond holdings by 42 percent on average. The decline is stronger for constrained than unconstrained P&Is. Furthermore, I show that the aggregate decline in demand resulted in an increase of long-term bond yields by 24 basis points on average. These findings have important implications for the evaluation of other regulatory or monetary policy measures, such as quantitative easing, because they show how demand shifts, and subsequently the impact on yields, depend on the regulatory framework and time-varying characteristics of investors.

In the second chapter, 'Pension Funds and Heterogeneous Investment Strategies', which is joint work with Dirk Broeders, we study the heterogeneity in investment decisions across defined-benefit pension funds. Globally, 50 percent of all occupational retirement savings is in defined-benefit pension funds (Willis Towers Watson, 2019). Yet, so far only a few studies have analysed the investment strategies of pension funds. The lack of access to comprehensive and detailed data on pension funds is the main reason for the limited number of studies. We show that pension funds make very distinct investment decisions, despite having similar objectives. Consistent with a model of mean-variance preferences over asset minus liabilities, we first show that the funding ratio, risk aversion, and liability duration affect investment strategies of pension funds. However, together these characteristics only explain 36 percent of the heterogeneity in the average returns across pension funds. The heterogeneity that remains reflects an economically important difference in expected retirement income of 16-32 percent over a 40-year accrual phase. We show that these remaining differences reflect heterogeneity in beliefs across pension funds. Pension funds reveal these differences in beliefs through their choices of asset management firms to which they delegate the implementation of their investment strategies. Our findings are important because beneficiaries are typically not free to choose their own pension fund as it comes with the job.

In the third chapter, 'The Liquidity Premium Across Asset Classes', which is joint work with Bas Werker, we study how liquidity affects the portfolio choice of investors and we compute the costs of holding these illiquid assets. We solve a flexible model that captures transactions costs and infrequencies of trading opportunities. The latter implies that investors are unable to trade the illiquid asset for an uncertain period of time. We show that illiquidity that results in suboptimal asset allocations carries low costs for the investor, whereas these costs are high when illiquidity results in suboptimal consumption. As a result, the costs of holding illiquid assets are high for short-term investors, investors who face substantial liquidity shocks, and investors who desire to allocate a substantial fraction of their wealth to illiquid assets. Looking at separate asset classes, back-of-the-envelope calculations suggest that the holding costs for private equity and real estate asset classes are low: varying between 5 and 30 basis points, whereas the ranges are higher for stocks and corporate bonds: varying between 20 and 45 basis points. Our results give important guidance to the opposing findings of empirically estimated liquidity premiums across asset classes.

In the fourth chapter, 'Pension Fund's Illiquid Asset Allocation under Liquidity and Capital Requirements', which is joint work with Dirk Broeders and Bas Werker, we study how pension funds decide to allocate towards illiquid assets. We show that liquidity and capital requirements are two key channels through which illiquid asset allocations are affected. Liquidity requirements consist of short-term pension payments and margin calls on derivative positions. Capital requirements result from regulation that requires pension funds to have sufficient capital to manage the risks they are exposed to, such as interest rate risk. Liquidity and capital requirements interact through the liability duration as a measure of a pension fund's average investment horizon. On the one hand, a pension fund with a high liability duration is less liquidity constrained as it will have to pay less pensions in the short-term.

This allows for a higher allocation to illiquid assets. On the other hand, a high liability duration also implies more exposure to interest rate risk through the present value of its liabilities. This restricts the opportunity to invest in illiquid assets as more of the available capital is required for interest rate risk. Consistent with this intuition, we theoretically and empirically find that these two requirements create a hump-shaped impact of liability duration of the fraction of risky assets invested in illiquid assets. These findings are important to better understand the decisions that drive the allocation to illiquid assets.

In the fifth chapter, 'A Survey of Institutional Investors' Investment and Management Decisions on Illiquid Assets', which is joint work with Patrick Tuijp, we interviewed Dutch and Canadian pension funds and fiduciary managers on the investment and management decisions regarding illiquid assets to achieve better understanding of investors' own attitudes towards illiquid assets. Survey data are important to understand investors' decisions, because the process to get to an investment decision are often not fully observed by the econometrician. We find that both Dutch and Canadian survey participants indicated the risk-return trade-off and diversification benefits as their main reasons to invest in illiquid assets. However, Dutch pension funds in our sample invest 15 percent of their portfolio in illiquid assets, while for the Canadian pension funds this is 34 percent. We put forward three reasons for the stark difference in the average illiquid asset allocations. First, the strong focus of Dutch survey participants on investment costs, which are made available to the public and higher for illiquid assets. Second, supervisory requirements that are risk-based and hence more strict for Dutch pension funds. Third, the division of Dutch pension fund assets into a liability matching portfolio and a return portfolio, which may lead to liquid assets crowding out illiquid assets. Our findings shed important light on how illiquid assets are perceived by large institutional investors that operate in different regulatory frameworks.

Summarizing, this dissertation has three main messages. First, regulation drives a large part of the investment decisions of institutional investors. Second, their investment decisions matter for asset prices. And third, their investment decisions have important welfare implications for the investors where we ultimately care about, namely, the households.

Chapter 1

Long-term Investors and the Yield Curve[1]

1.1 Introduction

Over recent years academics have uncovered evidence that long-term investors, such as pension funds and insurance companies, affect yields. For instance, Domanski et al. (2017) argue that 'hunt-for-duration' behavior by German insurance companies might have amplified the decline in euro area bond yields. If liabilities are linked to market interest rates, a reduction in interest rates increases the duration gap between assets and liabilities and solvency positions decrease. To reduce their exposure to this risk, long-term investors have an incentive to buy long-term bonds and thereby reducing yields at the long-end of the curve.[2] Additionally, Greenwood and Vayanos (2010) and Greenwood and Vissing-Jorgensen (2018) provide suggestive evidence for regulatory effects on yields. They show that changes in regulation which increase the incentive to buy (sell) long-term bonds result in a decline (increase) in long-term yields around policy announcement days. All these findings are consistent with the preferred habitat view: clientele demand creates price pressure in bond

[1]First version: May 2020. First and foremost, I would like to thank my supervisors Theo Nijman and Bas Werker for their invaluable support and guidance. I also thank Aleksandar Andonov, Jules van Binsbergen, Martijn Boons, Marie Brière, Dirk Broeders, Maria Chaderina, Stefano Cassella, Joost Driessen, Esther Eiling, Frank de Jong, Ralph Koijen, Jac Kragt, Martin van der Schans, and conference and seminar participants at the ECB Young Economist Competition, EEA, PhD Mentoring Day (Nova), Tilburg University, Netspar Pension Day, De Nederlandsche Bank, FMA doctoral consortium, FMA Special PhD session, and AFA PhD Poster session for very useful comments. I am grateful to the Dutch Central Bank for providing me with the data and acknowledge financial support from Inquire Europe. Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

[2]Similarly, Klinger and Sundaresan (2018) explain the negative 30-year US swap spreads as a result of underfunded pension plans optimally using swaps for duration hedging rather than long-term bonds.

markets.

Because of data limitations, the literature so far uses price data or aggregate holdings data alone to study the implications of the preferred habitat theory. As a result, there are two questions largely left unanswered. First, event studies based on price data alone do not reveal the *shift* in demand that is causing the price effect. In other words, how large are the shifts in demand that cause the yields to change? Second, and more importantly, price data or aggregate holdings data alone do not reveal the *motives* of long-term investors to change their bond holdings. For instance, why do investors react to regulatory changes in the first place? Which assets do they buy or sell in return? Do investors close to their solvency constraint react differently to regulatory changes compared to non-constrained ones?

I aim to answer these questions by providing direct evidence how long-term investors shifted their bond holdings following a regulatory change and how this behavior subsequently affected yields. First, I find a substantial shift in demand that is long-lasting and with large heterogeneity across institutions. Second, the aggregate shift in demand created substantial price effects on long-term yields. These findings have important implications for the evaluation of other regulatory shocks, such as QE. In preferred habitat models, the demand for long-term bonds is assumed to be exogenous. My findings show how demand shifts, and subsequently the impact on yields, depend on the regulatory framework and time-varying characteristics of investors.

My study combines holdings data and price data for institutional investors domiciled in the Netherlands. In particular, I exploit a positive shock to the regulatory discount curve at which insurers and pension funds (henceforth: P&Is) have to value their liabilities that was introduced in June 2012. The introduced regulatory discount curve made the long-end of the discount curve less dependent on market interest rates. The discount curve uses market interest rates for maturities up to 20 years, whereas interest rates for maturities exceeding 20 years are set equal to a weighted average between market interest rates and a fixed rate, the Ultimate Forward Rate (UFR). The UFR is substantially higher than market interest rates and as a result, the new regulatory discount curve reduces the value of the liabilities and its sensitivity towards changes in market interest rates.

Why does a change in the regulatory discount curve affect demand for long-term bonds? The demand for long-term bonds arises mainly in two parts: economic and regulatory hedging incentives. The long-term nature of P&Is' liabilities creates a natural preference for long-term bonds from a liability hedge perspective (Sharpe and Tint, 1990a; Campbell and Viceira, 2002). Regulatory hedging incentives are particularly important when the regulatory framework does not fully reflect the economic state in which investors are operating. For instance, the regulatory discount curve is important in solvency assessments, as its used to estimate the solvency position and hence the financial position of P&Is. As a result, incentives to hedge the regulatory discount curve may increase if the regulatory discount curve diverges from the economic discount curve. The introduction of the UFR thus decreased regulatory hedging demand whereas economic hedging demand was unaffected. The extent to which regulatory hedging demand decreases, as I show, depends on the liability structure and solvency positions of P&Is.

I report the following key results. First, I find that P&Is that are more exposed to the regulatory change, i.e. the ones with long liability durations, decrease long-term bond holdings to a larger extent than less exposed ones. The decrease in long-term bond holdings is economically significant: The total decline in long-term bond holdings ($T \geq 30$) due to the regulatory change equals 15.30 billion, which is equivalent to a relative decrease in demand of 42 percent. Besides, to give additional support for the economic effects, P&Is in my sample invest 20 percent of their bond portfolio in Dutch government bonds, which corresponds to a decline in holdings equivalent to 22 percent of its long-term bonds outstanding. Second, I find that P&Is close to their solvency constraint decrease long-term holdings to a larger extent than non-constrained ones. Third, P&Is increase their allocation to equities following the regulatory change, with a stronger effect for more constrained P&Is. These findings are consistent with a mean-variance optimization problem in an asset liability context with regulatory constraints.

Second, I estimate the effect of the aggregate decline in long-term bond holdings on yields. To cleanly identify the effects of demand on yields, I apply an instrumental variable approach that uses the weights assigned to the UFR for different maturity buckets as instrument for changes in demand. Even though investors may have anticipated the UFR, the determinants of the shape of the UFR such as its level and the slope were unknown. I show that the change in the regulatory discount curve results in an increase of Dutch long-term bond yields by 24 basis points on average, with larger magnitudes for longer maturity bonds. My estimates are larger than the estimates found by typical event studies because P&Is did not sell everything at once, but spread out the decrease in long-term bond holdings over three to four quarters.

Finally, I connect the changes in yields to responses in the demand curves of the different investor types by using the framework of Koijen and Yogo (2019). The estimates show substantial heterogeneity in demand curves across investor types, with P&Is having strong upward sloping demand curves in prices, whereas demand curves are strongly downward sloping for banks and the foreign sector. Moreover, the steepness of the upward sloping demand curves depend, as I show, on the liability duration and solvency positions of P&Is. These findings add to further understand the drivers behind the estimated price effect. Additionally, they are important for the recent intermediary asset pricing literature which directly models intermediaries and how they matter for asset prices, e.g. He and Krishnamurthy (2013). Typically, these models use only one class of intermediaries. My results highlight the importance of incorporating heterogeneity across investor types in order to understand the effects of intermediaries on asset prices, adding to findings of Greenwood et al. (2018), Timmer (2018), and Koijen and Yogo (2019).

My findings also have important policy implications. In recent years, government bond yields have not always reacted in a predictable way to macroeconomic or monetary policy announcements. For instance, long-term yields in the US remained low even as the FED initiated a series of interest rate increases away from zero starting in 2015. My findings show that regulation plays an important role in understanding these patterns. The demand for bonds by long-term investors increases when interest rates decline, reinforcing the decline in long-term yields. My results show that this reinforcing effect decreases if the valuation of assets and liabilities becomes less dependent on market interest rates. Policy makers should take the regulatory framework of long-term investors into account when analyzing the impact of conventional and unconventional monetary policies.

Related Literature

This paper contributes to the preferred-habitat theory proposed by Culbertson (1957) and Modigliani and Sutch (1966), who argue that there are investor clienteles with preferences for specific maturities, and the interest rate for a given maturity is influenced by the demand of the corresponding clientele and the supply of bonds with that maturity. Vayanos and Vila (2009) and Greenwood and Vayanos (2014) study supply effects on yields. Supply shocks positively affect yields, because supply shocks change the amount of bonds arbitrageurs are holdings and thus the duration risk they carry. Similarly, Guibaud et al. (2013) model a clientele-based yield curve. They show that an increase in the relative importance of the clientele with the longer investment horizon, i.e. the young, has two related effects: it renders long-term bonds more expensive, and it increases their optimal supply by the government. I contribute to this literature by showing direct empirical evidence in favor of the preferred habitat theory by using data on holdings and yields simultaneously.

My paper also links to the recent demand based asset pricing literature. For instance, Koijen and Yogo (2019) propose an asset pricing model with flexible heterogeneity in asset demand across investors. Koijen et al. (2017) and Koijen et al. (2020) apply this model to study the effects of quantitative easing in the euro area. I contribute to this work by relating institutional investor specific characteristics to their demand curves. For instance, I show that the steepness of the upward sloping demand curves of P&Is depends on their liability durations and solvency positions.

This paper also links to Sen (2019), who studies interest rate risk hedging activities by US life insurers after a shift in regulation. The regulatory change leads to distorted hedging incentives due to different treatments of interest rate risk for products with similar economic exposures. Insurers underwriting products that are regulatory sensitive to interest rates do increase hedging activities, and vice versa. I contribute to this paper in two ways: (1) studying spillovers to other asset classes following a shift in hedging incentives and (2) linking changes in hedging incentives to changes in long-term yields.

Finally, this study contributes to the literature on fire sales: forced selling of assets that result in a significant price drop followed by price reversals. Coval and Stafford (2007) study securities commonly held by mutual funds that experience large outflows. Mitchell et al. (2007) study convertible bond prices around hedge fund redemptions. Pulvino (1998) considers commercial aircraft transactions for capital constrained versus unconstrained airlines. Campbell et al. (2011) study house prices for houses sold after foreclosures, or shortly after the death or bankruptcy of a seller. Finally, Ellul et al. (2011) show fire sales as a result of regulatory constraints imposed on insurance companies for corporate bond markets. I also show evidence in favor of regulatory effects on asset prices. Different from the fire sale literature, but consistent with stock additions and deletions to market indexes in e.g. Chang et al. (2015), I detect a permanent effect on prices.

The remainder of the paper is organized as follows. I start with describing the introduction of the regulatory discount curve based on the UFR in Section 1.2. Section 1.3 provides a simple model to derive testable implications of the effect of the change in the regulatory discount curve on long-term bond holdings and yields. A description of the data is given in Section 1.4. In Section 1.5, I test the empirical predictions that follow from the model by using a difference-in-difference specification, and in Section 1.6, I connect changes in holdings directly to changes in yields by using an instrumental variable approach. Section 2.8 concludes.

1.2 Institutional setting - Ultimate Forward Rate (UFR)

The regulatory discount curve is important in solvency assessments, as its used to estimate the liability value and hence the financial position of P&Is. As such, it shows whether P&Is are expected to meet nominal obligations. Important decisions are made based on the solvency positions, such as the amount of dividends paid to the shareholders or the ability to index pension rights. In the Netherlands, the Dutch Central Bank (DNB) constructs and publishes the regulatory discount curve on a monthly basis.

1.2.1 Regulatory discount curve without UFR

Prior to the end of June 2012, the regulatory discount curve was based on the euro swap curve for all maturities. Market interest rates were used until a maturity of 50 years, and interest rates with maturities beyond 50 years equaled the last observed forward rate. Because the regulatory discount curve was based on market interest rates only, the regulatory discount curve approximately equaled the economic discount curve. Formally, the regulatory discount curve was constructed as follows:[3]

1. European semi-annual swap rates from Bloomberg for the time to maturities 1 to 10, 12, 15, 25, 30, 40, and 50 years.[4]
2. Zero-coupon interest rates are derived from the swap rates by using bootstrapping (Veronesi, 2010).
3. Interest rates for which swap rates are non-observable are estimated by assuming constant forward rates, thereby iterating the following relationship:

$$(1+y^{(h)})^h = (1+y^{(h-1)})^{h-1}(1+f_{h-1}^h) \quad (1.1)$$

where $y^{(h-1)}$ equals the interest rate for time to maturity $h-1$ and f_{h-1}^h the forward rate for time-to-maturity $h-1$ to h. For instance, the forward rate from 24 to 25 years (f_{24}^{25}) is used to derive the zero-coupon interest rates for maturities 26-29 years.

[3]See https://www.toezicht.dnb.nl/binaries/50-212329.pdf.

[4]Bloomberg also offers swap rates for all maturities from 1 to 30 years, and for 35 and 45 year time to maturities. However, the regulator refrained from using some of these interest rates because of less liquid markets for these maturities.

1.2.2 Regulatory discount curve with UFR

DNB announced a change in the regulatory discount curve to anticipate on the new regulatory framework of Solvency II for insurance companies on July 2, 2012. The introduced regulatory discount curve is similar to the regulatory discount curve applicable to all European insurers when Solvency II was introduced in 2016. DNB announced a similar regulatory discount curve for pension funds on September 24, 2012.

The new regulatory discount curve uses an extrapolation method based on the UFR, where the UFR is the convergence of long interest rates to a stable level. In essence, the regulatory discount curve with UFR uses market interest rates up to a maturity of 20 years, and interest rates with maturities longer than 20 years are determined by using a weighted average between market interest rates and a fixed rate, the UFR. The main argument that was used to justify the implementation of the UFR is that the market for long durations (>20 years) is fairly illiquid and only few securities with such long durations exists. As a result, the implied market interest rates were regarded unreliable: a discount curve purely based on market data is highly sensitive to supply and demand shocks, and therefore also the solvency positions of P&Is. A regulatory discount curve based on the UFR solves this issue by making long-term interest rates less dependent on market interest rates.

Formally, the discount curve with UFR is constructed as follows:

1. For maturities 1 to 20, zero-coupon interest rates are still derived as before.

2. For pension funds, forward rates exceeding maturities of 20 years are a weighted average between the market forward rate and the UFR. The weights are constant over time. As of a maturity of 60 years, forward rates equal the UFR:

$$f_{h-1}^{h,*} \begin{cases} f_{h-1}^{h} & 1 \leq h \leq 20 \\ (1-w_h) \times f_{h-1}^{h} + w_h \times \text{UFR} & 21 \leq h \leq 60 \\ \text{UFR} & h \geq 60 \end{cases} \tag{1.2}$$

   For insurance companies, the regulatory discount curve is slightly different and uses the forward rate $f_{h-1}^{h} = f_{19}^{20}$ for all maturities $21 \leq h \leq 60$.

3. The weights are equal to

$$w_h = \frac{f_{h-1}^{h,SW} - f_{19}^{20}}{f_{60}^{61,SW} - f_{19}^{20}} \qquad \text{for} \qquad h = 21, ..., 60, \tag{1.3}$$

where $f_{h-1}^{h,SW}$ are the one year forward rates that follow from the Smith-Wilson method.[5] The Smith-Wilson technique uses the following parameter values: the last liquid point which defines the start of the UFR equals 20 years, the full convergence to the UFR equals 60 years, the UFR level equals 4.2%, and the convergence parameter that defines how quickly the discount curve converges to the UFR equals $\alpha = 0.1$. Details on the parameter values for the Smith-Wilson technique are described in Appendix A. Table 1.14 shows the corresponding weights, where the weights are fixed and increase in h.

4. Zero-coupon interest rates $y^{(h)}$ are computed as follows:

$$(1 + y^{(h)})^h = \prod_{n=1}^{h}(1 + f_{n-1}^{n,*}) \qquad \text{for} \qquad h = 1, 2, ...120 \tag{1.4}$$

The regulatory discount curve with UFR has two important effects. First, it decreases current liability values as liabilities are discounted against higher rates. Second, it decreases the impact of interest rate changes. Figure 1.1 shows both effects. The red solid line shows the economic discount curve and the blue solid line the economic discount curve after a parallel shock in interest rates of -1%. The dashed green line and the dotted black line show the same discount curves including the UFR.

1.2.3 Impact of the UFR on the liability value

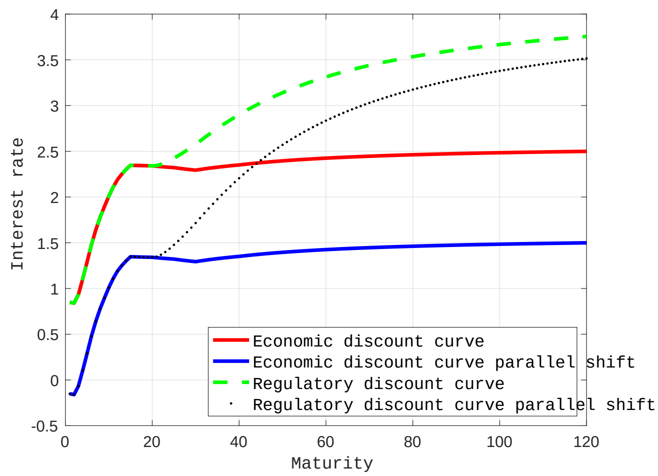
In order to show the economic effects of the UFR, I compute the liability value using both the economic and the regulatory discount curve. Figure 1.2 shows the cash flow pattern of a (fictitious) pension fund. The cash flows are the average cash flow patterns across the Dutch pension funds in my sample. The peak of the cash flow distribution is at a maturity of 20 years, reflecting the importance of the UFR as half of the cash flows materialize at maturities beyond 20 years. The cash flows allow me to compute the value of the liabilities both under the economic and regulatory discount curve. Formally, I compute:

$$L_t = \sum_{n=1}^{N} \frac{CF_n}{(1 + y_t^{(n)})^n} \tag{1.5}$$

[5] The Smith-Wilson technique is described in an EIOPA paper: 'QIS 5 Risk-free interest rates – Extrapolation method': `eiopa.europa.eu/Publications/QIS/ceiops-paper-extrapolation-risk-free-ratesen-20100802.pdf`.

Figure 1.1. **Regulatory discount curve**

This graph shows the economic discount curves (solid red line) and the regulatory discount curve (dashed green line) at implementation of UFR on September 30, 2012. The graph also shows the economic (solid blue line) and regulatory (dotted black line) discount curve after a parallel shock in market interest rates of $\triangle y = -1\%$.



where CF_n are the average projected pension payments for maturity n, where $y_t^{(n)} = y_{E,t}^{(n)}$ under the economic discount curve and $y_t^{(n)} = y_{R,t}^{(n)}$ under the regulatory discount curve.

In Table 1.1, I compute the liability values for the projected pension payments for an average pension fund in my sample using the discount curve with and without UFR on September 30, 2012. Moreover, the table shows the change in the liability value after a parallel decrease in the economic discount curve of 1%. The liability value at implementation of the UFR decreases with 664 million for the average pension fund, or a decrease of 4.23%. This reflects the first effect of the UFR: a direct decrease in the liability values. The average liability value after a negative 1% parallel shift in interest rates equals 19,878 million using the economic discount curve, whereas using the regulatory discount curve this value equals 18,433 million. In other words, following the table, the increase in the value of liabilities equals 3,518 million after the negative interest rate shock pre UFR, and only increases with 2,737 million at implementation of the UFR, or a relative decrease of 28.5%. This reflects the second effect of the UFR: a dampening impact of changes in interest rates on liability values, which is much larger in magnitude than the first effect. Obviously, this effect is particularly visible looking at cash flows that materialize after 20 years in isolation. A negative 1% parallel shock in interest rates increases the value of the liabilities with 1,680 million after implementation of the UFR, which is 46.5% less than the increase in the liability value prior to the implementation of the UFR.

Figure 1.2. **Cash flows of pension payments**

This graph shows the cash flows of pension payments (*not* discounted) for an average pension fund in million euros.

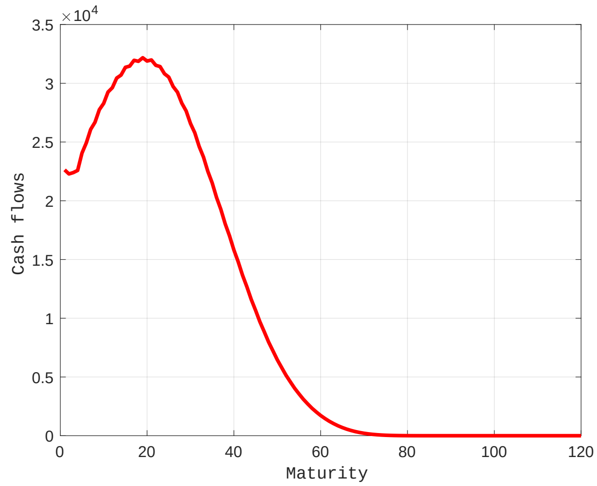


Table 1.1. **Value liabilities with and without UFR**: This table shows the value of the liabilities with and without UFR for an average pension fund in my sample on September 30, 2012. The table also shows the liability value after a parallel shock in interest rates of −1%. The liability values are computed for all projected cash flows and for cash flows with maturities longer than 20 years only. The relative change computes the percentage drop in the liability value due to implementation of the UFR. The values are in million euros.

Cash flows all maturities	without UFR	with UFR	relative change
Discounted value liabilities	16360	15696	−4.23%
Discounted value liabilities $\triangle r = -1\%$	19878	18433	−7.84%
Change value liabilities	3518	2737	−28.52%
Cash flows maturities $T > 20$	without UFR	with UFR	relative change
Discounted value liabilities	6694	6030	−11.01%
Discounted value liabilities $\triangle r = -1\%$	9155	7711	−18.74%
Change value liabilities	2461	1680	−46.5%

1.3 Model

I derive my main testable predictions from a mean-variance optimization framework with liabilities, where P&Is care about both their economic and regulatory solvency constraints. Prior to the UFR, economic and regulatory hedging demand were identical, whereas after implementation of the UFR regulatory hedging demand deviated from economic hedging demand. The extent to which economic and regulatory hedging demand deviate depends on the liability structure and solvency positions of P&Is. This results in heterogeneity in the effect of the regulatory change on long-term bond holdings across P&Is.

To derive testable asset pricing implications of P&I demand for long-term bonds, I close the section by solving a simple equilibrium framework where arbitrageurs, or myopic investors, determine yields in equilibrium.

1.3.1 The financial market

The financial market consists of an equity index and a set of bonds. The equity index is denoted by S_t and its corresponding return by r^S_{t+1}. The set of bonds is denoted by B_t, where each bond is characterized by its maturity h and corresponding yield $y^{(h)}_t$.

The return on each bond is defined as:

$$r^{(h-1)}_{t+1} \quad = \quad \ln(\frac{P^{(h-1)}_{t+1}}{P^{(h)}_t}) = y^{(h)}_t - (h-1)[y^{(h-1)}_{t+1} - y^{(h)}_t]. \tag{1.6}$$

The vector of bond returns is denoted by r^B_{t+1}, the return expectations by $\mathbb{E}_t[r^B_{t+1}]$, and the variance-covariance matrix by $\mathrm{Var}_t[r^B_{t+1}]$. I assume that the bond returns are imperfectly correlated, whereas the equity index and the set of bonds are uncorrelated. Furthermore, I assume throughout that the yield curve can be determined using this set of bonds.

1.3.2 Long-term investors

The wealth of the long-term investor evolves as follows:

$$A_{t+1} = \Big(R_f + w^S_t(r^S_{t+1} - r_f) + w^{B'}_t(r^B_{t+1} - r_f)\Big)A_t, \tag{1.7}$$

where R_f equals the gross risk-free interest rate, w^S_t the portfolio weight to stocks and w^B_t the vector of portfolio weights to the bonds.

For the liabilities, I assume P&Is have to pay out a fixed set of cash flows CF_t, where each cash flow is characterized by its maturity h. I also assume that P&Is have a large enough number of participants such that idiosyncratic longevity risk is fully diversified. Large projected cash flows for long maturities h implies that liabilities have to be paid out in the more distant future.

Finance theory implies that risk-free market interest rates are the applicable discount for guaranteed benefits to exclude arbitrage (e.g. Brown and Wilcox, 2009; Novy-Marx and Rauh, 2009). Hence, the economic value of the liabilities at time t equals:

$$L_t^E = \sum_h CF_t^{(h)} \exp(-hy_t^{(h)}). \tag{1.8}$$

A first-order Taylor expansion in $hy_t^{(h)}$ results in the following economic value of the liabilities at time $t+1$:

$$\begin{aligned} L_{t+1}^E &= \sum_h CF_t^{(h)} \exp(-hy_t^{(h)})\Big(1 + y_t^{(h)} - (h-1)(y_{t+1}^{(h-1)} - y_t^{(h)})\Big) \\ &= a_t' R_{t+1}^B L_t^E, \end{aligned} \tag{1.9}$$

where

$$a_t^{(h)} = \frac{CF_t^{(h)} \exp(-hy_t^{(h)})}{L_t^E}. \tag{1.10}$$

Notice that the discounted cash flows are P&I specific, so that $a_t^{(h)}$ is high for long maturities h if the corresponding cash flow $CF_t^{(h)}$ is large relative to L_t^E.

The regulatory value of the liabilities is similar to its economic counterpart, except that for long maturities the regulatory discount curve is less sensitive to market interest rates. The sensitivity of the regulatory discount curve to market interest rates is defined by ξ_L, where ξ_L has the same length as the set of bonds and $0 \leq \xi_L^{(h)} \leq 1$ for all h. This means that the economic and regulatory value of the liabilities are identical if $\xi_L^{(h)} = 1$ for all h, as was the case prior to implementation of the UFR. If on the other hand $\xi_L^{(h)} = 0$ for all h, the regulatory value of the liabilities is insensitive to changes in interest rates. An example is a regulatory discount curve that uses a fixed rate for all maturities. In case of the specific event I look at here, the introduction of the UFR, we have that $\xi_L^{(h)} = 1$ for $h \leq 20$ and

$\xi_L^{(h)} < 1$ for $h > 20$. The regulatory value of the liabilities thus evolves as:

$$L_{t+1}^R = (\xi_L \circ a_t)' R_{t+1}^B L_t^R, \tag{1.11}$$

where ($\circ$) is the Hadamard product.

I furthermore assume P&Is have mean-variance preferences over the assets minus liabilities, or the surplus, similar to Sharpe and Tint (1990a) and Hoevenaars et al. (2008). Following Koijen and Yogo (2015), I also assume P&Is care about the volatility in the regulatory funding ratio. Important decisions are made based on funding positions of P&Is, such as the amount of dividends paid to shareholders or the ability to index pension rights. The optimization problem of P&Is equals:

$$\begin{aligned} \max_{w_t} \quad & \mathbb{E}[u(\frac{A_{t+1}}{A_t} - \frac{L_{t+1}}{A_t})] \\ = \quad & \arg\max_{w_t} \mathbb{E}[\frac{A_{t+1}}{A_t}] - \frac{\gamma}{2}\text{Var}[\frac{A_{t+1}}{A_t} - \frac{L_{t+1}^E}{A_t}] - \frac{\lambda(F_t^R)}{2}\text{Var}[\frac{A_{t+1}}{A_t} - \frac{L_{t+1}^R}{A_t}], \end{aligned} \tag{1.12}$$

subject to

$$w_t'\iota = w_t^S + w_t^B\iota \leq 1, \tag{1.13}$$

$$w_t^S, w_{h,t}^B \geq 0 \qquad \forall h, \tag{1.14}$$

where γ equals the risk-aversion parameter, $F_t^R = \frac{A_t}{L_t^R}$, and $\lambda(F_t^R)$ defines the importance of the regulatory funding ratio. As in Sen (2019), I assume that the variance of the regulatory funding ratio is proportional to $\lambda(F_t^R)$, where $\lambda'(F_t^R) < 0$, or in other words P&Is care more about the regulatory funding ratios when the regulatory funding ratio is low. I additionally assume that $\lambda(F_t^R)$ is convex: P&Is care more about a decline in the regulatory funding ratio when the regulatory funding ratio is already low than in case its high.[6]

[6] To keep the model tractable, the functional form of $\lambda(F_t^R)$ is a reduced form of the strict constraint that the funding ratio should be higher than a certain threshold.

As I show in Appendix B, solving for w_t results in:

$$w_t^{S*} = \underbrace{\frac{\mathbb{E}_t[r_{t+1}^S - r_f] + \nu_t + \delta_t^S}{(\gamma + \lambda(F_t^R))\mathrm{Var}_t[r_{t+1}^S]}}_{\text{speculative portfolio}}, \tag{1.15}$$

$$w_t^{B*} = \underbrace{\frac{\mathbb{E}_t[r_{t+1}^B - r_f] + \nu_t \iota + \delta_t^B}{(\gamma + \lambda(F_t^R))\mathrm{Var}_t[r_{t+1}^B]}}_{\text{speculative portfolio}} + \underbrace{\frac{\gamma}{\gamma + \lambda(F_t^R)} a_t \frac{1}{F_t^E}}_{\text{economic hedging portfolio}} + \underbrace{\frac{\lambda(F_t^R)}{\gamma + \lambda(F_t^R)} (\xi_L \circ a_t) \frac{1}{F_t^R}}_{\text{regulatory hedging portfolio}}, \tag{1.16}$$

with

$$\begin{aligned} w_t^{*S}, w_{h,t}^{*B} &\geq 0, \\ \delta_t^S, \delta_{h,t}^B &\geq 0, \\ \delta_t^S w_t^{S*} = 0, \delta_{h,t}^B w_{h,t}^{B*} &= 0 \ \forall h, \end{aligned}$$

where ν_t equals the Lagrange multiplier for the restriction that $w_t' \iota = 1$, and δ_t the Kuhn-Tucker multipliers for the restrictions that the portfolio weights are nonnegative.

The optimal demand for stocks consists of speculative demand only, because the liabilities are valued using the yield curve and yields are assumed to be independent of the stocks. The liability hedge portfolio consists of three components: the speculative demand, the economic hedging demand, and the regulatory hedging demand. The economic (regulatory) hedging demand equals the desired hedge against changes in the economic (regulatory) liability value. The heterogeneity in demand for long-term bonds across P&Is depends on two main factors. First, the relative weights of the liabilities in the different maturity buckets. Second, the weight assigned to the economic versus regulatory hedging demand depends on the relative magnitudes of $\lambda(F_t^R)$ and γ, which is driven by solvency positions.

These results together lead to three important model implications. Throughout I indicate variables at implementation of the UFR with a plus sign ($^+$).

Implication 1 - bond holdings

Prior to the UFR, the regulatory funding ratio exactly equals the economic funding ratio, i.e. $F_t^E = F_t^R$, and the optimal weights are defined as:

$$w_t^{B*} = \frac{\mathbb{E}_t[r_{t+1}^B - r_f] - \nu_t \iota + \delta_t^B}{(\gamma + \lambda(F_t^E))\text{Var}_t[r_{t+1}^B]} + a_t \frac{1}{F_t^E} \tag{1.17}$$

Right after implementation of the UFR, the optimal holdings equal:

$$w_t^{B*+} = \frac{\mathbb{E}_t[r_{t+1}^B - r_f] - \nu_t \iota + \delta_t^B}{(\gamma + \lambda(F_t^R))\text{Var}_t[r_{t+1}^B]} + \frac{\gamma}{\gamma + \lambda(F_t^R)} a_t \frac{1}{F_t^E} + \frac{\lambda(F_t^R)}{\gamma + \lambda(F_t^R)} (\xi_L \circ a_t) \frac{1}{F_t^R} \tag{1.18}$$

Subtracting (1.17) from (1.18), we get the change in holdings due to the implementation of the UFR:

$$\begin{aligned} c_t = w_t^{B*+} - w_t^{B*} &= \underbrace{\frac{\mathbb{E}_t[r_{t+1}^B - r_f] - \nu_t \iota + \delta_t^B}{\text{Var}_t[r_{t+1}^B]} \Big(\frac{1}{\gamma + \lambda(F_t^R)} - \frac{1}{\gamma + \lambda(F_t^E)} \Big)}_{\text{change in speculative demand}>0} \\ &+ \underbrace{\frac{\lambda(F_t^R)}{\gamma + \lambda(F_t^R)} \Big((\xi_L \circ a_t) \frac{1}{F_t^R} - a_t \frac{1}{F_t^E} \Big)}_{\text{change in liability hedge demand}<<0} \leq 0 \end{aligned} \tag{1.19}$$

Because $F_t^E < F_t^R$ we have that speculative demand increases, whereas liability hedge demand decreases. The UFR substantially decreases the sensitivity towards interest rate changes, but only leads to a small decline in current solvency positions. As a result, the decline in the liability hedge demand is stronger than the increase in the speculative demand.[7]

Furthermore, we have that $\xi_L^{(h)}$ converges to zero for long maturities, and hence P&Is with large projected cash flows $a_t^{(h)}$ in the distant future decrease long-term bond holdings to a larger extent than the ones with projected cash flows in the near future. Formally, for the change in liability hedge demand we have:

$$\lim_{h \to \infty} c_t^{(h)} = -\frac{\lambda(F_t^R)}{\gamma + \lambda(F_t^R)} a_t^{(h)} \frac{1}{F_t^E} < \lim_{h \to 0} c_t^{(h)} = -\frac{\lambda(F_t^R)}{\gamma + \lambda(F_t^R)} a_t^{(h)} \Big(\frac{1}{F_t^E} - \frac{1}{F_t^R} \Big) \tag{1.20}$$

In other words, my model predicts that P&Is with long liability durations decrease long-term bond holdings more than the ones with short liability durations.

[7] The average increase in the regulatory funding ratio is from 0.99 to 1.03, which equals the 4% difference in the change in the liability value. On the other hand, the sensitivity towards interest rates decline with 29% (see Table 1.1).

Implication 2 - bond holdings
Constrained P&Is put a larger weight on the regulatory hedging demand relative to the economic hedging demand compared to non-constrained ones, and only regulatory hedging demand is affected by the UFR. Formally, for non-constrained investors we have:

$$\lim_{\lambda(F_t^R)\to 0} c_t = 0. \tag{1.21}$$

For constrained investors we have ($\xi_L^{(h)} < 1$ and $F_t^E < F_t^R$):

$$\lim_{\lambda(F_t^R)\to \infty} c_t = \left((\xi_L \circ a_t)\frac{1}{F_t^R} - a_t\frac{1}{F_t^E}\right) < 0. \tag{1.22}$$

In the limit unconstrained investors do not decrease long-term bond holdings, whereas constrained P&Is do.

Implication 3 - stock holdings
My model also predicts a positive change in the stock holdings due to implementation of the UFR ($\lambda(F_t^R) < \lambda(F_t^E)$):

$$w_t^{S*+} - w_t^{S*} = \underbrace{\frac{\mathbb{E}_t[r_{t+1}^S - r_f] - \nu_t\iota + \delta_t^S}{\mathrm{Var}_t[r_{t+1}^S]}\left(\frac{1}{\gamma+\lambda(F_t^R)} - \frac{1}{\gamma+\lambda(F_t^E)}\right)}_{\text{change in speculative demand}} > 0 \tag{1.23}$$

Because the weight that is assigned to the regulatory hedge demand, $\lambda(F_t^R)$, decreases more sharply for P&Is with low funding ratios than for the ones with high funding ratios at implementation of the UFR (convexity), the speculative demand for stocks increases more for P&Is with low funding ratios (similar limits as in (1.21)-(1.22)).

1.3.3 Testable predictions holdings

The first prediction of the model is that the decrease in long-term bond holdings is stronger for P&Is with long liability durations at implementation of the UFR:

Prediction 1 - bond holdings P&Is with long liability durations decrease long-term holdings more compared to P&Is with short liability durations.

Second, the model shows that more capital constrained P&Is decrease long-term holdings to a larger extent compared to non-constrained ones because they have a stronger incentive to hedge the regulatory value of the liabilities. This leads to the second prediction:

Prediction 2 - bond holdings P&Is close to their solvency constraint decrease long-term holdings more compared to non-constrained P&Is.

Third, the model predicts that more capital constrained P&Is increase their stock holdings to a larger extent than less constrained ones:

Prediction 3 - stock holdings P&Is close to their solvency constraint increase stock holdings more compared to non-constrained P&Is.

1.3.4 Model implied impact on yields

Why would the change in long-term bond holdings have such a significant effect on yields? The regulatory change introduces a shock to the demand for long-term bonds. However, the supply of long-term bonds was not affected by the regulatory change. This implies that the interest rate risk, or duration risk, carried by other investors in the market increases. In the preferred habitat models of Vayanos and Vila (2009) and Greenwood and Vayanos (2014), these other investors are defined as the arbitrageurs.[8] In order to carry the increased duration risk, arbitrageurs (or myopic investors) require a higher return on the long-term bond. The level, however, depends on the risk-bearing capacity of the myopic investors.

I start with describing the optimization problem of the myopic investor. The wealth of the myopic investor evolves as follows:

$$B_{t+1} = \Big(R_f + \alpha_t'(r_{t+1}^B - r_f)\Big)B_t. \tag{1.24}$$

The myopic investor has mean-variance preferences over excess returns:

$$\max_{\alpha_t} \mathbb{E}_t[\frac{B_{t+1}}{B_t}] - \frac{\gamma}{2}\text{Var}_t[\frac{B_{t+1}}{B_t}] \quad = \quad R_f + \alpha_t'\mathbb{E}_t[r_{t+1}^B - r_f] - \frac{\gamma}{2}\alpha_t'\text{Var}_t[r_{t+1}^B]\alpha_t, \tag{1.25}$$

[8]Similarly, to explain the bond pricing implications of the prepayment option in MBS in the US, Hanson (2014) assumes arbitrageurs price interest rate risk in the market.

Solving for α_t^*, the optimal solution to the mean-variance investors equals:

$$\alpha_t^* = \frac{\mathbb{E}_t[r_{t+1}^B - r_f]}{\gamma \text{Var}_t[r_{t+1}^B]}, \tag{1.26}$$

First, the two set of investors in the market have to clear. This implies that the yields are determined endogenously depending on the preferences of the long-term and myopic investors. Therefore, the market clearing condition implies:

$$\alpha_t^{(h)} B_t + w_t^{(h)} A_t = Q_t^{(h)} \quad \text{for all } h. \tag{1.27}$$

Plugging in the optimal solution of the myopic investor (1.26) for $\alpha_t^{(h)}$, solving for $y_t^{(h)}$ and using (1.6) results in:

$$y_t^{(h)} - r_f = \frac{(h-1)(\mathbb{E}_t[y_{t+1}^{(h-1)}] - r_f)}{h} + \frac{Q_t^{(h)} - w_t^{(h)} A_t}{B_t} \frac{\gamma (h-1)^2 \text{Var}_t[y_{t+1}^{(h-1)}]}{h} \tag{1.28}$$

where $Q_t^{(h)} - w_t^{(h)} A_t$ is equal to the wealth of the myopic investor in maturity bucket h, i.e. $B_t^{(h)} = Q_t^{(h)} - w_t^{(h)} A_t$. Moreover, this implies that the excess return equals:

$$\mathbb{E}_t[r_{t+1}^{(h-1)}] - r_f = \frac{Q_t^{(h)} - w_t^{(h)} A_t}{B_t} \gamma (h-1)^2 \text{Var}_t[y_{t+1}^{(h-1)}]. \tag{1.29}$$

In other words, the excess return decreases in the holdings of long-term investors: the larger the holdings of the long-term investors, the less interest rate risk has to be carried by the myopic investors, which decreases expected returns.

The market clearing condition should still hold after implementation of the UFR[9], which implies an excess return that equals:

$$\mathbb{E}_t^+[r_{t+1}^{(h-1)}] - r_f = \frac{Q_t^{(h)} - w_t^{(h)+} A_t}{B_t} \gamma (h-1)^2 \text{Var}_t^+[y_{t+1}^{(h-1)}] \tag{1.30}$$

Under the assumption that the conditional variance of future yields does not change because of the introduction of the UFR, i.e. $\text{Var}_t[y_{t+1}^{(h-1)}] = \text{Var}_t^+[y_{t+1}^{(h-1)}]$, subtracting (1.30)

[9] i.e. $\alpha_t^{(h)+} B_t + w_t^{(h)+} A_t = Q_t^{(h)}$

from (1.29) results in:

$$\begin{aligned}\mathbb{E}_t^+[r_{t+1}^{(h-1)}] - \mathbb{E}_t[r_{t+1}^{(h-1)}] &= \frac{(w_t^{(h)} - w_t^{(h)+})A_t}{B_t}\gamma(h-1)^2\text{Var}_t[y_{t+1}^{(h-1)}] \\ &= \frac{c_t^{(h)}A_t}{B_t}\gamma(h-1)^2\text{Var}_t[y_{t+1}^{(h-1)}] \end{aligned} \tag{1.31}$$

For the changes in yields that result from the implementation of the UFR we get:

$$y_t^{(h)+} - y_t^{(h)} = \underbrace{\frac{(h-1)(\mathbb{E}_t^+[y_{t+1}^{(h-1)}] - \mathbb{E}_t[y_{t+1}^{(h-1)}])}{h}}_{\text{change expectations}} + \underbrace{\frac{c_t^{(h)}A_t}{B_t}\frac{\gamma(h-1)^2\text{Var}_t[y_{t+1}^{(h-1)}]}{h}}_{\text{change risk-bearing capacity}} \tag{1.32}$$

This result shows that the price impact of the regulatory change depends on changes in expectations about future yields, $\mathbb{E}_t^+[y_{t+1}^{(h-1)}] - \mathbb{E}_t[y_{t+1}^{(h-1)}]$, the demand shock, $c_t^{(h)}$, the risk-aversion parameter γ, and the wealth of the arbitrageurs, B_t, relative to the wealth of the long-term investors, A_t. Equation (1.29) and (1.32) result in the following two additional model implications.

Implication 3 - future excess returns

Future excess returns decrease if the aggregate holdings of P&Is increase:

$$\lim_{w_t^{(h)}A_t \to Q_t^{(h)}} \mathbb{E}_t[r_{t+1}^{(h-1)}] - r_f = 0, \tag{1.33}$$

and

$$\lim_{w_t^{(h)}A_t \to 0} \mathbb{E}_t[r_{t+1}^{(h-1)}] - r_f = \frac{Q_t^{(h)}}{B_t}\gamma(h-1)^2\text{Var}_t[y_{t+1}^{(h-1)}] > 0. \tag{1.34}$$

Implication 4 - yields

Under the assumption that expectations about future yields did not change or increased, i.e. $\mathbb{E}_t^+[y_{t+1}^{(h-1)}] - \mathbb{E}_t[y_{t+1}^{(h-1)}] \geq 0$, the change in yields is positive and its magnitude depends on the risk-bearing capacity of myopic investors:

$$y_t^{(h)+} - y_t^{(h)} \geq \frac{c_t^{(h)}A_t}{B_t}\frac{\gamma(h-1)^2\text{Var}_t[y_{t+1}^{(h-1)}]}{h} > 0 \tag{1.35}$$

1.3.5 Testable predictions future excess returns and yields

The model predicts that future excess return increase if long-term investors hold a smaller share of long-term bond holdings, which according to my model occurs if the funding ratio is high:

Prediction 3 - future excess returns Yields and future excess bond returns are negatively related to the aggregate funding positions of P&Is.

Second, the UFR leads to a structural decrease in P&Is long-term bond holdings, which, in turn, increase the yields:

Prediction 4 - yields Yields increase due to the implementation of the UFR.

1.4 Data

In this section I describe the three data sources that I use for my analysis: the SHS database (Subsection 1.4.1), the CSDB database (Subsection 1.4.2), and the supervision database (Subsection 1.4.3).

1.4.1 SHS database

I use Dutch security holdings (SHS) data for four types of institutional investors: banks, insurance companies, investment funds, and pension funds. The investment funds mainly consist of mutual funds. All institutions that report are domiciled in the Netherlands and the regulator decides which institutions have to report, with the aim to have sufficient coverage in terms of AUM for every sector. Institutions have to report their holdings of all securities, both foreign and domestic, to the regulator on a quarterly basis.[10]

DNB gathers holdings data to setup, among others, the Dutch balance of payments, the international investment position, and the financial accounts, and subsequently reports the holdings data to the ECB for the setup of the aforementioned statistics at an euro area level. The data that I use is therefore also available at the euro area level. I have three main reasons to use the Dutch data instead. First, the European data starts at the end of

[10] All institutions report their foreign holdings on a monthly basis, whereas this is not the case for domestic holdings. However, since Dutch institutions hold significant fixed income holdings in the Netherlands, I use quarterly data to ensure data consistency.

2013 only, whereas introductions of the ultimate forward rates (UFR) in several European countries already happened in 2011 and 2012. Moreover, the European data aggregates over all sectors, whereas the Dutch data is at the institutional level. This allows me to make use of the cross-sectional variation in institutions. For instance, measuring effects of the solvency positions on holdings is only possible when there is data availability at the institutional level. Third, looking at the total AUM of pension funds alone in my database, I already cover 53 percent of the assets of pension funds in the euro area, OECD (2019).

The data provide bond and stock holdings at the International Securities Identification Number (ISIN) level. Institutions report their positions at the start of the corresponding quarter, the total purchases and sales of each position, and the positions at the end of the quarter, all in euros. For both stocks and bonds, purchases and sales are in market values. For stocks, start and end holdings are available in number of shares and market values. For bonds, start and end holdings are available in both nominal and market values.

1.4.2 CSDB database

The SHS database is linked to the Centralised Securities Database (CSDB). The aim of the CSDB database is to hold accurate information on all individual securities relevant for the statistical purposes of the European System of Central Banks, ECB (2010). From the CSDB database I obtain market relevant information: debt type, maturity dates, coupon rates, coupon frequencies, coupon type (e.g. fixed, floating or zero-coupon), last coupon payment date, yield-to-maturity, and closing price. The data from the CSDB database allows me to assign bonds in maturity buckets and compute bond durations.

1.4.3 Supervision database

The supervision database is from mandatory annual and quarterly statements that P&Is report to DNB. P&Is have to report, among others, solvency positions, the value of the assets and liabilities, liability durations, asset allocations, and derivative positions. I describe the solvency requirements for both pension funds and insurance companies in the next two subsections.

Solvency requirements pension funds

A pension fund's solvency position is assessed by computing its funding ratio, or its assets divided by its liabilities. The minimum funding requirement is a flat rate equal to a funding ratio of about 104.2%. In contrast, the required funding ratio is based on a pension fund's risk profile and is calculated such that the probability that the funding ratio falls below 100 percent on a one-year horizon equals 2.5 percent. For a median pension fund this ratio amounts to a required funding ratio of 116 percent.

Solvency requirements insurance companies

Instead of funding ratios, insurance companies compute solvency ratios to assess the solvency position. Solvency ratios equal the available capital divided by the required capital. Prior to the introduction of Solvency II in 2016, solvency ratios of insurance companies were not risk-based. The required eligible capital prior to 2016 equaled 4 percent of the value of the liabilities. At the introduction of Solvency II, the required capital is computed in a similar way as for pension funds, except that the required capital is calculated such that the probability that the funding ratio falls below 100 percent on a one-year horizon equals 0.5 percent, rather than the 2.5 percent for pension funds.

Solvency ratios can be converted into funding ratios and vice versa. Because the model makes predictions based on funding ratios, I convert insurers' solvency ratios to funding ratios. Formally, prior to Solvency II regulation solvency ratios equal $SR = \frac{A-L}{0.04L}$, which implies that the funding ratio equals $\frac{A}{L} = 0.04 * SR + 1$. The solvency ratios under Solvency II are more complex and hence I collect data on the assets and the liabilities for each insurer to compute the funding ratios manually.

1.4.4 The sample

The total sample covers 20 banks, 42 pension funds, 12 life insurers, 27 non-life insurers and 160 non-equity mutual funds. This group of institutional investors represents on average 80-90 percent in terms of AUM for all institutional investors domiciled in the Netherlands.[11]

I only analyze investors' direct holdings, that is, investments that are not made via other investor types such as mutual funds. The data, unfortunately, does not allow for a linkage between the indirect holdings of the investor to its direct holdings, except for the two largest pension funds and the two largest insurance companies. For these P&Is I know their shares in mutual funds which allows me to use both their direct and indirect holdings.

[11] See for details on reporting requirements `https://statistiek.dnb.nl/statistiek/index.aspx`.

1.4.5 Summary statistics

This section briefly describes the summary statistics. Banks are the largest in terms of AUM, followed by life insurers and pension funds.[12] Life insurers and pension funds also have the highest bond duration of their fixed income portfolios. The average bond duration equals 11.3 and 10.6 years for life insurers and pension funds respectively, whereas this equals 4.3 years for banks, 7.3 for mutual funds and 6.3 for non-life insurers.

Life insurers and pension funds have the longest liability durations, equal to 11.0 and 17.8 years respectively. The liability duration of non-life insurers is much shorter and equals 4.2 years. The average funding ratio of pension funds equals 109% and 110% for insurers. The heterogeneity in the funding ratios for pension funds is substantially larger than for insurers. Insurers generally hedge their liabilities more closely than pension funds because they face costs of financial distress, whereas pension funds cannot default.[13] Life insures and non-life insurers do not substantially deviate in terms of their solvency ratios.

1.5 Empirical methodology changes in holdings

I now turn to the testing of the empirical predictions from my theoretical framework. As the regulatory change affected the pension and insurance sector only, I focus in this section on P&Is and come back to the other investor types in Section 1.6. For bond holdings, I use the *notional* values in all my analyses such that market prices are not driving the results. A change in notional values reflects active choices by investors, which is exactly the focus of this paper.

1.5.1 Long-term bond holdings and the regulatory discount curve

I start with the main regression specification. Even though the regulatory discount curve already affected interest rates as of maturities of 21 years, I focus here on long-term bonds with maturities of 30 years or longer. The weight assigned to the UFR is relatively small for the first affected maturities and these interest rates are closely linked to the 20 year interest

[12] Note that these summary statistics are based on the *direct* holdings only.

[13] In case a pension fund is not compliant with funding requirements, it files a recovery plan to the supervisor. Recovery measures may include an increase in contributions, a reduction of the future benefit accrual rate or, as a measure of last resort, a reduction of accrued benefits.

Table 1.2. **Summary statistics**: This table shows the following summary statistics: total AUM of directly reported assets (AUM), AUM in bonds (AUM bonds), AUM in stocks (AUM stocks), bond duration (Bond duration), liability duration (Liability duration), and the solvency positions (Funding ratio). The funding ratio is in percentage points, AUM in million euro, bond and liability duration in years. Equity mutual funds are excluded from the sample.

AUM	mean	std.dev.	p50	AUM bonds	mean	std.dev.	p50
Banks	20,695	26,558	8,893	Banks	19,591	25,185	8,893
Life insurers	19,917	17,695	21,534	Life insurers	14,557	13,788	13,594
Non-life insurers	1,383	1,332	831	Non-life insurers	1,112	1,237	650
Mutual funds	763	1,422	432	Mutual funds	622	853	371
Pension funds	14,760	39,731	4,322	Pension funds	7,876	20,143	2,450
AUM stocks	**mean**	**std.dev.**	**p50**	**Bond duration**	**mean**	**std.dev.**	**p50**
Banks	1,104	3,291	9	Banks	4.3	3.5	3.7
Life insurers	5,360	4,644	3,743	Life insurers	11.3	3.5	11.4
Non-life insurers	271	417	117	Non-life insurers	6.3	4.1	6.2
Mutual funds	141	668	145	Mutual funds	7.3	4.8	6.8
Pension funds	6,884	20,197	1,851	Pension funds	10.6	3.7	10.4
Liability duration	**mean**	**std.dev.**	**p50**	**Funding ratio**	**mean**	**std.dev.**	**p50**
Life insurers	11.0	3.5	11.7	Life insurers	110	4	109
Non-life insurers	4.1	2.8	3.5	Non-life insurers	110	5	108
Pension funds	17.8	2.9	17.6	Pension funds	109	12	108

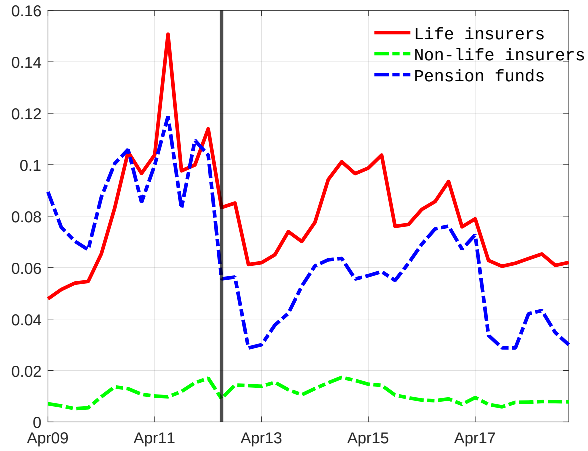
rates and hence a good substitute to hedge the 20 year interest rate.

Figure 1.3 shows the average fraction of long-term bonds in the bond portfolio for P&Is over time. Following the two quarters after the UFR was implemented, there is a sharp decline in long-term bond holdings for both life insurers and pension funds. Long-term bond holdings slightly increase again towards the end of 2014, but remain substantially lower than the pre-UFR levels.

To bring the predictions of the model to the data, I use a difference-in-difference specification which compares long-term bond holdings before and after implementation of the UFR. I exploit the heterogeneity in exposure towards the UFR, which depends on the liability duration of P&Is. I conjecture that investors with long liability durations decrease long-

Even though investors may have anticipated the UFR, the determinants of the shape of the UFR such as its level and the slope were unknown.[14]

Figure 1.3. **Long-term bond holdings by institutional investor type**
This graph shows the average fraction of bonds with a maturity of 30 years or longer for life insurers, non-life insurers, and pension funds over the period 2009q1-2018q1.



term bond holdings more compared to investors with short liability durations:

$$w_{it}^B = \alpha + \beta_0 \text{UFR}_t + \beta_1 \text{UFR}_t \times D^L_{2012q1,i} + \beta_2 \text{FR}_{it-1} + \beta_3 D^L_{it-1} + \nu_i + \epsilon_{it}, \tag{1.36}$$

where UFR_t equals one after implementation of the UFR and zero otherwise, $D^L_{2012q1,i}$ is the liability duration as of 2012q1, FR_{it-1} the lagged funding ratio, D^L_{it-1} the lagged liability duration, and ν_i are fund fixed effects.

Table 1.3 shows the results. P&Is with long liability durations decrease long-term holdings to a larger extent than the ones with short liability durations, supporting the first prediction of my theoretical framework in Section 1.3. The effect is also economically significant. The average liability duration in the cross-section of P&Is equals 14 years, which implies long-term bond holdings decreased by approximately $14 \times 0.0018 = 2.5$ percent. The total decline in long-term bond holdings due to the regulatory change equals:

$$\sum_{i=1}^{N} \hat{\beta}_1 \times D^L_{2012q1,i} \times AUM_i^B = 15.30 \text{ billion}, \tag{1.37}$$

where AUM_i^B is the total AUM in bonds. The total AUM in long-term bonds prior to the regulatory change equals 36.10 billion, so this means a relative decrease of 42 percent. Besides, to give additional support for the economic effects, P&Is invest 20 percent of the total bond portfolio in Dutch government bonds on average, which means a decline in these holdings of 25% × 15.30 = 3.06 billion. The average amount outstanding of 30-year Dutch government bonds equals 14 billion, and hence, the total decline corresponds to 22 percent of its amount outstanding.[15]

Table 1.3 also shows the changes in bond holdings with maturities varying between 15 and 25 years, and maturities less than 15 years. P&Is increased their holdings towards bonds with maturities varying between 15 and 25 years, whereas they did not change their holdings to bonds with maturities less than 15 years. These results show that P&Is moved their long-term bonds with maturities of 30 years or longer to bonds with maturities around 20 years.

1.5.2 Long-term bond holdings and constraints

My model also predicts that P&Is closer to their solvency constraint decrease long-term bond holdings to a larger extent than funded P&Is. I use a triple difference-in-difference estimation technique to test this hypothesis:

$$w_{it}^B = \alpha + \beta_0 \text{UFR}_t + \beta_1 \text{UFR}_t \times D^L_{2012q1,i} \times \text{FR}^{-1}_{2012q1,i} + \beta_2 \text{FR}^{-1}_{it-1} + \beta_3 D^L_{it-1} + \nu_i + \epsilon_{it}, \quad (1.38)$$

where $FR^{-1}_{2012q1,i}$ is the inverse of the funding ratio as of 2012q1.

Table 1.4 summarizes the results. P&Is that are more constraint, i.e. have a larger inverse of their funding ratio, decrease long-term bond holdings to a larger extent: A one standard deviation increase in the inverse of the funding ratio (0.08), increases the decline in long-term bond holdings by 25 basis points, which is equivalent to 1.89 billion, or 5.26% of the long-term bond holdings. P&Is that are more constrained also increase their holdings towards bonds with maturities between 15 and 25 years to a larger extent than non-constrained ones.

1.5.3 Stock allocation and the regulatory discount curve

The final model implication for the changes in holdings is that P&Is closer to their solvency constraint allocate more of their assets to stocks at implementation of the UFR. I

[15] As a robustness check, I have also added mutual funds to estimate (1.36): Mutual funds do not have liabilities and therefore their liability durations essentially equal zero. Including mutual funds to the sample with a liability duration forced to zero does not affect the sign and the magnitude of the coefficients.

Table 1.3. **Long-term bond holdings and the regulatory discount curve**: This table presents the results of the main regression described in Equation (1.36): $w^B_{it} = \alpha + \beta_0 \text{UFR}_t + \beta_1 \text{UFR}_t \times D^L_{2012q1,i} + \beta_2 \text{FR}_{it-1} + \beta_3 D^L_{it-1} + \nu_i + \epsilon_{it}$, with UFR equal to 1 as of 2012Q1 and zero otherwise, $D^L_{2012q1,i}$ the duration of the liabilities as of 2012Q1, and controls include the lagged inverse of the funding ratio and the liability duration. Column (1) and (2) show the results for bond holdings with a maturity of 30 years or longer, column (3) and (4) for maturities between 15 and 25 years, and column (5) and (6) for maturities shorter than 15 years. ICL is a dummy that equals one for life insurers and zero otherwise and PF equals one for pension funds and zero otherwise. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Holdings $T \geq 30$		Holdings $15 \leq T \leq 25$		Holdings $T \leq 15$	
UFR	0.0115		−0.0361**		0.0514	
	(0.0080)		(0.0160)		(0.0317)	
UFR × D^L_{2012q1}	−0.0023***	−0.0018***	0.0033***	0.0034***	−0.0014	−0.0028
	(0.0007)	(0.0007)	(0.0012)	(0.0012)	(0.0021)	(0.0022)
1/Funding ratio	0.0418	0.0431	−0.1371**	−0.1324	0.0335	0.0471
	(0.0359)	(0.0480)	(0.0684)	(0.0939)	(0.1054)	(0.1447)
Liability duration	0.0030*	0.0064***	0.0026	0.0029	−0.0085	−0.0219***
	(0.0017)	(0.0023)	(0.0027)	(0.0039)	(0.0055)	(0.0065)
ICL	0.0370*		0.0324		−0.0934	
	(0.0199)		(0.0337)		(0.0724)	
PF	0.0043		0.0187		−0.0448	
	(0.0273)		(0.0432)		(0.0899)	
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	No	Yes	No	Yes	No	Yes
N	2,376	2,376	2,376	2,376	2,376	2,376
R^2	0.11	0.61	0.15	0.66	0.16	0.73

use the following difference-in-difference specification to test this hypothesis formally:

$$w^S_{it} = \alpha + \beta_0 \text{UFR}_t + \beta_1 \text{UFR}_t \times \text{FR}^{-1}_{2012q1,i} + \beta_2 \text{FR}_{it-1} + \nu_i + \epsilon_{it}. \tag{1.39}$$

Table 1.5 shows that more constrained P&Is increase their stock allocation to a larger extent. A one standard deviation increase in the inverse of the funding ratio (0.08) increases the stock allocation with 2.43%, which is equivalent to an average increase of 225 million that is allocated to stocks.

Table 1.4. **Long-term bond holdings and constraints**: This table present the results of the regression described in Equation (1.38): $w_{it}^B = \alpha + \beta_0 \text{UFR}_t + \beta_1 \text{UFR}_t \times D^L_{2012q1,i} \times \text{FR}^{-1}_{2012q1,i} + \beta_2 \text{FR}^{-1}_{it-1} + \beta_3 D^L_{it-1} + \nu_i + \epsilon_{it}$, with UFR equal to 1 as of 2012Q1 and zero otherwise, $D^L_{2012q1,i}$ the duration of the liabilities as of 2012Q1, and controls include the lagged inverse of the funding ratio and the liability duration. Column (1) and (2) show the results for bond holdings with a maturity of 30 years or longer, column (3) and (4) for maturities between 15 and 25 years, and column (5) and (6) for maturities shorter than 15 years. ICL is a dummy that equals one for life insurers and zero otherwise and PF equals one for pension funds and zero otherwise. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Holdings $T \geq 30$		Holdings $15 \leq T \leq 25$		Holdings $T \leq 15$	
UFR	0.0128		-0.0378^{**}		0.0599^{*}	
	(0.0088)		(0.0160)		(0.0327)	
$\text{UFR} \times D^L_{2012q1} \times$	-0.0027^{***}	-0.0021^{**}	0.0039^{***}	0.0040^{***}	-0.0023	-0.0037
$\text{FR}^{-1}_{2012q1,i}$	(0.0009)	(0.0009)	(0.0012)	(0.0013)	(0.0025)	(0.0025)
1/Funding ratio	0.0341	0.0317	-0.1266^{*}	-0.1090	0.0199	0.0137
	(0.0332)	(0.0446)	(0.0680)	(0.0948)	(0.1009)	(0.1394)
Liability duration	0.0032^{*}	0.0065^{***}	0.0025	0.0028	-0.0079	-0.0210^{***}
	(0.0019)	(0.0023)	(0.0027)	(0.0038)	(0.0054)	(0.0064)
ICL	0.0360^{*}		0.0325		-0.0944	
	(0.0200)		(0.0336)		(0.0720)	
PF	0.0028		0.0192		-0.0493	
	(0.0271)		(0.0429)		(0.0895)	
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	No	Yes	No	Yes	No	Yes
N	2,349	2,349	2,349	2,349	2,349	2,349
R^2	0.11	0.61	0.15	0.67	0.15	0.72

1.5.4 Derivative positions

The empirical analysis so far uses long-term bond holdings only. However, interest rate risk is also managed by using derivative contracts, especially for very long-term maturities. As of the start of 2012, pension funds have to report interest rate derivative positions on an aggregate level: They report the market value of interest rate derivative contracts broken down in different types of derivative contracts. Moreover, they report the values of these

Table 1.5. **Stock allocation and the regulatory discount curve**: This table present the results of the regression described in Equation (1.39): $w_{it}^S = \alpha + \beta_0 \text{UFR}_t + \beta_1 \text{UFR}_t \times \text{FR}_{2012q1,i}^{-1} + \beta_2 \text{FR}_{it-1} + \nu_i + \epsilon_{it}$, with UFR equal to 1 as of 2012Q1 and zero otherwise, $FR_{2012q1,i}^{-1}$ the inverse of the funding ratio as of 2012Q1, and the control includes the lagged inverse of the funding ratio. Column (1) and (2) show the results for bond holdings with a maturity of 30 years or longer, column (3) and (4) for maturities between 15 and 25 years, and column (5) and (6) for maturities shorter than 15 years. ICL is a dummy that equals one for life insurers and zero otherwise and PF equals one for pension funds and zero otherwise. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Equity allocation	
UFR	−0.2073	
	(0.1406)	
UFR × $\text{FR}_{2012q1,i}^{-1}$	0.2646*	0.3042**
	(0.1601)	(0.1558)
1/Funding ratio	−0.0289	0.0751
	(0.0859)	(0.1160)
ICL	0.0773	
	(0.0869)	
PF	0.1919***	
	(0.0554)	
Fund FE	No	Yes
Time FE	No	Yes
N	2,407	2,407
R^2	0.16	0.86

positions after a parallel shock in interest rates of +1% (-1%) and +0.5% (-0.5%).[16] This allows me to compute the dollar durations of the derivative positions.[17] Because the data on derivative positions is available for only two quarters prior to the regulatory change, the time series is not long enough to statistically test if pension funds decreased their interest rate risk exposure via derivatives as well. However, using the time series of the cross-sectional average implied duration of the derivative portfolios, I show suggestive evidence that pension

[16]Unfortunately, insurance companies only started reporting derivative positions at the start of 2016 when Solvency II was introduced.

[17]As the majority of interest rate derivative positions consist of swaps, and swaps have a linear pay off function, I narrow down the analysis to the swap portfolio only.

funds also substantially decreased their derivative positions after the regulatory change.

Formally, I approximate the dollar duration of the swap position as follows:

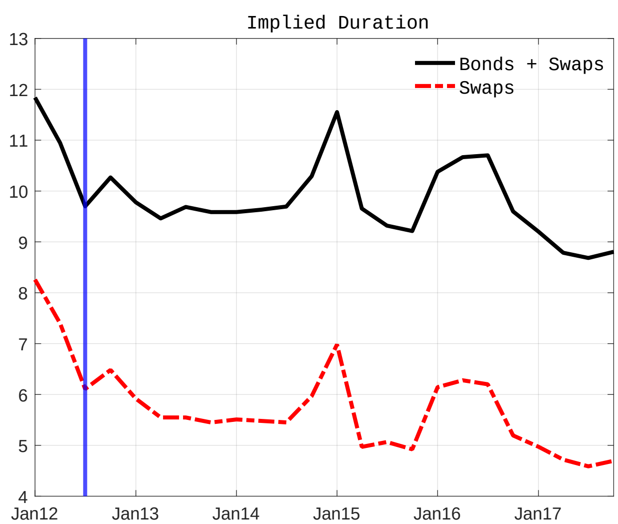
$$D^{\$}_{p,t} \approx -\frac{dV_t}{dr} = \frac{V_t^{-dr} - V_t^{+dr}}{2|dr|} \tag{1.40}$$

where V_t^{-dr} (V_t^{+dr}) is the value of the derivative portfolio after a negative (positive) change in interest rates, $D^{\$}_p$ the dollar duration of the portfolio, and dr the change in interest rates.

Figure 1.4 depicts the cross-sectional average duration implied by the swap portfolio over time, where the duration is computed as the dollar duration in (1.40) relative to total AUM. The graph also shows the total balance sheet duration as the sum of the relative implied duration of the swap portfolio and the duration of the fixed income portfolio multiplied by the allocation to fixed income. On average, pension funds have a balance sheet duration equal to 10 years. As the duration of the liabilities equals 18 years on average, this means that pension funds hedge approximately half of their interest rate risk. Importantly, the portfolio duration shows a sharp decline at the implementation of the UFR, consistent with the predictions of the model and the empirical findings for long-term bond holdings.

Figure 1.4. **Implied duration of pension funds' portfolios**

This graph shows the relative implied duration of the swap portfolio and the duration of the total portfolio of pension funds. The (relative) duration of the swap portfolio is determined as the implied dollar duration of the swaps divided by total pension assets. The duration of the total portfolio equals the sum of relative implied duration of the swap portfolio and the duration of the fixed income portfolio times the allocation to fixed income.



1.6 Bond yields and future excess returns

In this section, I test the empirical predictions of my model for yields and future excess returns. As opposed to the previous section, I use data on Dutch government bonds holdings only, because P&Is hold a substantial fraction of their assets in Dutch bonds and as a result, price effects will be particularly visible for this subset of bonds. I start with the first prediction: future excess returns are high when the P&I sector as a whole is underfunded. Then, I estimate the effect of the UFR on yields by using the construction of the UFR that affects yields at different maturities differently as an exogenous shock to demand. Finally, I use this construction as an instrument to estimate the effect of yields on Dutch government bond holdings for various investor types by using the framework of Koijen and Yogo (2019).

1.6.1 Aggregate underfunding and future excess returns

My model predicts that future excess returns are low if the P&I sector is underfunded. Underfunding means that P&Is have less capital than the minimal required capital. If P&Is are underfunded, their demand for long-term bonds increases and hence the interest rate risk that has to be carried by myopic investors decreases, which in turn lowers expected future returns. To test this hypothesis formally, I determine the aggregate level of underfunding as the fraction of pension funds that are underfunded relative to the total at the end of a given quarter. The data are from the website of DNB and cover the period 2007q1-2019q4.[18]

I use data from Bloomberg on the nominal Dutch yield curve to compute future excess returns. The log excess return is defined as in (1.6), minus the risk-free interest rate: $rx_{t+1}^{(h)} = y_t^{(h)} - (h-1)[y_{t+1}^{(h-1)} - y_t^{(h)}] - y_t^{(1)}$. Table 1.6 provides the summary statistics on the annual excess returns $rx_{t+1}^{(h)}$ for bonds with maturities 10, 20 and 30 years, together with summary statistics on the instantaneous forward rates f_t^h for $h = 1, 2, 3, 4, 5$.

Then, to formally test this model implication, I run the following regression:

$$rx_{t+1}^{(h)} = \alpha + \beta_0 UNF_t + \beta_1' x_t + \epsilon_{t+1}^{(h)}, \tag{1.41}$$

[18] The data can be found here: `https://statistiek.dnb.nl/en/dashboards/pensions/index.aspx`. Because the solvency positions of insurers only go back till 2009, I use data on pension funds alone. Because the solvency positions of both insurers and pension funds are driven by the same factors, using aggregate pension fund data alone is sufficient. Robustness checks that use a weighted average of the solvency positions of pension funds and insurance companies indeed confirm this.

Table 1.6. **Summary statistics Dutch yields**: This table presents the means, medians standard deviations, minimum, and maximum of Dutch zero-coupon government bond yields. Panel A shows the summary statistics on Dutch yields, where the data is from Bloomberg and covers the period 2007-2020. Panel B presents the summary statistics on the measures for aggregate underfunding. All reported numbers are in percentage points, except the fraction of underfunded pension plans which is in percent. rx^h_{t+1} is the excess return for a bond with maturity h, y^h_t is the yield for a bond with maturity h, $f^{(h)}_t$ is the instantaneous forward rate for a bond with maturity h.

	mean	median	std.dev.	min	max	N
Panel A: Dutch zero-coupon government bond yields (%)						
rx^{10}_{t+1}	5.31	5.16	6.08	−5.73	18.35	48
rx^{20}_{t+1}	8.11	8.66	13.19	−14.06	41.56	48
rx^{30}_{t+1}	10.37	9.63	19.43	−23.05	61.34	48
$y^{10}_t - y^1_t$	1.43	1.25	0.84	0.03	3.09	48
$f^1_t (= y^1_t)$	0.60	0.01	1.56	−0.78	4.65	48
f^2_t	1.27	0.72	1.67	−0.79	4.80	48
f^3_t	1.70	1.47	1.72	−0.68	4.82	48
f^4_t	2.03	1.92	1.68	−0.55	4.55	48
f^5_t	2.34	2.45	1.60	−0.33	4.72	48
Panel B: Underfunded pension plans						
1. Fraction underfunded (percent)	37	31	24	0	83	48
2. Level underfunded (%)	2.12	0	3.26	0	12.2	48
3. Liability return (%)	2.62	2.61	6.13	−12.37	20.95	48
$\rho(1,2)$	0.84					
$\rho(1,3)$	0.33					
$\rho(2,3)$	0.46					

where $rx_{t+1}^{(h)}$ is the annual excess bond return from time t to time $t+1$ for a bond with maturity h, UNF_t equals the fraction of pension funds that are underfunded at time t, and x_t includes a set of controls.

Because I only observe the fraction of underfunded pension funds at a quarterly frequency, I estimate the regressions on a quarterly frequency.[19] This implies I forecast returns for every four quarters. I compute standard errors using the Newey and West (1987) standard errors that allow for serial correlation up to 6 lags. The controls include the term spread, following Campbell and Shiller (1991), or the first five forward rates, following Cochrane and Piazzesi (2005).

Table 1.7 shows the results of the forecasting regressions. Figure 1.5 plots the fraction of underfunded pension funds and the one-year ahead excess return on a 10-year bond. As the figure shows and the table confirms, a higher fraction of underfunded pension funds is associated with lower future excess returns. As expected, the effect is stronger for longer maturity bonds.

The economic magnitude of the effects are substantial. A one standard deviation increase in the fraction of underfunded pension funds (0.24) decreases the excess future returns with 8.24 percent. Assuming that the change in underfunded pension funds has no effect on expected returns beyond a year, this corresponds to a decline in contemporaneous 30-year yields of 27 basis points (see Equation (1.28): 8.24%/30).[20] This equals 19 basis points for a 20-year bond and 12 basis points for a 10-year bond. As a robustness check, Table 1.15 and 1.16 of the Appendix summarize the results if I use the average percentage points of underfunding and the return on the liabilities as alternative proxies for the degree of underfunding. The effects using these alternative proxies are similar to the results discussed here.[21]

Running a regression of the aggregate allocation to fixed income on the level of underfunding indeed confirms that the fraction of underfunding increases the allocation to bonds: a

[19] The literature tends to use monthly data, however results of standard forecasting regressions using the term spread or forward rates do not substantially change when using a quarterly or a monthly frequency.

[20] In untabulated regressions, I find that the forecasting power substantially decreases when predicting 5 quarter future excess returns and completely vanishes using 6 quarters or more.

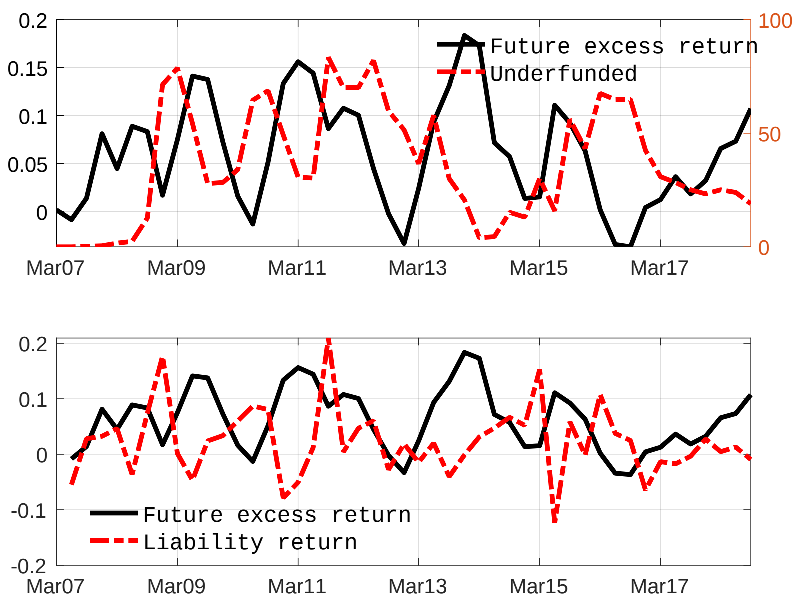
[21] For the first proxy, the effect of a one standard deviation increase on the 30-year yield equals 32 basis points, whereas for the second proxy this effect equals 19 basis points. The effect of the second proxy is smaller because the degree of underfunding is largely determined by both the returns on equity and bonds, whereas the return on the liabilities is only picking up the latter part.

one standard deviation increase in the fraction of underfunded pension funds increases the allocation to fixed income by 1.97%.[22]

Evidently, running a regression of returns on a proxy for demand does generally not allow to cleanly identify the causality between demand shocks and asset prices, because there could be omitted variables that drive demand for bonds and is correlated with the degree of underfunding. Therefore, I turn to the asset pricing implications of the regulatory change that uses the construction of the UFR as an exogenous shock to demand next.

Figure 1.5. **Future excess returns and underfunded pension plans**

This graph shows the one year future excess return and the fraction of underfunded pension plans or the liability return ($r_t^L = \frac{L_t - L_{t-1}}{L_{t-1}}$). The upper figure shows the excess returns (percentage points) on the left y-axis and the fraction of underfunded pension plans (percent) on the right y-axis. The lower figure shows both the excess returns and liability return on the left y-axis (percentage points).



[22]Formally, I run the following regression: $w_t^{FI} = \alpha + \beta_0 UNF_t + \epsilon_t$. I find a coefficient of $\beta_0 = 0.0821$ with a t-stat equal to 3.73 with an $R^2 = 0.25$.

Table 1.7. **Forecasting excess bond returns using the fraction of underfunded pension plans**: This table presents the regressions of the future 4-quarter excess returns on the fraction of underfunded pension plans: $rx_{t+1}^{(h)} = \alpha + \beta_0 UNF_t + \beta_1' x_t + \epsilon_{t+1}^{(h)}$. The regressions are estimated with quarterly data from 2007 until 2019q4. I forecast the excess return each quarter for the following 4 quarters. I use Newey and West 1987 standard errors to correct for the overlapping nature of the regressions (parentheses), with a total of 6 lags. Controls include the term spread (Campbell and Shiller, 1991) and the first five instantaneous foward rates (Cochrane and Piazzesi, 2005). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

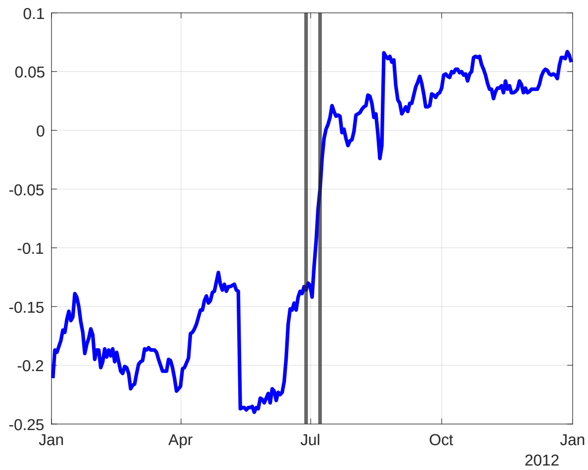
	30-year			20-year			10-year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
UNF_t	−35.677***	−34.324***	−57.786***	−15.807*	−15.937*	−33.201***	−4.135	−5.657*	−10.896***
	(10.811)	(10.795)	(6.639)	(8.563)	(8.555)	(5.291)	(3.522)	(3.363)	(2.689)
$y_t^{(10)} - y_t^{(1)}$		2.467			2.201			1.737*	
		(3.730)			(2.511)			(0.984)	
$f_t^{(1)}$			−13.397***			−12.117***			−4.991***
			(4.506)			(2.811)			(1.519)
$f_t^{(2)}$			3.504			6.441			4.031
			(9.513)			(6.920)			(3.571)
$f_t^{(3)}$			−5.338			−3.225			−2.902
			(7.709)			(4.843)			(2.887)
$f_t^{(4)}$			5.062			2.537			3.017
			(11.943)			(6.332)			(3.400)
$f_t^{(5)}$			8.823			5.203			0.904
			(13.566)			(7.909)			(3.887)
N	48	48	48	48	48	48	48	48	48
R^2	0.22	0.18	0.49	0.10	0.08	0.51	0.03	0.07	0.43

1.6.2 The connection between portfolio holdings and yields

The regulatory change had a significant effect on Dutch long-term bond yields, as already shown by Greenwood and Vissing-Jorgensen (2018) using event studies. Figure 1.6 shows the 30-20 government bond spread. The spread increased significantly after the announcement of the UFR, and remained at a higher level thereafter.

Figure 1.6. **Government bond yield spreads**

This graph shows the spread between 30 year and 20 year Dutch government bonds. The vertical lines are three days before and after the announcement of the UFR.



In this section, I connect investors' portfolio holdings to yields using the asset demand system developed by Koijen and Yogo (2019). The asset demand system allows me to compute demand elasticities with respect to price, which, in turn, allow me to study the importance of various investor types in creating price effects.

Investor i's investment in Dutch government bonds within maturity bucket m is denoted by $H_{it}(m)$, and the investment in the outside asset is denoted by O_{it}.[23] Because I cannot observe what investors consider to be the outside asset, I use the 10-year German yield as proxy for the outside asset. German government bonds are important alternative liability hedge assets outside of the Netherlands. The results, however, are robust using other proxies for the outside asset. Furthermore, I assume that holdings of the outside asset move only due to changes in the German yield.

[23]The results do not materially change using all bonds outside of the Netherlands as the outside asset.

The portfolio weight in the framework of Koijen and Yogo (2019) is then defined as:

$$w_{it}(m) = \frac{H_{it}(m)}{O_{it} + \sum_{m=1}^{M=7} H_{it}(m)} = \frac{\delta_{it}(m)}{1 + \sum_{m=1}^{M=7} \delta_{it}(m)}, \quad (1.42)$$

where $\delta_{it}(m) = H_{it}(m)O_{it}^{-1}$ and $w_{it}(0) = 1 - \sum_{m=1}^{M=7} w_{it}(m)$ equals the fraction invested in the outside asset. Demand for government bonds with maturity m is a function of bond yields and characteristics (Koijen et al., 2020):

$$\begin{aligned} \ln H_{it}(m) &= \ln \delta_{it}(m) + \ln O_{it} \\ &= \hat{\alpha}_i + \beta_{0i} y_t(m) + \beta_{1i}' x_t(m) + \beta_{2i} \ln H_i^{2009q2}(m) + \hat{\beta}_{3i} y_t^{DE} + \epsilon_{it}(m), \quad (1.43) \end{aligned}$$

in which $\hat{\alpha}_i = \alpha_i + \ln O_i$, $\hat{\beta}_{3i} = \beta_{3i} + \psi_i$, $y_t(m)$ is the average yield for maturity bucket m, $x_t(m)$ includes bond characteristics, $H_i^{2009q2}(m)$ equals the initial holdings in each maturity bucket m, and y_t^{DE} is the German yield and captures alternative liability hedge opportunities outside of the Netherlands.

Koijen and Yogo (2019) show that (1.43) is consistent with a model in which investors have mean-variance preferences over returns, assume that returns follow a factor model, and assume that both expected returns and factor loadings are affine in a set of characteristics. The component of demand that is not captured by prices, characteristics, and time-invariant characteristics, $\epsilon_{it}(m)$, is referred to as latent demand.

Safe, (long-term) government bond returns are primarily driven by duration and convexity. The vector of bond characteristics therefore includes the average duration of the bond in every maturity bucket and the average convexity, measured as the duration squared. I also include the average coupons.

In order to obtain consistent estimates of the parameters in (1.43) using OLS one has to assume that characteristics are exogenous to latent demand. However, positive latent demand for Dutch government bonds of a particular maturity may result in lower yields. The demand curves are therefore estimated using an instrumental variable approach. I use the weights assigned to the UFR as an instrument for changes in demand. Even though investors may have anticipated the UFR, the determinants of the shape of the UFR such as its level and the slope were unknown.[24]

The weights assigned to the UFR for each maturity bucket are summarized in Table 1.14

[24] `https://www.dnb.nl/en/news/news-and-archive/dnbulletin-2012/dnb276012.jsp`

Table 1.8. **Instrument for every maturity bucket**: This table shows the instrument for every maturity bucket used for the instrumental variable approach. The instrument is constructed as the average weight assigned to the UFR for each maturity bucket. An overview of the weights for separate maturities is given in Table 1.14.

	$[0,5]$	$(5,10]$	$(10,15]$	$(15,20]$	$(20,25]$	$(25,30]$	$(30,\infty)$
ξ_m	0	0	0	0	0.263	0.579	0.910

of the Appendix. The instrumental variable is defined as $z_t(m) = \xi(m)D_t$, where $\xi(m)$ is the average weight assigned to the UFR for maturity bucket m and D_t equals one after implementation of the UFR and zero otherwise. The first-stage regression of the instrumental variable estimator equals:

$$y_t(m) = \beta_0 + \beta_1 z_t(m) + \beta_2' x_t(m) + y_t^{DE} + \epsilon_t(m), \tag{1.44}$$

The first stage is summarized in column (1) of Table 1.9. The t-statistic equals 4.95 and is higher than the proposed threshold of 4.05 by Stock and Yogo (2005) for rejecting the null of weak instruments at the 5 percent level, suggesting that the instrument is not weak. The coefficient for the instrument equals 0.397, with a standard error of 0.092. A coefficient of 0.435 implies that government bond yields with time-to-maturity between 21 and 25 years went up with 11 basis points, for time-to-maturities between 26 and 30 years with 25 basis points, and for time-to-maturities longer than 30 years with 39 basis points. This implies an increase in the 30-20 year spread of approximately 24 basis points. These estimates are larger than the estimates found in Greenwood and Vissing-Jorgensen (2018), who find an increase in the Dutch 30-10 year spread of 15 basis points by conducting an event study (Figure 1.6). Event studies only capture the immediate decrease in long-term bond holdings around the announcement of the regulatory change. However, P&Is did not sell everything at once, but instead spread out the decrease in long-term bond holdings over four quarters (Figure 1.3).

I estimate the demand curves for banks, insurance companies, mutual funds, pension funds, and the foreign sector. I first show the results aggregated by investor type as I do not have investor specific characteristics for all types in my sample that would allow me to take advantage of cross-sectional heterogeneity within types. The investments of the foreign sector are defined as the difference between the total amount outstanding minus the holdings by the other sectors. The data on total amounts outstanding is from the Dutch State Treasury Agency.[25]

Columns 2-6 of Table 1.9 show the estimates of the demand system. P&Is have demand curves that are upward sloping, which is consistent with my model. Because of duration mismatch between the assets and the liabilities, a decrease in interest rates decreases the funding ratio. From (1.16), we observe that a low funding ratio increases the demand for long-term bonds. Foreign investors prefer shorter duration bonds, whereas P&Is prefer longer duration bonds, consistent with Section 1.5. Moreover, P&Is prefer bonds with higher coupons, potentially resulting from the desire to match the cash flows of their liabilities. In all cases, the initial holdings are positive and statistically significant, meaning that unobserved time-invariant characteristics explain a substantial part of the holdings.

I can use the demand system to connect prices to elasticity of demand with respect to price for all investor types (Koijen and Yogo, 2019; Koijen et al., 2020):

$$\frac{\partial q_{it}(m)}{\partial p_{it}(m)} = 1 + 100\frac{\beta_{0i}}{T_{mt}}(1 - w_{it}(m)), \tag{1.45}$$

where lowercases are log of variables and T_{mt} is the average maturity for maturity bucket m. To compute $w_{it}(m)$, I use the investment in euro area bonds except Dutch ones as the outside asset.

The demand elasticities with respect to price for each investor type are summarized in Table 1.11. A demand elasticity close to zero implies that demand is inelastic and a large value implies that demand is sensitive to the price. Banks have the highest demand elasticity, followed by mutual funds and the foreign sector. However, the estimate for banks is very imprecise. Banks are not holding the longest maturity bonds and therefore the instrument is weak. Consistent with the findings before, demand elasticities are negative for the P&I sector. The weighted average elasticity equals 2.05 and the weight of each sector is computed as the average weights of the different investor types in each maturity bucket prior to the implementation of the UFR. The weights of each sector are summarized in Table 1.10. As in Koijen et al. (2020), demand elasticities are substantially higher than the estimates for stock markets, e.g. Chang et al. (2015) find an elasticity close to one. However, the average weighted price elasticity of demand is lower than measured in Koijen et al. (2020), where the unit of observation are the holdings of government debt in a particular country. This means

[25] `https://english.dsta.nl`

Table 1.9. **Demand system**: This table shows the regression results of the demand system described in (1.43): $\ln H_{it}(m) = \hat{\alpha}_i + \beta_{0i} y_t(m) + \beta_{1i}' x_t(m) + \beta_{2i} \ln H_i^{2009q2}(m) + \hat{\beta}_{3i} y_t^{DE} + \epsilon_{it}(m)$. The first column shows the first stage regression for the foreign investors. The instrument $z_t(m)$ equals the weights assigned to the UFR for each maturity bucket m. The controls $x_t(m)$ include the average bond duration, convexity, coupon, and initial bond holdings. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	$y_t(m)$	Holdings Banks	Holdings Foreign	Holdings IC	Holdings MF	Holdings PF
$y_t(m)$		2.171	1.156**	−2.639**	0.531**	−1.640***
		(3.493)	(0.559)	(1.205)	(0.258)	(0.632)
$z_t(m)$	0.435***					
	(0.088)					
Duration	0.168***	0.405	−0.730***	0.910***	−0.289	0.523***
	(0.034)	(0.568)	(0.127)	(0.286)	(0.296)	(0.130)
Convexity	−0.006***	−0.019	0.019***	−0.028***	−0.011	−0.014***
	(0.001)	(0.016)	(0.003)	(0.007)	(0.008)	(0.003)
Coupon	−0.021	−0.079	−0.267***	0.375***	0.013	0.106***
	(0.017)	(0.092)	(0.050)	(0.049)	(0.015)	(0.035)
Initial holdings	−0.192***	0.361***	0.129	1.654***	0.895***	0.773***
	(0.062)	(0.089)	(0.222)	(0.253)	(0.122)	(0.113)
10-year German yield	1.019***	2.079	−1.409	2.795	−1.366	2.361**
	(0.015)	(3.544)	(0.878)	(1.725)	(1.930)	(0.967)
N	243	209	243	243	243	243
R^2	0.98	0.68	0.55	0.28	0.75	0.41

that investors are less price elastic across maturity buckets than they are across countries. Government bonds issued by (some) countries in the euro area may be closer substitutes than bonds of different maturities from a balance sheet perspective.

In order to derive pricing effects from the demand system, I can perform a simple back-of-the-envelope calculation. Pension funds and insurers sold 22 percent of the amount outstanding of 30-year Dutch government bonds. The weighted average price elasticity of demand equals 2.05 and thus the price effect equals 22%/2.05 = 10.73%. For a bond with a maturity of 30 years, this implies an increase in long-term yields of 36 basis points, which is close to the price effect found for the first stage regression.

Table 1.10. **Weights of investor types in each maturity bucket**: This table shows the weights of the investor types (banks, insurance companies, foreign investors, mutual funds, and pension funds) at the start of 2012q1. The fraction of foreign investors is determined as the fraction of total amount outstanding that is not held by one of the Dutch institutions. The column tot. (tot. long) defines the total fraction that each investor is holding relative to the total amount outstanding (total amount outstanding maturities exceeding 10 years).

	$[0,5]$	$(5,10]$	$(10,15]$	$(15,20]$	$(20,25]$	$(25,30]$	$(30,\infty)$	tot.	tot. long
Banks	3	16	2	9	3	4	0	9	4
Foreign investors	90	70	75	52	44	42	49	75	52
Insurers	3	6	12	21	29	30	27	8	24
Mutual funds	1	1	1	2	1	1	1	1	1
Pension funds	3	7	10	16	23	23	23	9	19

Table 1.11. **Price elasticity of demand**: This table shows the price elasticity of demand, computed as in Equation (1.45). The average, standard deviation, minimum, and maximum over time are given. Total elasticity is the weighted average elasticity, using the weights of each sector defined in Table 1.10.

	obs.	mean	std.dev.	min	max
Banks	209	23.93	25.57	5.67	83.88
Foreign investors	243	4.53	1.89	1.84	11.28
Insurance companies	243	−29.95	31.68	−102.44	−6.93
Mutual funds	243	8.30	6.82	1	22.23
Pension funds	243	−18.61	20.19	−63.63	−3.97
Total	2.05				

1.6.3 Demand curves P&Is including characteristics

My model predicts that the demand for bonds depends primarily on the liability structure and solvency positions of P&Is. My model predicts that demand for long-term bonds is higher when liability duration is longer as well as when the funding ratio is low. In this section, I extend the framework of Koijen and Yogo (2019) by also including two key P&Is characteristics: the liability duration and the solvency position. In this setting, demand for government bonds with maturity m becomes a function of bond yields, bond characteristics, and fund characteristics interacted with bond characteristics:

$$\begin{aligned}\ln H_{it}(m) &= \hat{\alpha}_i + \beta_{0i} y_t(m) + \beta_{1i}' x_t(m) + \beta_{2i}'(x_{1t}(m) \times v_{it}) \\ &+ \beta_{3i} \ln H_i^{2009q2}(m) + \hat{\beta}_{4i} y_t^{DE} + \epsilon_{it}(m) \end{aligned} \tag{1.46}$$

where v_{it} includes the liability duration and the solvency position for investor i at time t, $x_t(m)$ includes bond characteristics as defined before, and $x_{1t}(m)$ includes bond duration and convexity, and α_i includes investor fixed effects. Again, I include the initial holdings as well as the 10-year German yield.

Table 1.12 shows the results for insurers. On average, insurance companies with long liability durations prefer bonds with long durations, but relatively low convexity. This means that insurance companies prefer long-term bonds, but not the bonds with the longest maturities. The UFR creates incentives to hedge the duration of the liabilities, but less so the convexity of the liabilities, i.e. the cash flows at the very long-end of the maturity spectrum. I also compute the demand system for insurers with high versus low liability durations and high and low solvency positions, respectively. Interestingly, insurers with long liability durations have much stronger upward sloping demand curves than average, whereas insurers with low liability durations have neither upward nor downward sloping demand curves. Moreover, insurers with low solvency positions have slightly stronger upward sloping demand curves than insurers with high solvency positions, again consistent with the predictions of my model.

Table 1.13 shows the results for pension funds. Pension funds with long liability durations generally have a preference for bonds with long liability durations but lower convexity, as for insurance companies. There is some evidence that pension funds with high solvency positions have a stronger preference for bonds with high convexity, consistent with the finding in Section 1.5 that pension funds with high solvency positions decreased long-term bond holdings to a smaller extent than the ones with low solvency positions. As opposed to insurance companies, pension funds with long versus short liability do not differ as much

Table 1.12. **Demand system with insurer characteristics** This table shows the results of the demand system including insurers characteristics (liability duration and solvency ratio) described in (1.46): $\ln B_{it}(m) = \hat{\alpha}_i + \beta_{0i} y_t(m) + \beta'_{1i} x_t(m) + \beta'_{2i}(x_{1t}(m) \times v_{it}) + \hat{\beta}_{3i} y_t^{DE} + \alpha_i + \epsilon_{it}(m)$. The first column shows the first stage regression. The instrument $z_t(m)$ equals the weights assigned to the UFR for every maturity bucket m, described in Table 1.8. The results are reported for all insurers, as well as insurers that are above the 70th percentile or below the 30th percentile of the liability duration (solvency ratio). The 30th and 70th percentile are determined in each quarter. Controls include the bond characteristics, the 10-year German yield, and the initial holdings. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	$y_t(m)$	Holdings all	Holdings high dur	Holdings low dur	Holdings high FR	Holdings low FR
$y_t(m)$		-2.432^{***}	-3.903^{***}	1.300	-3.138^{***}	-3.714^{**}
		(0.697)	(1.340)	(1.568)	(0.984)	(1.837)
$z_t(m)$	0.435^{***}					
	(0.088)					
bond dur × liability dur		0.011^{***}	-0.032^{***}	-0.020^{*}	0.020^{***}	0.016^{***}
		(0.001)	(0.007)	(0.012)	(0.003)	(0.003)
bond convex × liability dur		-0.001^{***}	0.002^{***}	0.003^{***}	-0.001^{***}	-0.001^{***}
		(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
bond dur × solvency ratio		-0.003	0.002	0.019	-0.008	0.075
		(0.004)	(0.027)	(0.012)	(0.008)	(0.054)
bond convex × solvency ratio		0.000	-0.001	-0.002^{**}	0.001	-0.002
		(0.000)	(0.002)	(0.001)	(0.001)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	243	3,418	848	1,105	910	1,066
R^2	0.98	0.68	0.44	0.68	0.68	0.63

in the slope of their demand curves. Notice, however, that the heterogeneity in liability durations is much smaller for pension funds than for insurers.

1.7 Conclusion

In this paper, using holdings data and price data simultaneously, I study changes in hedging incentives of long-term investors and its effect on asset prices. My findings suggest that regulation plays an nontrivial role in the demand for long-term bonds which, in turn,

Table 1.13. **Demand system with pension fund characteristics** This table shows the results of the demand system including pension fund characteristics (liability duration and funding ratio) described in (1.46): $\ln B_{it}(m) = \hat{\alpha}_i + \beta_{0i} y_t(m) + \beta'_{1i} x_t(m) + \beta'_{2i}(x_{1t}(m) \times v_{it}) + \hat{\beta}_{3i} y_t^{DE} + \alpha_i + \epsilon_{it}(m)$. The first column shows the first stage regression. The instrument $z_t(m)$ equals the weights assigned to the UFR for every maturity bucket m, described in Table 1.8. The results are reported for all pension funds, as well as pension funds that are above the 70th percentile or below the 30th percentile of the liability duration (funding ratio). The 30th and 70th percentile are determined in each quarter. Controls include the bond characteristics, the 10-year German yield, and the initial holdings. Robust standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	$y_t(m)$	Holdings all	Holdings high dur	Holdings low dur	Holdings high FR	Holdings low FR
$y_t(m)$		-0.565^{*}	-1.038	-0.284	-1.844^{***}	-1.685^{*}
		(0.323)	(0.777)	(0.508)	(0.507)	(0.994)
$z_t(m)$	0.456^{***}					
	(0.087)					
bond dur × liability dur		0.007^{***}	0.013^{***}	0.019^{***}	0.004^{*}	-0.016^{***}
		(0.001)	(0.005)	(0.005)	(0.002)	(0.004)
bond convex × liability dur		-0.0002^{***}	-0.001^{***}	-0.001^{**}	-0.000	0.001^{***}
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
bond dur × funding ratio		-0.032	0.141	-0.078	-0.217^{**}	0.080
		(0.043)	(0.099)	(0.076)	(0.102)	(0.222)
bond convex × funding ratio		0.001	0.008	0.002	0.010^{**}	0.001
		(0.002)	(0.006)	(0.004)	(0.005)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	243	6,085	1,580	2,115	1,980	1,497
R^2	0.98	0.40	0.53	0.38	0.41	0.46

affect the asset prices of these bonds. This has important policy implications as these findings can be used to design long-term investor regulation in a way that is desirable for the economy as a whole. In particular, my findings show the relevance of incorporating the regulatory framework of long-term investors to analyze effects of conventional and unconventional monetary policy.

1.8 Appendix

A Further details on UFR

The UFR was initially discussed as part of the Long-Term Guarantee Assessment (LTGA) of Solvency II regulation. EIOPA proposed the regulatory discount curve based on the UFR method first in 2010. There are three important decisions policy makers have to make when introducing the UFR: the level of the UFR, the point on the curve at which the UFR method starts, and the interpolation method, or the convergence path. The initial EIOPA proposals are first discussed in detail.

The UFR was initially set at 4.2%, which is based on 2% expected inflation and 2.2% historical average of the real short interest rate. The expected inflation rate aligns with the ECB's target inflation. The real interest rate is based on a study by Dimson et al. (2002). The point of curve at which the UFR method starts was set at 20 years and the convergence period is set at 40 years. The extrapolation method proposed by EIOPA is the Smith-Wilson technique. The Smith-Wilson technique only uses the forward rates at time-to-maturity 19 to 20 years and the UFR to compute the yield curve.

For pension funds a slight modification was used, namely the market interest rates at each maturity in combination with the UFR. For pension funds, the convergence is such that its a weighted average between market interest rates and the UFR. So as opposed to insurers, not only the forward rate from time-to-maturity 19 to 20 years is used, but the implied market forward rate for each maturity and the UFR.

B Model derivation

This appendix solves the optimization problems of P&Is. The mean-variance optimization problem equals:

$$\begin{aligned} \max_{w_t} \quad & \mathbb{E}[u(\frac{A_{t+1}}{A_t} - \frac{L_{t+1}}{A_t})] \\ = \quad & \arg\max_{w_t} \mathbb{E}[\frac{A_{t+1}}{A_t}] - \frac{\gamma}{2}\text{Var}[\frac{A_{t+1}}{A_t} - \frac{L^E_{t+1}}{A_t}] - \frac{\lambda(F^R_t)}{2}\text{Var}[\frac{A_{t+1}}{A_t} - \frac{L^R_{t+1}}{A_t}], \end{aligned} \tag{A1}$$

subject to

$$w_t' \iota = w_t^S + w_t^B \iota \leq 1, \tag{A2}$$

$$w_t^S, w_{h,t}^B \geq 0 \qquad \forall h, \tag{A3}$$

The Lagrange equals:

$$\begin{aligned}
\mathcal{L}(w_t, \nu_t, \delta_t) &= R_f + w_t' \mathbb{E}_t[r_{t+1} - r_f] \\
&- \frac{\gamma}{2}\Big(w_t' \mathrm{Var}_t[r_{t+1}] w_t + a_t' \mathrm{Var}_t[r_{t+1}^B] a_t \frac{1}{F_t^E} - 2 w_t' \mathrm{Cov}_t[r_{t+1}, r_{t+1}^B] a_t \frac{1}{F_t^E}\Big) \\
&- \frac{\lambda(F_t^R)}{2}\Big(w_t' \mathrm{Var}_t[r_{t+1}] w_t + (\xi_L \circ a_t)' \mathrm{Var}_t[r_{t+1}^B](\xi_L \circ a_t) \frac{1}{F_t^R} \\
&- 2 w_t' \mathrm{Cov}_t[r_{t+1}, r_{t+1}^B](\xi_L \circ a) \frac{1}{F_t^R}\Big) + \nu_t (w_t' \iota - 1) + \delta_t' w_t.
\end{aligned} \tag{A4}$$

Taking the derivative with respect to w_t^S, w_t^B, and ν_t gives:

$$\frac{\partial \mathcal{L}(w_t^S, \nu_t, \delta_t^S)}{\partial w_t^S} = \mathbb{E}_t[r_{t+1}^S - r_f] - (\gamma + \lambda(F_t^R)) \mathrm{Var}_t[r_{t+1}^S] w_t^S + \nu_t + \delta_t^S = 0, \tag{A5}$$

$$\begin{aligned}
\frac{\partial \mathcal{L}(w_t^B, \nu_t, \delta_t^B)}{\partial w_t} &= \mathbb{E}_t[r_{t+1}^B - r_f] - (\gamma + \lambda(F_t^R)) \mathrm{Var}_t[r_{t+1}^B] w_t^B - \gamma \mathrm{Var}_t[r_{t+1}^B] a_t \frac{1}{F_t^E} \\
&- \lambda(F_t^R) \mathrm{Var}_t[r_{t+1}](\xi_L \circ a_t) \frac{1}{F_t^R} + \nu_t \iota = 0,
\end{aligned} \tag{A6}$$

$$\frac{\partial \mathcal{L}(w_t, \nu_t, \delta_t)}{\partial \nu_t} = w_t' \iota - 1 = 0. \tag{A7}$$

This results in the optimal weights (1.15) and (1.16):

$$w_t^{S*} = \underbrace{\frac{\mathbb{E}_t[r_{t+1}^S - r_f] + \nu_t + \delta_t^S}{(\gamma + \lambda(F_t^R)) \mathrm{Var}_t[r_{t+1}^S]}}_{\text{speculative portfolio}} \tag{A8}$$

$$w_t^{B*} = \underbrace{\frac{\mathbb{E}_t[r_{t+1}^B - r_f] + \nu_t \iota + \delta_t^B}{(\gamma + \lambda(F_t^R))\mathrm{Var}_t[r_{t+1}^B]}}_{\text{speculative portfolio}} + \underbrace{\frac{\gamma}{\gamma + \lambda(F_t^R)} a_t \frac{1}{F_t^E}}_{\text{economic hedging portfolio}} + \underbrace{\frac{\lambda(F_t^R)}{\gamma + \lambda(F_t^R)} (\xi_L \circ a_t) \frac{1}{F_t^R}}_{\text{regulatory hedging portfolio}}. \tag{A9}$$

with ν_t (if the constraint binds):

$$\nu_t = \frac{1 - \left(\frac{\mathbb{E}_t[r_{t+1}^S - r_f] + \delta_t^S}{(\gamma + \lambda(F_t^R))\mathrm{Var}_t[r_{t+1}^S]} + \left(\frac{\mathbb{E}_t[r_{t+1}^B - r_f] + \delta_t^B}{(\gamma + \lambda(F_t^R))\mathrm{Var}_t[r_{t+1}^B]}\right)'\iota + \left(\frac{\gamma}{\gamma + \lambda(F_t^R)} a_t \frac{1}{F_t^E}\right)'\iota + \left(\frac{\lambda(F_t^R)}{\gamma + \lambda(F_t^R)} (\xi_L \circ a_t) \frac{1}{F_t^R}\right)'\iota \right)}{\left(\frac{\iota}{(\gamma + \lambda(F_t^R))\mathrm{Var}_t[R_{t+1}]}\right)'\iota}. \tag{A10}$$

C Tables

Table 1.14. **Weights UFR in regulatory discount curve**: This table shows the weights assigned to the UFR to compute the regulatory discount curve. The weights are derived using the Smith-Wilson technique.

time-to-maturity	weight	time-to-maturity	weight
21	0.086	41	0.903
22	0.186	42	0.914
23	0.274	43	0.923
24	0.351	44	0.932
25	0.420	45	0.940
26	0.481	46	0.947
27	0.536	47	0.954
28	0.584	48	0.960
29	0.628	49	0.965
30	0.666	50	0.970
31	0.701	51	0.970
32	0.732	52	0.978
33	0.760	53	0.982
34	0.785	54	0.985
35	0.808	55	0.988
36	0.828	56	0.990
37	0.846	57	0.993
38	0.863	58	0.995
39	0.878	59	0.997
40	0.891	60	0.998

Table 1.15. **Forecasting excess bond returns using the percentage points of underfunding**: This table presents the regressions of the future 4-quarter excess returns on the percentage points of underfunding ($\min(0, FR_t - 104.2)$): $rx^{(h)}_{t+1} = \alpha + \beta LUNF^L_t + \beta' x_t + \epsilon^{(h)}_{t+1}$. The regressions are estimated with quarterly data from 2007 until 2019q4. I forecast the excess return each quarter for the following 4 quarters. I use Newey and West 1987 standard errors to correct for the overlapping nature of the regressions (parentheses), with a total of 6 lags. Controls include the term spread (Campbell and Shiller, 1991) and the first five instantaneous forward rates (Cochrane and Piazzesi, 2005). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	30-year			20-year			10-year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$LUNF_t$	-2.941^{***}	-2.932^{***}	-3.100^{***}	-1.416^{***}	-1.476^{***}	-1.648	-0.415^{*}	-0.503^{**}	-0.530^{***}
	(0.572)	(0.573)	(0.332)	(0.475)	(0.455)	(0.216)	(0.235)	(0.222)	(0.123)
$y^{(10)}_t - y^{(1)}_t$		-0.140			0.917			1.325	
		(3.459)			(2.524)			(1.076)	
$f^{(1)}_t$			-9.154^{**}			-9.562^{***}			-4.124^{***}
			(4.379)			(2.885)			(1.508)
$f^{(2)}_t$			10.869			10.777			5.445
			(12.043)			(8.337)			(3.980)
$f^{(3)}_t$			-7.144			-4.808			-3.456
			(8.784)			(5.522)			(2.917)
$f^{(4)}_t$			-6.943			-4.972			0.533
			(14.578)			(8.983)			(4.446)
$f^{(5)}_t$			13.570			8.956			2.183
			(19.517)			(12.343)			(5.526)
N	48	48	48	48	48	48	48	48	48
R^2	0.27	0.27	0.41	0.14	0.15	0.40	0.06	0.09	0.37

Table 1.16. **Forecasting excess bond returns using the return on liabilities**: This table presents the regressions of the future 4-quarter excess returns on the liability return ($\frac{L_t - L_{t-1}}{L_{t-1}}$): $rx^{(h)}_{t+1} = \alpha + \beta r^L_t + \beta' x_t + \epsilon^{(h)}_{t+1}$. The regressions are estimated with quarterly data from 2007 until 2019q4. I forecast the excess return each quarter for the following 4 quarters. I use Newey and West 1987 standard errors to correct for the overlapping nature of the regressions (parentheses), with a total of 6 lags. Controls include the term spread (Campbell and Shiller, 1991) and the first five instantaneous forward rates (Cochrane and Piazzesi, 2005). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	30-year			20-year			10-year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
r^L_t	−1.001***	−0.950***	−0.809**	−0.582**	−0.579**	−0.440**	−0.231**	−0.252**	−0.172
	(0.313)	(0.318)	(0.332)	(0.231)	(0.231)	(0.217)	(0.117)	(0.114)	(0.106)
$y^{(10)}_t - y^{(1)}_t$		−2.466			−0.123			1.043	
		(4.007)			(2.832)			(1.169)	
$f^{(1)}_t$			−4.086			−6.862*			−3.239*
			(6.430)			(3.915)			(1.776)
$f^{(2)}_t$			7.756			9.076			4.759
			(13.874)			(9.205)			(4.244)
$f^{(3)}_t$			−11.720			−7.152			−3.947
			(13.488)			(6.901)			(2.544)
$f^{(4)}_t$			−15.353			−9.408			−0.792
			(18.130)			(10.863)			(5.221)
$f^{(5)}_t$			26.670			15.830			4.128
			(20.781)			(13.300)			(6.223)
N	47	47	47	47	47	47	47	47	47
R^2	0.11	0.12	0.22	0.08	0.08	0.28	0.06	0.12	0.32

Chapter 2

Pension Funds and Drivers of Heterogeneous Investment Strategies[1]

2.1 Introduction

Defined-benefit pension funds play a pivotal role in society as many people depend on them for their retirement savings and investments. Globally, 50 percent of all occupational retirement savings is in defined-benefit pension funds (Willis Towers Watson, 2019). The investments of these pension funds serve a similar objective, namely to finance the future liabilities towards their beneficiaries. Therefore, understanding what drives pension funds to structure their investments in a particular way is important. Even small differences in investment strategies may lead to large divergences in performance across pension funds over time. Consequently, these divergences may have a substantial impact on beneficiaries' purchasing power.[2] This is particularly relevant because beneficiaries are typically not free

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[2]In a defined benefit pension plan, benefits are determined by a formula that takes into account an employee's salary and years of service. Many defined benefit plans, however, also contain elements that depend on the investment returns, such as the cost-of-living adjustment or indexation.

to choose their own pension fund because it "comes with the job". Neither can beneficiaries make individual investment decisions within a defined-benefit pension fund. As a result, these pension funds operate in an environment where they do not have to compete for market share as many other institutional investors do, such as mutual funds.

Despite their pivotal role in society, so far only a few studies have analysed the investment strategies of pension funds. The lack of access to comprehensive and detailed data on this type of investor is the main reason for the limited number of studies. Exceptions are Rauh (2009) and Andonov et al. (2017) who study the effects of regulatory incentives on risky asset allocations for US corporate and public pension plans respectively as well as Anantharaman and Lee (2014) who link risky asset allocations to the compensation incentives of the top management in US corporate pension plans.[3] Our approach differs from these studies because we do not focus on regulatory or compensation incentives.

The primary objective of our study is to measure the heterogeneity in investment strategies across pension funds, the drivers of this heterogeneity, and the effects it has on expected retirement income. We start with a model that solves a mean-variance optimization problem of assets minus liabilities and show that the following characteristics affect the investment decisions of pension funds: liability duration, funding ratio, and risk aversion. In addition to the model, we show that institutional factors, in particular the pension fund's size and type, influence the investment strategies. Nonetheless, these characteristics only explain 36 percent of the heterogeneity in the average returns across pension funds. The heterogeneity that remains reflects an economically sizeable difference in average annual returns of 0.70-1.50 percentage points between the pension funds with the highest and those with the lowest factor exposures. This is equivalent to a difference in expected retirement income of 16-32 percent over a 40-year accrual phase or to an increase in contributions of 19-46 percent to receive the same retirement income. We show that these differences reflect heterogeneity in beliefs across pension funds that they partially reveal through their choices of the asset management firms that they hire to execute their investment strategies. Our findings are remarkable, because the pension funds in our sample have similar investment objectives, yet even after controlling for differences in their characteristics they make distinct investment decisions.

The object of our study is occupational defined-benefit pension funds in the Netherlands.

[3]Lakonishok et al. (1992), Blake et al. (1999), Del Guercio and Tkac (2002), Tonks (2005), Goyal and Wahal (2008), and Blake et al. (2013) also examine the investment decisions of pension assets, but the focus in these studies is on the asset managers hired by the pension funds.

The Dutch occupational pension system is economically important because it is large in terms of total assets under management (AUM). In 2018, the AUM equaled approximately 1.4 trillion euros, and the Dutch system represented 53 percent of the total assets of pension funds in the euro area, (OECD, 2019).[4] The proprietary data that we use are the quarterly returns of asset classes over the period from 1999 to 2017, and the return computations are based on the Global Investment Performance Standards (GIPS) as of 2010. The reporting requirements are mandatory, and the data are therefore free from self-reporting biases.

We study investment strategies through factor exposures. Traditionally, the investment strategies of pension funds focus on the optimal asset allocations to stocks, bonds, real estate, and alternative assets (e.g. Campbell and Viceira, 2002). However, the rise of the global factor literature enables a more granular study of investment strategies within and across asset classes. This literature shows that factors based on a particular signal perform robustly across countries and asset classes. Prime examples include momentum and value (Asness et al., 2013), low beta (Frazzini and Pedersen, 2014), and carry (Koijen et al., 2018). We use the existing global factors for equities: the market, value, momentum, carry, and low beta. For fixed income, we construct European factors as the pension funds in our sample primarily invest in euro-dominated bonds, which confirms the currency bias in Maggiori et al. (2020). The market factor consists of investment-grade bonds. Next to the market factor and a credit factor for fixed income, we again use value, momentum, carry, and low beta factors. With the exception of the market and the credit factors, we refer to factors as long-short factors.

We analyze the heterogeneity in investment strategies in the following three steps: first, we measure factor exposures and estimate the cross-sectional average and heterogeneity in factor exposures for both equity and fixed income portfolios; second, we identify the drivers of factor exposures; and third, we measure the differences in the implied beliefs on factor returns. Along these lines we report the following key results.

First, we show that the average pension fund has a stock market beta lower than one and a fixed income market beta larger than one. Further, for both equities and fixed income the average pension fund has a positive exposure to low beta but a negative exposure to value and carry. We also find substantial heterogeneity in both equity and fixed income factor exposures across pension funds.

Second, we find that pension fund's characteristics drive the heterogeneity in the factor

[4]See the infographic in the Internet Appendix (Figure 2.2).

exposures, which follows our theoretical framework. Consistent with the predictions of our model we find that pension funds with a low funding ratio, high risk aversion, and long liability duration have higher exposures to the investment-grade fixed income market factor but lower exposures to the other factors. The pension funds' characteristics explain 50 percent of the heterogeneity in the return contribution of the fixed income market factors, but only 20 percent in case of the long-short factors. Motivated by the academic literature, we also study the effects of institutional factors, in particular the effects of the pension fund's size and type. Size as measured by AUM results in more global investment portfolios but does not have an effect on the exposures to long-short factors. Corporate pension funds follow market benchmarks more closely as opposed to industry-wide or professional group pension funds. However, correcting for these institutional factors does not further reduce the heterogeneity in average returns across pension funds.

Third, we show that the remaining differences in investment strategies can be attributed to differences in the implied beliefs on expected returns. We infer these implied beliefs by using our theoretical framework and show evidence in favor of this conjecture. We then show that the pension funds reveal these differences in beliefs through their choices of asset management firms, at least to a reasonable degree. We assess the effect of newly hired asset management firms and find that these have a statistically and economically sizeable effect on the factor exposures.

Fourth, we show that regulations and in particular the discount rate, affect investment strategies. In 2007 a fixed discount rate of 4 percent was replaced by risk-free market interest rates to determine the present discounted value of accrued benefit obligations. This change in methodology has led pension funds to increase their exposure to the fixed income market index and to low beta factors.

Literature review

Our study contributes to the literature on investment behavior in a regulated environment. Rauh (2009) shows that underfunded corporate defined-benefit pension funds in the US invest less in equities than do overfunded pension funds. The author states that the incentive of risk management to avoid costly financial distress dominates the shifting of risk to the Pension Benefit Guaranty Corporation (PBGC) in pension fund investing. We extend this study by showing that underfunded pension funds take less risk within an asset class. We find that within their fixed income portfolio, underfunded pension funds invest more in investment-grade bonds and take less credit risk. This finding confirms the risk management incentive from Rauh (2009). In the Netherlands, no pension guarantee system exists, but underfunded pension funds may try to shift risks to their sponsors (see Broeders and Chen, 2012). Employer representatives on a pension fund board may therefore push for risk reduction to avoid this shift.

Andonov et al. (2017) and Lu et al. (2019) find that US public pension funds increase their risk-taking in financial markets when interest rates are lower, particularly for underfunded pension funds. This increase is a way that these public pension funds can artificially support their funding ratio because they discount pension liabilities against the expected returns on their assets. This incentive is created through the US GASB guidelines. We add to this work by analysing the investment behavior in a regulatory environment in which the liability discount rate is linked to the term structure of market interest rates. This is similar to the regulatory environment for US and Canadian private pension funds, and some European pension funds. Our results are therefore more in line with the investment behavior of German insurance companies that demand more as opposed to less safe long-term bonds when interest rates are low (Domanski et al., 2017).

Greenwood and Vissing-Jorgensen (2018) show that regulatory changes in the liability discount rate that link to market interest rates affect the yield curve due to a shock in demand for long-term bonds from these investors. Our results also support the view that the liability structure shapes pension funds' investment behavior, in particular within fixed income portfolios. Our results show that pension funds prefer safe long-term bonds as well as securities denominated in euros. More importantly, we extend Greenwood and Vissing-Jorgensen (2018) by showing the existence of a large heterogeneity in the demand for safe long-term bonds whereby this demand is larger for pension funds with a low funding ratio, high risk aversion, or long liability duration.

Our study also contributes to the broad literature that assesses the effect of institutional investors on asset prices. For example, Coval and Stafford (2007), Gutierrez and Kelley (2009), and Dasgupta et al. (2011) present evidence that institutional investors contribute to mispricing. In particular, Edelen et al. (2016) find that institutional investors trade contrary to anomalies. Our results support this finding because we find many factor exposures to be negative on average. We conjecture that regulation with respect to the liability discount rate is one driving force behind the preference for assets in the short leg of the anomaly. For instance, the exposure to the fixed income value and carry factors decreased substantially when the fixed liability discount rate was replaced by risk-free market interest rates in 2007. Dutch and German government bonds resemble the risk-free term structure of interest rates better as opposed to Italian and Spanish bonds. Yet, at the same time the former have lower value and carry ranks. These two forces may contribute to a negative exposure to the value and carry factors.

The remainder of the study is organized as follows: Section 2.2 provides a model to derive the optimal portfolio weights and factor exposures. A description of the data is given in Section 2.3. In Section 2.4, we estimate the factor exposures and we analyse their drivers in Section 2.5. In Section 2.6 we identify the pension funds' implied beliefs on factor returns. We show how factor exposures changed when the fixed liability discount rate was replaced by market interest rates in Section 2.7. Section 2.8 concludes.

2.2 Motivating model

In this section, we present a model to derive the factor exposures within asset classes and to explain the heterogeneity across pension funds. Our theoretical framework considers the derivation of factor exposures from the perspective of a pension fund.[5] First, we identify the optimal portfolio weights for a mean-variance investor who optimizes their surplus, that is, the value of assets minus that of the liabilities, subject to borrowing and short-sale constraints. Starting with portfolio weights allows us to closely map the model to the existing mean-variance portfolio theory (Markowitz, 1952) and to include borrowing and short-sale constraints that are typically applicable to pension funds. Second, we show the implication of the portfolio weights for factor exposures.

We start with the liability structure. A pension fund i pays benefits $B_{i,t+h}$ to its participants in period $t+h$. These benefits can in practice take any value, but because we only consider defined-benefit pension funds, we assume that benefits are known at time t. This assumption is known as the accumulated benefit obligation (ABO). Dutch pension funds do not guarantee inflation protection and we therefore refrain from indexation policies in our analysis. We also assume that the pension fund has a large enough number of participants such that idiosyncratic longevity risk is fully diversified. The present discounted value of all future benefit payments for pension fund i is given by:

$$L_{i,t} = \int_0^\infty B_{i,t+h} \exp\left(-hr_t^h\right) dh, \tag{2.1}$$

[5] This framework distinguishes itself from the literature that considers the perspective of an individual life-cycle investor as in, for example, Bodie et al. (1992).

in which r_t^h is the regulatory discount rate as observed at time t for time-to-maturity h.[6] Regulatory discount rates vary widely across jurisdictions. For instance, under the US Government Accounting Standards Board (GASB) guidelines, public pension funds are partially free to discount their liabilities at the expected rate of return on the assets (Andonov et al., 2017).[7] By contrast, US corporate pension funds use the yield on high-quality corporate bonds. In our case, pension funds in the Netherlands used a fixed discount rate of 4 percent until 2007. However, the regulations introduced in 2007 required Dutch pension funds to use the risk-free term structure of market interest rates based on the euro swap curve as the discount rate. Finance theory argues that risk-free market interest rates are indeed the applicable discount for guaranteed pension benefits to exclude arbitrage (e.g. Brown and Wilcox, 2009; Novy-Marx and Rauh, 2009). The value of the liabilities at time $t+1$ is then follows from:

$$L_{i,t+1} = \left(1 + r_{i,t+1}^L\right) L_{i,t} \approx \left(1 + \psi_{i,t} r_{t+1}^b\right) L_{i,t}, \tag{2.2}$$

in which $r_{i,t+1}^L$ is the liability return that is approximated by the return on the risk-free bonds traded in the market r_{t+1}^b times $\psi_{i,t}$ that represents the duration of pension liabilities over the duration of those bonds. The value of $\psi_{i,t}$ is typically larger than one because the duration of pension liabilities is larger than the average duration of bonds in the market.[8]

Next, we assume the pension fund has access to M assets, and its wealth evolves as follows:

$$A_{i,t+1} = \left(1 + w_{i,t}' r_{t+1}\right) A_{i,t}, \tag{2.3}$$

in which $w_{i,t}$ is a vector of portfolio weights that pension fund i chooses at time t, and r_{t+1} is a vector of returns from t to $t+1$. Following Sharpe and Tint (1990a) and Hoevenaars et al. (2008), we assume that the pension fund has mean-variance preferences over the value of its assets minus the value of its liabilities, or its surplus. We normalize this surplus by

[6] Table 2.12 of the Internet Appendix summarizes the symbols that we use in this study.

[7] New GASB rules distinguish between the discount rate calculations for funded and for unfunded pension funds.

[8] We performed a regression of liability returns on factor exposures and found a regression coefficient of 2.2 on the investment-grade fixed income market returns ($R^2 = 0.76$).

dividing it by the value of assets to get the following optimization problem:

$$\begin{aligned} \max_{w_{i,t}} \quad & \mathbb{E}_{i,t}\left[u\left(\frac{A_{i,t+1}-L_{i,t+1}}{A_{i,t}}\right)\right] \\ = \quad & \max_{w_{i,t}} \mathbb{E}_{i,t}\left[\frac{A_{i,t+1}-L_{i,t+1}}{A_{i,t}}\right] - \frac{\gamma_i}{2}\mathrm{Var}_t\left[\frac{A_{i,t+1}-L_{i,t+1}}{A_{i,t}}\right], \end{aligned} \tag{2.4}$$

subject to

$$w'_{i,t}\iota_M \leq c, \tag{2.5}$$

$$w_{i,j,t} \geq 0 \ \ \forall j, \tag{2.6}$$

in which γ_i captures the pension fund's i time invariant risk aversion parameter, ι_M is a vector of ones with length M, c is a constant that defines the constraint on the sum of the weights where typically $c = 1$ that means the pension fund cannot invest more than its entire wealth, and $w_{i,j,t}$ the weight in asset j where $j = 1, ..., M$. Solving (2.4) for the portfolio weights $w_{i,t}$ results in (see derivation in Appendix A):

$$w^*_{i,t} = \underbrace{\frac{\mathbb{E}_{i,t}[r_{t+1}] + \lambda_{i,t}\iota_M + \delta_{i,t}}{\gamma_i \mathrm{Var}_t[r_{t+1}]}}_{\text{speculative portfolio}} + \underbrace{\frac{\mathrm{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\mathrm{Var}_t[r_{t+1}]}F^{-1}_{i,t}}_{\text{hedging portfolio}}, \tag{2.7}$$

with

$$\begin{aligned} w^*_{i,j,t} &\geq 0, \\ \delta_{i,j,t} &\geq 0, \\ \delta_{i,j,t}w^*_{i,j,t} &= 0 \ \ \forall j. \end{aligned} \tag{2.8}$$

The subjective expectations of pension fund i about the expected returns is defined by $\mathbb{E}_{i,t}[r_{t+1}]$. Because second moments can be estimated more accurately than first moments (e.g Merton, 1980), we assume that the variance and covariance of the returns are common knowledge across pension funds. The funding ratio for pension fund i is defined as $F_{i,t} = \frac{A_{i,t}}{L_{i,t}}$, $\lambda_{i,t}$ is the Lagrange multiplier for the restriction that $w'_{i,t}\iota_M = c$, and $\delta_{i,t}$ consists of the Kuhn-Tucker multipliers for the restriction that the portfolio weights are nonnegative. If the

Lagrange multiplier is binding, then $\lambda_{i,t}$ equals:

$$\lambda_{i,t} = \frac{c - \left(\frac{\mathbb{E}_{i,t}[r_{t+1}]+\delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}\right)' \iota_M - \left(\frac{\text{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\text{Var}_t[r_{t+1}]} F^{-1}_{i,t}\right)' \iota_M}{\left(\frac{\iota_M}{\gamma_i \text{Var}_t[r_{t+1}]}\right)' \iota_M}. \tag{2.9}$$

The solution in (2.7) shows that the optimal portfolio weights consist of the sum of two components: a speculative portfolio and a liability hedge portfolio. The Lagrange multiplier (2.9) ensures that the speculative demand decreases if the hedging demand increases, and vice versa.

Unfortunately, we do not have full access to the portfolio weights of the individual assets. In our empirical analysis, we therefore choose an alternative approach and measure factor exposures. The exposure of the portfolio return r^P to the return on the k^{th} factor r^k is measured as:

$$\beta^k = \frac{\text{Cov}(r^P, r^k)}{\text{Var}(r^k)}. \tag{2.10}$$

In case the factors are long-short factors, it can be further decomposed to:

$$\beta^k = \frac{\text{Cov}(r^P, r^{k,L} - r^{k,S})}{\text{Var}(r^{k,L} - r^{k,S})} = \frac{\text{Cov}(r^P, r^{k,L})}{\text{Var}(r^{k,L} - r^{k,S})} - \frac{\text{Cov}(r^P, r^{k,S})}{\text{Var}(r^{k,L} - r^{k,S})}, \tag{2.11}$$

in which $r^{k,L}$ is the return on the "long leg" of the factor, and $r^{k,S}$ is the return on the "short leg" of the factor. Although the pension fund may be restricted to shorting assets, it can have a positive or a negative exposure to a long-short factor. A positive exposure results from a higher demand for the long leg compared to that for the short leg of the factor, and vice versa. To illustrate this point, assume we have a portfolio consisting of value stocks and growth stocks. The portfolio return equals:

$$r^P = w_V r^V + w_G r^G, \tag{2.12}$$

in which w_V is the portfolio weight of value stocks and r^V is the corresponding return, and w_G is the portfolio weight of growth stocks and r^G is the corresponding return. In this example, let us assume that the portfolio weight of value stocks exceeds the weight of growth stocks, so that $w_V > w_G$. We now explore the exposure of this portfolio return to the long-short factor return. The return correlation between the value and growth stocks is less than one, that is, $\rho_{V,G} < 1$. For a beta neutral factor, we also know that the volatility of the value stock is approximately equal to that of the growth stocks, that is, $\sigma_V \approx \sigma_G$. This condition results in the following factor exposure:

$$\beta^{V-G} = \frac{\text{Cov}(r^P, r^V - r^G)}{\text{Var}(r^V - r^G)} = \frac{(w_V - w_G)\sigma_V^2(1 - \rho_{V,G})}{\text{Var}(r^V - r^G)} > 0 \tag{2.13}$$

In other words, a higher portfolio weight for value stocks compared to growth stocks results in a positive factor exposure to value, and vice versa.

2.2.1 Testable implications

This subsection describes the testable implications that follow from our theoretical framework. To formulate the predictions, we first summarize the data that we use to empirically test the model implications.

In our empirical analysis, we use an investment-grade fixed income market index to represent the return on the set of bonds r^b_{t+1}.[9] Further, we use the following factors for fixed income: credit, value, momentum, carry, and low beta. For equities we use a global market, European market, value, momentum, carry, and low beta factor.

Pension funds report their funding ratio and liability duration. We cannot observe the risk aversion parameter directly, but we conjecture that it will be inversely related to the, so-called "required funding ratio". This required funding ratio is prescribed by law and is comparable to the solvency requirements for banks and insurance companies. If a bank or an insurance company takes more risk, then it will have a higher capital requirement. Similarly, pension funds that have a large mismatch between assets and liabilities have a higher required funding ratio. This higher ratio shows a willingness to accept more risk (Broeders et al., 2020). Thus, we propose the following testable hypotheses:

1. *Funding ratio*

   A low funding ratio increases demand for the investment-grade fixed income market factor and decreases the overall demand for other factors, and vice versa.

2. *Risk aversion*

   Pension funds with a low risk aversion have larger exposures to factors other than the investment-grade fixed income market factor, and vice versa. We approximate risk aversion through the inverse of the required funding ratio.

[9] The empirical analysis is robust to including other proxies, such as a 10-year German government bond.

3. *Liability duration*
   Pension funds with a long liability duration have a high exposure to the investment-grade fixed income market factor, but lower overall exposure to the other factors, and vice versa.

2.3 Data

2.3.1 Pension fund returns

For the core of our analysis, we use proprietary quarterly return data on Dutch occupational pension funds from 1999Q1 through 2017Q4. The prudential supervisor in the Netherlands collects these data for regulatory purposes. Pension funds report the return on investments as the time-weighted return that takes into account the buying and selling in the asset class during the quarter. As of 2010, pension funds used standardized principles to compute the returns in accordance with the Global Investment Performance Standards (GIPS). Pension funds separately report the overall portfolio return as well as the returns from the equity and the fixed income portfolios. Total returns are in euros net of transaction costs. The returns of the equity and fixed income portfolios exclude the returns from derivative positions. The sample contains 572 distinct pension funds. We correct for pension funds that report the same returns during consecutive periods. Because these are clearly reporting errors, we replace the unvaried returns with missing values.

We distinguish between three different types of pension funds: corporate pension funds, industry-wide pension funds, and professional-group pension funds. Corporate pension funds execute a pension scheme for a particular company. Industry-wide pension funds organize pensions for a specific industry or sector; for example, for civil servants or for the care and welfare sector. These pension funds are typically mandatory, so the collective labor agreement in this sector prescribes that employers must join this pension fund. Professional-group pension funds provide pensions for a specific profession, such as veterinarians or pharmacists. Although corporate and professional-group pension funds are not mandatory, for historical reasons most employers offer a pension scheme to their employees. The fraction of the labor force that participates in a pension scheme exceeds 90 percent. The number of corporate pension funds in the sample is 474, the total number of industry-wide pension funds equals 88, and the number of professional-group pension funds is 10.

Table 4.1 shows the time series of total AUM for all Dutch pension funds. The AUM grew by a factor of 2.6 over the sample period. The AUM increases each year with the exceptions of a significant drop during the downturn in the stock market following the burst of the Dot-com bubble in 2002 and following the 2008 financial crisis. A continuous and significant drop in the total number of pension funds occurs during the sample period. In 2000, the total number of pension funds was 676; it lowered to a total of 200 in 2017. This drop is in particular due to a large decrease in the number of small corporate pension funds. Because pension funds cannot go bankrupt, our data does not suffer from a survivorship bias. Instead, for cost-efficiency reasons, small pension funds may decide to discontinue their operations and transfer assets and liabilities to an industry-wide pension fund or an insurance company. Not all pension funds fully report returns each year. The table also shows the AUM of pension funds that fully report returns and are therefore in our sample. These pension funds represent on average 93 percent of the AUM of all Dutch pension funds.

Panel A of Table 2.2 presents the summary statistics for pension funds' equity and fixed income returns and allocations. We measure excess returns against the 3-month Euribor rate that we get from the website of the Dutch Central Bank. The equally weighted average excess return on equities across pension funds and time equals 4.38 percent per year with a standard deviation of 21.28 percent.[10] The negative skewness indicates the equity return series has relatively strong negative values. The mean excess return on fixed income is 3.89 percent per year with a standard deviation of 10.04 percent. The high kurtosis demonstrates fat tails and that is, as we show later, due to the large cross-sectional variation in interest rate hedges. In our analysis, we use equally weighted returns. However, the fact that the Dutch occupational pension fund sector has a few very large industry-wide pension funds is well known. Therefore, for comparison reasons, Table 2.2 also presents the value-weighted statistics for returns. The value-weighted mean excess return for equities equals 4.80 and for fixed income it equals 3.73 percent.

Table 2.2 also presents the strategic allocations to equity and fixed income, the duration of the fixed income portfolio, the funding ratio, the required funding ratio, the liability duration, and the fraction of active participants to total participants (active participants plus retirees). Pension funds invest on average 31 percent in equities and 59 percent in fixed income. The average duration of the fixed income portfolio equals 8.2 years with a substantial standard deviation of 8.7 years that indicates the pension funds vary in the extent to which they hedge interest rate risk with bonds. The funding ratio on average equals 116 percent,

[10] We compute the standard deviation by using the law of total variance: $\sigma(r) = \sqrt{\mathbb{E}_i(\text{Var}[r]) + \text{Var}_i(\mathbb{E}[r])}$.

Table 2.1. **Total assets under management and number of pension funds**: This table shows the total asssets under management (AUM) in billion euros and the number of pension funds (N). The left hand columns present all pension funds in the Netherlands and the right hand columns all the pension funds that fully report returns and that are used in our analysis. AUM and N are at the end of each year.

	All		**Full reporting**	
year	AUM	N	AUM	N
1999	463.70	663	418.43	315
2000	480.78	676	453.09	408
2001	471.00	656	445.33	429
2002	429.51	658	405.67	447
2003	489.60	642	463.88	439
2004	529.93	605	510.39	450
2005	610.52	575	576.14	365
2006	657.57	524	604.64	390
2007	683.53	442	665.62	403
2008	576.32	413	557.21	376
2009	663.59	376	632.49	336
2010	746.28	350	729.31	328
2011	802.33	329	784.80	298
2012	897.09	260	753.51	287
2013	937.12	258	845.62	245
2014	1,131.74	247	984.73	228
2015	1,146.66	227	1,005.96	195
2016	1,262.54	216	1,122.37	190
2017	1,224.07	200	1,163.47	175

and the required funding ratio equals 115 percent. The liability duration on average equals 18.6 years, and the fraction of active participants equals 64 percent. The latter indicates that about a third of the participants is in the retirement phase.

Table 2.2. **Summary statistics**: Panel A reports the summary statistics for pension fund returns, both equally and value weighted. The mean returns and standard deviations of returns are measured across time and pension funds for 1999Q1-2017Q4. We also report the means and standard deviations for equity and fixed income allocations (percent), duration (years), funding ratio (fraction, as of 2007), required funding ratio (fraction, as of 2009), liability duration (years, as of 2007) and the ratio of actives to total participants (percent) that are computed from the quarterly reports. Panel B gives the summary statistics for the factor returns. The returns are annualized and in euros.

Panel A: Pension fund returns and characteristics				
Equally weighted	mean	stdev	skewness	kurtosis
Excess return equity	4.38	21.28	−0.53	3.51
Excess return fixed income	3.89	10.04	0.37	5.18
Value weighted				
Excess return equity	4.80	18.97	−0.45	3.85
Excess return fixed income	3.73	6.91	0.44	5.48
Characteristics				
Equity allocation	31.00	9.14		
Fixed income allocation	58.76	11.78		
Duration fixed income portfolio	8.20	8.71		
Funding ratio	1.16	0.16		
Required funding ratio	1.15	0.13		
Liability duration	18.63	5.53		
Fraction of active participants	64.25	24.89		
Panel B: Factor returns				
	mean	stdev	skewness	kurtosis
Euribor 3-month rate	1.94	0.83	0.22	1.76
Excess MSCI World Total Return Index	4.99	17.25	−0.70	3.83
Excess Euro Stoxx 50 Total Return Index	4.07	21.37	−0.32	4.11
Global value stock	4.00	15.81	0.57	11.51
Global momentum stock	5.20	16.88	0.26	6.44
Global carry stock	6.49	6.75	0.17	3.71
Global low beta stock	11.03	11.93	−0.10	6.81
Excess Bloomberg Barclays EuroAgg FI Index	2.55	3.66	−0.39	2.76
Excess Bloomberg Barclays EuroAgg High Yield Index	6.38	14.89	0.42	8.12
Europe value FI	1.17	5.56	−0.27	5.68
Europe momentum FI	1.24	4.54	−0.57	7.89
Europe carry FI	1.84	4.52	0.48	6.46
Europe low beta FI	0.86	4.41	0.18	3.29

2.3.2 Factor returns

In this subsection, we turn to the factors that explain the cross-section of returns. To distinguish between market factors and the other factors, we refer to the latter as long-short factors. Although controversy exists regarding whether long-short factor returns are rewards for risk or the result of mispricing, we do not take a stance on the underlying driver of these factor returns. We simply interpret these factors as diversified passive benchmark returns that capture patterns in average returns during the sample period we consider.

For the long-short factors we use the four factors that studies have shown to perform robustly across several asset classes and markets: value, momentum, carry, and low beta. The value factor for equities is a strategy that goes long in value stocks and short in growth stocks. As fixed income generally does not have measures of book value, value bonds are defined as bonds with high positive changes in the 5-year yield or high values for the negative 5-year past returns. Long-term past return measures for value come from de Bondt and Thaler (1985).[11] Momentum is defined in exactly the same way for equities and bonds: the past 12-month cumulative return that excludes the most recent month's return (see, e.g. Jegadeesh and Titman, 1993). Carry is defined as an asset's future return that assumes the price remains the same. Equity carry is approximately equal to the expected dividend yield minus the risk-free rate. Bond carry is the return that is earned if the yield curve stays the same over the next time period. Low beta is also similarly defined for stocks and bonds: low exposure to the corresponding market index.

Equity factors

We use the excess market return, value return, momentum return, carry return, and low beta return as factors that explain the pension funds' equity returns. Dutch pension funds have European as well as global equity holdings. The fraction of the equity portfolio they on average allocate to the euro area is 23 percent over the 2007-2017 period; and although we do not have data on the exposure to the euro area prior to 2007, we expect this fraction to be higher.[12] For instance, Berk and van Binsbergen (2015) show that the fraction of mutual funds that invests internationally has significantly increased over the last decade.

[11]For an extended discussion, see Asness et al. (2013).

[12]Data on investments in the euro and non-euro areas are published on the website of DNB: `https://statistiek.dnb.nl/en/downloads`.

We therefore include both global and European indices to define the market returns and to account for the currency bias (Maggiori et al., 2020). For the global market factor, we use the quarterly MSCI World Total Return Index in euros; for the European market factor, we use the Euro Stoxx 50 Total Return Index from Bloomberg in euros.[13]

Given that the majority of equity holdings are global, we use global value factors, global momentum factors, global carry factors, and global low beta factors to analyse the equity returns. We take the returns on the value, momentum, and low beta equity factors from the AQR website. The returns on the carry factor are from Ralph Koijen's website. Following the usual factor definitions, the global value and momentum factors are zero-cost, long-short portfolios in individual stocks in the US, the UK, continental Europe, and Japan (Asness et al., 2013). The data for carry and low beta include individual stocks from the following five regions: North America, the UK, continental Europe, Asia, and Australia.

The value, momentum, carry, and low beta returns are all monthly. To match with the pension funds' return cycle, we convert the monthly returns to quarterly returns by means of compounding. We assume pension funds fully hedge currency exposures and convert all dollar returns into euros.[14] The factor returns in euros are the dollar factor returns times the gross return on the exchange rate (Koijen et al., 2018) in which the exchange rate measures the number of euros per dollar. For the summary statistics, we furthermore convert quarterly returns into annual ones.

Panel B of Table 2.2 contains the summary statistics for the factor returns. Within equities, the low beta factor has the highest annualized return (11.03 percent), while value has the lowest (4.00 percent). Next to the market factors, momentum is the most volatile long-short factor over the sample period.

Fixed income factors

Compared to equities, Dutch pension funds invest substantially less globally within their fixed income portfolios. Measured over the period from 2007 through 2017, they invested

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[13] The Euro Stoxx 50 Total Return Index represents the 50 largest and most liquid stocks in the euro area. It comprises Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain. The MCSI World index includes the stocks in the Euro Stoxx 50 index.

[14] The AQR factors are not currency hedged, while the carry factor is fully hedged. Given that currency only explains a minor part of the returns for equities, our results do not materially change if we assume that the currency exposure is not hedged.

on average 87 percent of the fixed income portfolio in the euro area.[15] Again, we expect this fraction to be even larger prior to 2007. A currency bias for euro fixed income is logical because pension funds' liabilities are also denominated in euros, and fixed income is mainly used to hedge liabilities. We therefore use European factors for fixed income, as opposed to global factors for equities. Because bond returns are largely explained by duration and credit risk, we use the Bloomberg Barclays Euro Aggregate Bond Index and the Bloomberg Barclays Euro High Yield Index in euros as the market and credit factors respectively.[16] Table 2.2 shows that both the equally and value-weighted excess fixed income returns of pension funds are above the excess return of the investment-grade fixed income index. Pension funds have an incentive to invest in bonds with a high duration to match the high duration of their liabilities. The average duration of the fixed income portfolio equals 8.2 (Table 2.2). As such, benchmark durations are typically lower than the portfolio duration of pension funds. An upward-sloping term structure of interest rates therefore (in part) explains the higher pension fund returns.

As opposed to global, European fixed income long-short factors are not available, so we construct the value, momentum, carry, and low beta factors following the methods of Asness et al. (2013), Koijen et al. (2018), and Frazzini and Pedersen (2014). As the purpose of this study is to gain an insight into the factor exposures of institutional investors rather than the construction of factor returns themselves, we use the exact definitions of the aforementioned authors. We include the following European countries in constructing our factors: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and the UK. All these countries have investment-grade ratings over our sample period. In Appendix B, we describe the exact procedure for how we construct the factors. For all three factors, we assume the investor fully hedges currency exposures against the euro. Again, we convert monthly returns to quarterly returns by means of compounding. In the case of fixed income, carry has the highest annualized return (1.84 percent) followed by momentum (1.24 percent) and value (1.17). Low beta has a relative low average return equal to 0.86 percent, which is consistent with the findings in Frazzini and Pedersen (2014)

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[15]Data on investments in the euro and non-euro areas are published on the website of DNB: `https://statistiek.dnb.nl/en/downloads`.

[16]The Bloomberg Barclays Euro Aggregate Bond Index is a benchmark that measures the investment-grade, euro-denominated fixed-rate bond market that comprises Treasuries, government-related, corporate, and securitized fixed-rate bonds with issuers in Europe. The Bloomberg Barclays Euro High Yield Index measures the market for non-investment grade, fixed-rate corporate bonds with issuers in Europe.

who do not find a significant average return for the global low beta bond factor. Value has the highest standard deviation (5.56 percent) followed by momentum (4.54), carry (4.52), and low beta (4.41). Figure 2.1 shows the evolution of the long-short fixed income factors over time. The correlation matrix in Table 2.14 of the Internet Appendix also confirms the well-known stylized fact in the literature of the strikingly high negative correlation between value and momentum for the European fixed income factors (Asness et al., 2013).

2.4 Factor exposures

In this section, we proceed with the estimation of the (unconditional) factor exposures. We follow a three-step approach to account for measurement errors in the factor exposures. We describe this procedure in subsection 2.4.1. In Subsection 2.4.2 we show the implications of heterogeneity in factor exposures for heterogeneity in average performance across pension funds. Subsection 2.4.3 performs a variance decomposition to quantify how much of the cross-sectional differences in average returns are explained by the factors.

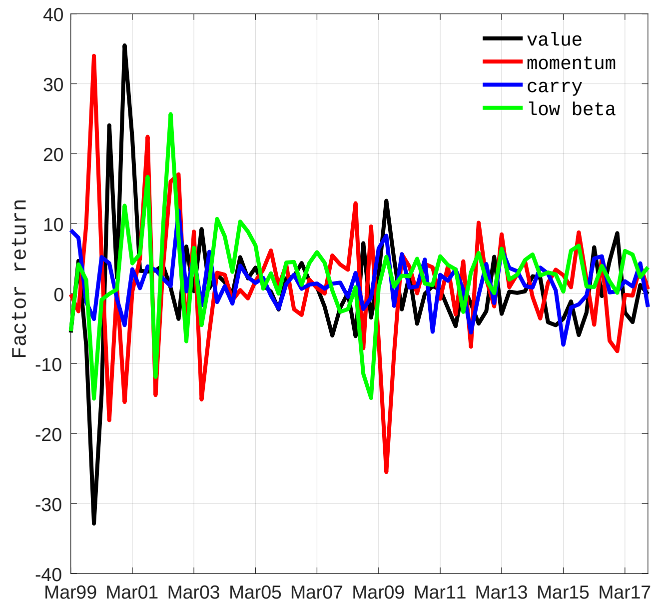
2.4.1 Factor exposures

We follow a three-step approach to account for measurement errors in the factor exposures. These measurement errors stem from the infrequent observations of pension fund returns. First, we estimate the factor exposures for equity and fixed income returns separately by using the arbitrage pricing theory (APT) developed by Stephen Ross (Ross, 1976). We denote equity by $a = E$ and fixed income by $a = FI$ and measure the factor exposures by regressing the excess returns of pension fund $i = 1, \ldots, N$ for asset class a on the excess factor returns in the following way:

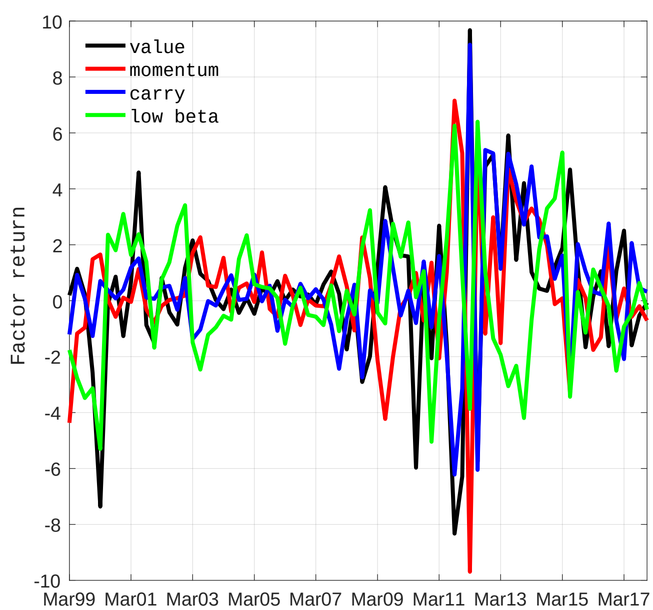
$$r_{i,t}^{a} - r_{t}^{f} = \alpha_{i}^{a} + \beta_{i}^{a\prime} f_{t}^{a} + \epsilon_{i,t}^{a}, \quad \text{for} \quad i = 1, \ldots, N, \tag{2.14}$$

in which r_t^f is our proxy for the risk-free rate: the Euribor 3-month rate, f_t^a is a vector of factor returns of length K for asset class a, and $\epsilon_{i,t}^a$ is the idiosyncratic error term with standard deviation σ_i^a. For equities, vector f_t^E contains the following six elements: the global excess market return, the European excess market return, the global value stock return, the global momentum stock return, the global carry stock return, and the global low beta stock return. For fixed income, the vector f_t^{FI} has the following six elements: the European excess investment-grade fixed income market return, the European excess high yield fixed income

Figure 2.1. **Long-short factor returns**: This figure shows the global (equity) and European (fixed income) quarterly long-short factor returns over our sample period, 1999Q1-2017Q4.



Equities factors



Fixed income factors

return, the European value fixed income return, the European momentum fixed income return, the European carry fixed income return, and the European low beta fixed income return. In the remainder of the study, we drop the superscript a to simplify the notations. In Table 2.15 of the Internet Appendix, we present the results of the estimated betas using the time-series OLS in detail.

Second, we use a random-coefficient model to estimate the priors for the factor exposures. The estimated factor exposures that use the time-series OLS suffer from measurement error because we only observe quarterly returns (Merton, 1980). The cross-sectional mean and standard deviation may therefore substantially deviate from the true moments. Because the focus is on the cross-sectional mean and standard deviation of factor exposures, we correct for this deviation by using a prior on the mean and the variance in the factor exposures that we derive from a random-coefficients model. Compared to a standard regression model in which the parameters are fixed to a single value, the random-coefficients model allows for cross-sectional variation in the parameters. We specify the random-coefficients model as follows:

$$\begin{aligned} r_{i,t} - r^f_t &= \alpha_i + \beta_i' f_t + \epsilon_{i,t} \\ &= \alpha + \beta' f_t + v_i' f_t + u_i + \epsilon_{i,t}, \end{aligned} \tag{2.15}$$

in which v_i is a vector of length L that captures all the random-effect coefficients, and $\epsilon_{i,t}$ is the idiosyncratic error term with variance σ_i. Furthermore, we assume that L is equal to the number of factors K; in other words, we allow all factor exposures to vary across pension funds. The exact procedure for estimating the random-coefficients model is in Internet Appendix D. We use the regression coefficients of the random coefficients model as the prior distribution in the analysis. Thus, the prior betas are defined as:

$$\beta_i^k \sim N(\hat{\beta}^k, \hat{\sigma}^2_{\beta^k}) \quad \text{for} \quad k = 1, \dots, K \quad \text{and} \quad i = 1, \dots, N, \tag{2.16}$$

in which $\hat{\beta}^k$ is the fixed-effect estimator, and $\hat{\sigma}^2_{\beta^k}$ is the variance in the random effect from Equation (2.15). The variances in the random effects facilitate the testing for the existence of true heterogeneity in the factor exposures. We find significant average factor exposures in both the equity and the fixed income portfolios. Similarly, we also find significant cross-sectional heterogeneity in all factor exposures except for momentum in the fixed income portfolios. The coefficient estimates that include a detailed interpretation appear in the Internet Appendix D.

Third, we derive posterior factor exposures. Following Vasicek (1973), Elton et al. (2003), and Cosemans et al. (2016), we combine the estimated factor exposures from the time-series OLS regressions with the prior to obtain the posterior betas. These exposures are approximately normally distributed with the following mean and variance:

$$\tilde{\beta}_i^k = \frac{\hat{\beta}_i^k / se(\beta_i^k)^2 + \hat{\beta}^k / \hat{\sigma}^2_{\beta^k}}{1/se(\beta_i^k)^2 + 1/\hat{\sigma}^2_{\beta^k}} \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N \tag{2.17}$$

$$\tilde{\sigma}^2_{\beta_i^k} = \frac{1}{1/se(\beta_i^k)^2 + 1/\hat{\sigma}^2_{\beta^k}} \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{2.18}$$

in which $\hat{\beta}_i^k$ is the estimated exposure to factor k from the time-series OLS regressions presented in Equation (2.14) for pension fund i, and $se(\beta_i^k)$ is the corresponding standard error. Equation (2.17) shows that the factor exposures of pension funds with less precise sample estimates shrink to the prior. The distribution of posterior factor exposures shows the heterogeneity across pension funds corrected for the measurement error. As a result, the posterior betas are economically interpretable.

For equities, Table 2.3 shows the average exposures to the world and European market factors as equaling 0.67 and 0.27 respectively and with standard deviations equaling 0.18 and 0.15. The sum of the market exposures equals 0.94 that indicates the pension funds, on average, take slightly less systemic risk than the market portfolio. The standard deviations of the posterior market exposures shrink by about one-half compared to the time series regressions that indicates that the substantial variation in the market exposures remains after correcting for the measurement error. The average exposures to value, momentum, carry, and low beta equal −0.05, −0.04, −0.06, and 0.08, respectively. Average negative momentum and value exposures for equities are consistent with recent findings for retail investors in e.g. Luo et al. (2020). The standard deviation in factor exposures for value, momentum, carry, and low beta are 0.07, 0.04, 0.13, and 0.08, respectively. The standard deviation in the posterior factor exposures shrinks by two-thirds for value, five-sixths for momentum, three-fourths for carry, and two-thirds for low beta compared to the time series regressions. A substantial part of the cross-sectional variation in the factor exposures is thus the result of measurement error. Yet, the heterogeneity in the factor exposures remains, especially for value, carry, and low beta.

For fixed income, the average exposure to the investment-grade market factor equals

1.11. A fixed income market beta larger than one is consistent with our model, because the duration of the liabilities is much longer compared to the duration of the bond market index. The cross-sectional standard deviation equals 0.31. The standard deviation of the posterior market exposure shrinks by one-half compared to the time-series regressions that indicates the substantial variation in the market exposures remains after correcting for the measurement error. The average exposures to credit risk, value, momentum, carry, and low beta are 0.02, −0.16, 0.07, −0.07, and 0.21, respectively. The cross-sectional standard deviations of credit, value, carry, and low beta equal 0.06, 0.15, 0.09, and 0.18 respectively. Again, substantial variation in factor exposures from the time series regressions is due to measurement error, although the heterogeneity in the factor exposures remains. Because we are not able to detect any variation in the exposure to momentum (Table 2.16), all estimates shrink to the mean; and the standard deviations obtained from the time-series regressions are almost all due to measurement error.

2.4.2 Heterogeneity in average excess returns

The variation in the factor exposures that we observe has consequences for the average excess return differences across pension funds. To determine these differences, we compute the contribution of each of the factors to the average excess returns. We use the posterior betas obtained from Equation (2.17). The contribution of each of the factors is then computed as:

$$\mathbb{E}(r_i^k) = \tilde{\beta}_i^k \lambda^k \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N, \tag{2.19}$$

in which λ^k is the historical average return for factor k.

The total average excess return for pension fund i equals $\mathbb{E}(r_i^e) = \sum_{k=1}^{K} \tilde{\beta}_i^k \lambda^k$. We rank pension funds based on the total average excess returns from highest to lowest and split them in five equally weighted groups. We then disentangle the contribution of each factor to the average excess returns using (2.19). Table 2.4 summarizes the results for equities, fixed income, and the total portfolio level.

For equities, we find that taking all factors together, the contribution of the factor exposures to average excess returns varies between 2.23 and 6.40 percentage points. Pension funds with the highest average excess returns have a return contribution of the market that is equal to 4.60 percentage points, while this return contribution for pension funds with the lowest average excess returns equals 4.11 percentage points. For the long-short factors,

Table 2.3. **Factor exposures**: This table displays the cross-sectional means and standard deviations of the OLS betas from Equation (2.14), the prior betas from Equation (2.15), and the posterior betas from Equation (2.17). M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class.

Panel A: Equity

	OLS		**Prior**		**Posterior**	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
$\hat{\beta}_i^{M,W}$	0.656	0.297	0.649	0.184	0.668	0.179
$\hat{\beta}_i^{M,EU}$	0.270	0.311	0.299	0.160	0.273	0.153
$\hat{\beta}_i^{VAL}$	-0.060	0.230	-0.043	0.085	-0.048	0.066
$\hat{\beta}_i^{MOM}$	-0.056	0.244	-0.041	0.048	-0.044	0.041
$\hat{\beta}_i^{CARRY}$	-0.106	0.549	-0.054	0.148	-0.057	0.126
$\hat{\beta}_i^{BAB}$	0.088	0.240	0.087	0.107	0.075	0.082

Panel B: Fixed income

	OLS		**Prior**		**Posterior**	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
$\hat{\beta}_i^{M,EU}$	1.139	0.564	1.126	0.485	1.107	0.306
$\hat{\beta}_i^{HY,EU}$	0.019	0.111	0.024	0.086	0.023	0.061
$\hat{\beta}_i^{VAL}$	-0.146	0.402	-0.208	0.155	-0.158	0.147
$\hat{\beta}_i^{MOM}$	0.024	0.623	0.071	0.000	0.070	0.007
$\hat{\beta}_i^{CARRY}$	-0.037	0.552	-0.079	0.092	-0.067	0.087
$\hat{\beta}_i^{BAB}$	0.253	0.508	0.271	0.194	0.205	0.176

the dispersion is much larger for carry and low beta compared to the market. The average return contribution of the carry factor equals 0.44 percentage points at the highest and −1.25 percentage points at the lowest percentiles. For low beta, the return contribution varies between 1.66 and −0.05.

For fixed income, taking both market and long-short factors together, the contribution of the factor exposures vary between 1.91 and 3.95 percentage points. The variation in the contributions of market exposures is larger than for equities and varies between 1.99 and 3.82 percentage points. The long-short factors play a subordinate role. The negative contribution of the long-short factor exposures is due to the typically negative exposure to value and carry factors.

We now turn to the total portfolio level. The average excess return for the total portfolio is computed as the sum of the equity average excess return times the equity weight and the fixed income average excess return times the fixed income weight. All factors taken together, the contribution to the average returns differs by 2.35 percentage points. In other words, pension funds with the highest factor exposures versus pension funds with the lowest factor exposures have a 2.35 percentage point higher average return on the entire portfolio. The contribution of the market factor has values that vary between 2.74 and 4.04 percentage points, and the contribution of the long-short factor exposures has values that vary between −0.53 and 0.51 percentage points.

2.4.3 Variance decomposition

Next, we perform a variance decomposition to quantify how much of the cross-sectional differences in average excess returns are explained by the factor exposures. We first calculate the average excess return of each pension fund per asset class using Equation (2.17):

$$\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i'\lambda \quad \text{for} \quad i = 1, \dots, N, \tag{2.20}$$

in which λ is a vector of historical average factor returns.

Second, we take the cross-sectional covariance of each side with $\tilde{\mu}$ that is the vector of average excess returns with a length that is equal to N. Because $\text{Cov}(\tilde{\mu}, \tilde{\mu}) = \text{Var}(\tilde{\mu})$, we can divide it by the variance of $\tilde{\mu}$ to get:

$$1 = \frac{\text{Cov}(\tilde{\beta}'\lambda, \tilde{\mu}) + \text{Cov}(\tilde{\alpha}, \tilde{\mu})}{\text{Var}(\tilde{\mu})} = \frac{\sum_{k=1}^{K} \text{Cov}(\tilde{\beta}^{k\prime}\lambda^k, \tilde{\mu}) + \text{Cov}(\tilde{\alpha}, \tilde{\mu})}{\text{Var}(\tilde{\mu})}, \tag{2.21}$$

Table 2.4. **Heterogeneity of average excess returns**: This table shows the distribution of the average excess return contributions of the market factors, long-short factors, and all factors, to the total equity returns (Panel A), fixed income returns (Panel B), and overall portfolio returns (Panel C). The overall portfolio contribution of the market factors (long-short factors) (all factors) is calculated as the equity weight times the contribution of market factors (long-short factors) (all factors) for equity, plus the fixed income weight times the contribution of the market factor (long-short factors) (all factors) for fixed income. We report the averages within the 0-20th, 20-40th, 40-60th, 60-80th, and 80-100th percentiles. The last column shows the difference between the 100th-80th and the 0-20th percentile. All values are percentage points and annualized.

Panel A: Equity

	0-20th	20-40th	40-60th	60-80th	80-100th	diff
All factors	2.23	3.92	4.66	5.26	6.40	4.17
Global market	3.15	3.49	3.31	3.38	3.32	0.17
EU market	0.96	0.96	1.20	1.17	1.28	0.32
Value	-0.31	-0.23	-0.16	-0.15	-0.10	0.21
Momentum	-0.28	-0.23	-0.22	-0.20	-0.20	0.07
Carry	-1.25	-0.61	-0.33	-0.08	0.44	1.69
Low beta	-0.05	0.55	0.87	1.14	1.66	1.71

Panel B: Fixed income

	0-20th	20-40th	40-60th	60-80th	80-100th	diff
All factors	1.91	2.61	2.93	3.29	3.95	2.04
Market	1.99	2.53	2.76	3.10	3.82	1.83
High yield	0.07	0.11	0.19	0.23	0.14	0.07
Value	-0.18	-0.12	-0.17	-0.22	-0.24	-0.06
Momentum	0.09	0.09	0.09	0.09	0.09	0.00
Carry	-0.17	-0.11	-0.12	-0.12	-0.09	0.08
Low beta	0.12	0.11	0.18	0.21	0.24	0.13

Panel C: Overall portfolio

	0-20th	20-40th	40-60th	60-80th	80-100th	diff
All factors	2.21	3.02	3.51	3.93	4.56	2.35
Market factors	2.74	3.24	3.46	3.78	4.04	1.31
Long-short factors	-0.53	-0.21	0.05	0.15	0.51	1.04

in which $\tilde{\mu}$ and $\tilde{\beta}^{k\prime}\lambda^k$ are both vectors of length N.

Table 2.5 shows the results for both equity and fixed income returns. The exposures to the global and European market returns explain 14.05 and 5.41 percent of the variation in average equity excess returns, respectively. For the long-short factors, the ones with the most explanatory power are carry and low beta, and they respectively explain 40.15 and 41.22 percent of the variation in average excess returns. Value explains 3.67 of the variation in average excess returns and momentum 2.58 percent. This finding is consistent with the highest return contribution heterogeneity found for the carry and low beta factors. Alpha has negative explanatory power for average excess returns, which means that the pension funds with a high alpha have slightly lower average excess returns.

For fixed income, the European investment-grade market return explains 71.32 percent of the variation in average excess returns, and the high yield return explains 2.79 percent. Low beta, value, and carry explain 4.83, 1.53, and 6.48 of the variation in average excess returns. Consistent with the absence of true heterogeneity across momentum exposures, momentum has negligible explanation power. Alpha has positive explanatory power for average excess returns equal to 13.28 percent.

Table 2.5. **Variance decomposition**: This table shows how much of the variance in estimated average excess returns $\tilde{\mu}$ is explained by the alpha and the factor exposures for equities and fixed income presented in Equation (2.21). We calculate the average return per asset class of each pension fund using $\tilde{\mu}_i = \tilde{\alpha}_i + \tilde{\beta}_i^{\prime}\lambda$ in which λ is the average factor return. All values are percentages.

Variance contribution			
Equity		Fixed income	
α	−7.08	α	13.28
Global market	14.05	Market	71.32
EU market	5.41	High yield	2.79
Value	3.67	Value	1.53
Momentum	2.58	Momentum	−0.22
Carry	40.15	Carry	6.48
Low beta	41.22	Low beta	4.83

2.5 Drivers of factor exposures

The previous section shows that there is substantial heterogeneity in the factor exposures across pension funds. In this section, we analyse the drivers behind these factor exposures. We have two groups of drivers. The first group are the pension funds' characteristics from our theoretical framework in Section 2.2. This group includes the funding ratio, risk aversion, and liability duration.[17] The second group consists of institutional factors, in particular the pension fund's size and type.

We perform a panel data regression of the funding ratio, the risk aversion, the liability duration, size, and type that we interact with the factor returns:

$$\begin{aligned} r^e_{i,t} &= \delta_0' f_t + \delta_1' f_t \times \mathrm{F}_{i,t-1} + \delta_2' f_t \times \gamma_{i,t-1} + \delta_3' f_t \times \mathrm{D}_{i,t-1} + \delta_4' f_t \times \mathrm{AUM}_{i,t-1} \\ &+ \delta_5' f_t \times \mathrm{Type}_i + \epsilon_{i,t}, \end{aligned} \tag{2.22}$$

in which $\mathrm{F}_{i,t-1}$ is the funding ratio of pension fund i at time $t-1$, γ_{it-1} is the risk aversion of pension fund i at time $t-1$, $\mathrm{D}_{i,t-1}$ is the liability duration for pension fund i at time $t-1$, AUM_{it-1} is the AUM for pension fund i at time $t-1$ for the corresponding asset class, and Type_i is the pension fund type. We demean FR_{it-1}, γ_{it-1}, D_{it-1}, and AUM_{it-1} such that δ_0 can be interpreted as the average (industry-wide) pension fund.

2.5.1 Pension funds' characteristics

Funding ratio

Our theoretical framework predicts that pension funds with a low funding ratio should have a high exposure to the fixed income market factor, and vice versa. Moreover, the lower the funding ratio, the less room for the speculative portfolio if the borrowing constraint is binding. Hence, we predict that on average, lower exposures will exist to factors other than the fixed income market factor for pension funds with low funding ratios, and vice versa. For equities, we find that pension funds with a high funding ratio do not have different equity factor exposures (Table 2.6). For fixed income, we find that pension funds with a high funding ratio have less exposure to the market factor and more exposure to the credit

[17] In this study, we focus on factor exposures. In the Internet Appendix we show that the predictions from our theoretical framework also empirically hold for the allocation to equity and fixed income (Table 2.17).

and carry factor. A one standard deviation increase in the funding ratio (0.16) decreases the exposure to the market factor by 0.18 and increases the exposure to the credit factor by 0.02 and the carry factor by 0.07. Overall, these findings are consistent with our theoretical framework: pension funds with a low funding ratio invest more in investment-grade fixed income securities that correlate positively with their liabilities, while they have a lower aggregate exposure to the other factors.

Andonov et al. (2017) find the opposite result for US public pension funds. This difference is driven by regulation: The discount rate of US public pension links to the expected returns on assets, while Dutch pension funds have to use a discount rate that links to market interest rates. The incentive to invest in risky assets to artificially improve the funding status of US public pension funds therefore does not apply to Dutch pension funds. A discount rate based on market interest rates is widely used and is the standard for US private pension funds, Canadian, and other European pension funds.

Risk aversion

We use the inverse of the required funding ratio as an implicit measure of the risk aversion in which $\gamma \propto 1/\text{RFR}$, as described in Section 2.2. Our theoretical framework predicts that pension funds with a higher risk aversion coefficient should have a higher exposure to the fixed income market factor and lower exposure to the other factors. For equities, an increase of one standard deviation in the proxy for risk aversion (0.04) slightly decreases the exposure to the global market factor by 0.01. For fixed income, a higher risk aversion coefficient increases the exposure to the market factor substantially and the exposure to momentum slightly. An increase of one standard deviation in the implicit risk aversion coefficient increases the exposure to the market factor by 0.39 and to momentum by 0.04. On the other hand, a higher implicit risk aversion coefficient decreases the exposure to the credit factor, value, carry, and low beta. An increase of one standard deviation in the implicit measure of the risk aversion coefficient decreases the exposure to the credit factor by 0.03, value by 0.04, carry by 0.15, and low beta by 0.07. Overall, these findings are consistent with our theoretical framework: pension funds with a higher risk aversion coefficient have a higher exposure to safe assets and less exposure to assets that are uncorrelated with their liabilities.[18]

[18]The relation between the required funding ratio and asset allocation decisions is mechanical: a higher allocation to equities increases the required funding ratio. However, *within* asset classes there is no such relation. Pension funds that for instance invest more in risky equities (i.e., high beta stocks) do not experience a higher required funding ratio.

Liability duration

Our theoretical framework predicts that pension funds with a long liability duration should have a higher exposure to the fixed income market factor and lower exposures to the other factors, and vice versa. For equities, pension funds with a long liability duration have a higher exposure to the global market index that is approximately offset by a lower exposure to the European market index. Moreover, a one standard deviation increase in the liability duration decreases the exposure to low beta by 0.02. For fixed income, pension funds with a long liability duration have a larger exposure to the market factor and a lower exposure to the credit factor. An increase of one standard deviation in the liability duration increases the exposure to the market factor by 0.40 and decreases the exposure to credit by 0.03. Pension funds with a long liability duration also have lower exposure to value and carry. An increase of one standard deviation in the liability duration decreases the exposure to value and carry by 0.05 and 0.14. Again, these findings are consistent with our theoretical framework. We find similar results when using the ratio of active participants relative to the retirees as a proxy for the liability duration (Table 2.18 in the Internet Appendix).

2.5.2 Institutional factors

Size

Size might affect market and long-short factor exposures for two competing reasons. First, large pension funds generally have economies of scale and therefore can bring more expertise to their investment process. As a result, we predict that large pension funds will invest in a more globally and sophisticated manner. Second, due to the price effect of large trades – see, for example, Easley and O'Hara (1987) – pension funds with a substantial AUM in a specific asset class are constrained and might choose to implement factor investing on a low scale relative to pension funds with a lower AUM. The results are in Table 2.7. For equities, size has a positive and significant effect on the exposure to the excess global market return, and a negative and significant effect on the exposure to the excess European market return. A pension fund that is 10 times larger has a 0.06 higher exposure to the global market and a 0.05 lower exposure to the European market. This finding confirms earlier conjectures that large pension funds have the means to diversify their equity investments more globally than small pension funds. Size does not affect the other factor exposures. These results thus do not confirm the conjecture that large pension funds might be constrained in implementing factor strategies.

Table 2.6. **Effect of pension fund's characteristics on factor exposures**: This table shows the coefficient estimates of Equation (2.22): We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the funding ratio, the risk aversion coefficient that we represent with the inverse of the required funding ratio, and the liability duration during the period from 2009Q1-2017Q4. We control in both specifications for the model parameters included in Table 2.7. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity				
	average	funding ratio	risk aversion	liability duration
$\beta^{M,W}$	0.646***	-0.0012	-0.302*	0.0042***
	[0.0144]	[0.0538]	[0.1757]	[0.0013]
$\beta^{M,EU}$	0.289***	0.0445	0.0052	-0.0032**
	[0.0209]	[0.0459]	[0.1806]	[0.0013]
β^{VAL}	0.041	-0.107	0.2520	0.0017
	[0.0299]	[0.0977]	[0.3615]	[0.0025]
β^{MOM}	-0.0668***	-0.0363	0.1300	-0.0012
	[0.0231]	[0.0645]	[0.2218]	[0.0015]
β^{CARRY}	0.0193	0.0836	-0.3960	0.001
	[0.0219]	[0.1253]	[0.3019]	[0.0020]
β^{BAB}	0.132***	0.0451	0.0068	-0.0041**
	[0.0203]	[0.0603]	[0.2308]	[0.0018]
obs.	8,774	adj. R-sq.	0.863	

Panel B: Fixed income				
	average	funding ratio	risk aversion	liability duration
$\beta^{M,EU}$	2.193***	-1.123***	9.755***	0.0736***
	[0.1579]	[0.2414]	[1.4087]	[0.0161]
$\beta^{HY,EU}$	-0.0272*	0.107***	-0.749***	-0.0058***
	[0.0157]	[0.0345]	[0.1570]	[0.0013]
β^{VAL}	-0.121***	-0.0036	-0.965*	-0.0084*
	[0.0464]	[0.0919]	[0.5134]	[0.0048]
β^{MOM}	0.0636*	-0.0685	1.016***	-0.0002
	[0.0338]	[0.0617]	[0.3225]	[0.0031]
β^{CARRY}	-0.667***	0.4270**	-3.732***	-0.0255**
	[0.1024]	[0.1767]	[0.9643]	[0.0108]
β^{BAB}	-0.170**	0.1680	-1.699**	-0.0129
	[0.0763]	[0.1306]	[0.7453]	[0.0084]
obs.	8,856	adj. R-sq.	0.574	

Pension fund type

Differences in the organizational structure across pension funds might also affect factor exposures. One important difference is that listed companies have to report on the status of their pension funds in their own financial disclosures. Also the risk of the pension fund may be reflected in the risk profile of the company (Jin et al., 2006). This is not the case for the sponsors of an industry-wide pension fund or a professional-group pension fund. Corporate pension funds may therefore be less willing to take risk or to deviate from market benchmarks. In Table 2.7 we use industry-wide pension funds as a reference group. We observe that the only notable difference between corporate pension funds and industry-wide pension funds is that they have a higher exposure to the global market equity index. This is consistent with corporate pension funds following benchmarks more closely as opposed to the industry-wide pension funds.

2.6 Heterogeneity in beliefs

So far, we have seen that pension fund's characteristics and institutional factors drive factor exposures. In this section, we first show that these do not fully explain investment strategies and that there still remains significant heterogeneity in the factor exposures. We then explain the remaining heterogeneity from implied beliefs in the factor returns. We also show that these beliefs (partially) reveal themselves via the choice of the asset management firm.

2.6.1 Remaining heterogeneity in factor exposures

Consistent with our theoretical framework, the previous section shows that part of the heterogeneity results from differences in the pension fund characteristics. The theoretical framework shows, and the empirical analysis confirms, that the relative weight of the liability hedge portfolio increases if the funding ratio is low, when the risk aversion is high and when the liability duration is long. In this section, we adjust the posterior betas for each pension fund such that the liability hedge demand is equal across pension funds and compute the heterogeneity in performance with the adjusted exposures.

Table 2.7. **Effect of institutional factors on factor exposures**: We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the log AUM (size) and the pension fund type (base group: industry pension funds, other groups: corporate and professional group pension funds) during the period from 2009Q1-2017Q4. We control in both specifications for the model parameters included in Table 2.6. Panel A shows the results for equities and Panel B for fixed income. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity

	average	size	corporate	professional
$\beta^{M,W}$	0.646***	0.0558***	0.0590***	0.0285
	[0.0144]	[0.0085]	[0.0156]	[0.0236]
$\beta^{M,EU}$	0.289***	-0.0506***	-0.0301	-0.0161
	[0.0209]	[0.0084]	[0.0210]	[0.0261]
β^{VAL}	0.041	-0.0127	-0.0098	0.0271
	[0.0299]	[0.0154]	[0.0310]	[0.0433]
β^{MOM}	-0.0668***	-0.0084	0.0199	0.0283
	[0.0231]	[0.0111]	[0.0230]	[0.0361]
β^{CARRY}	0.0193	0.0004	-0.0196	-0.0626*
	[0.0219]	[0.0130]	[0.0229]	[0.0361]
β^{BAB}	0.132***	-0.0057	-0.0326*	0.0052
	[0.0203]	[0.0110]	[0.0177]	[0.0324]
obs.	8,774	adj. R-sq.	0.863	

Panel B: Fixed income

	average	size	corporate	professional
$\beta^{M,EU}$	2.193***	0.1170	-0.0422	-0.3200
	[0.1579]	[0.0960]	[0.1828]	[0.2920]
$\beta^{HY,EU}$	-0.0272*	0.0125	-0.0067	0.001
	[0.0157]	[0.0099]	[0.0176]	[0.0317]
β^{VAL}	-0.121***	-0.0366	-0.0644	0.0914
	[0.0464]	[0.0295]	[0.0543]	[0.1125]
β^{MOM}	0.0636*	-0.0162	-0.0675*	-0.0019
	[0.0338]	[0.0194]	[0.0384]	[0.0724]
β^{CARRY}	-0.667***	-0.0566	0.1810	0.1180
	[0.1024]	[0.0635]	[0.1204]	[0.1955]
β^{BAB}	-0.170**	0.0138	0.1350	0.1420
	[0.0763]	[0.0469]	[0.0894]	[0.1629]
obs.	8,856	adj. R-sq.	0.574	

Formally, we adjust the posterior betas of each pension fund as follows:

$$\tilde{\beta}^k_{adj,i} = \tilde{\beta}^k_i - \hat{\delta}^k_1 \times \overline{\mathrm{F}}_i - \hat{\delta}^k_2 \times \overline{\gamma}_i - \hat{\delta}^k_3 \times \overline{\mathrm{D}}_i \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad i = 1, \ldots, N. \tag{2.23}$$

Because the time series averages $\overline{\mathrm{F}}_i$, $\overline{\gamma}_i$, and $\overline{\mathrm{D}}_i$ are defined relative to the cross-sectional sample average, the adjusted factor exposures decrease for a positive coefficient (i.e. $\hat{\delta}^k_1, \hat{\delta}^k_2, \hat{\delta}^k_3 > 0$) when the funding ratio, risk aversion, or liability duration is higher than average, and vice versa. We do the same for the institutional factors. The heterogeneity that remains is unexplained by the pension fund characteristics or institutional drivers.

We redo the analysis from Section 2.4 (subsection 2.4.2) and Table 2.8 summarizes the results. In Panel A, we present the unadjusted excess returns. Pension funds with the highest factor exposures versus pension funds with the lowest factor exposures have a higher average return by 2.35 percentage points on the entire portfolio. Of this difference, 1.30 percentage points are driven by market factors and 1.05 by long-short factors. In Panel B, we correct the excess returns for the pension fund characteristics. The return difference between the top and bottom percentiles is 1.50 percentage points. The contribution of the market factors varies from 3.22 to 3.91 percent, and the contribution of long-short factors varies between −0.25 and 0.56 percent. A total return difference of 1.50 percentage points that cannot be explained by the pension fund characteristics is an economically sizable effect. A lower annual return by 1.50 percentage points decreases the expected retirement income by 32 percent over a 40-year accrual phase or increases contributions by 46 percent to get the same income.

The heterogeneity in the average excess returns remains the same in Panel C if we also adjust the factor exposures for institutional factors in the same way as in (2.23). Because pension funds do not differ substantially in their aggregate equity market exposure, Panels B and C show that the differences in the pension fund characteristics account for roughly 50 percent of the heterogeneity in the return contribution of the fixed income market factors. The pension fund characteristics only explain 20 percent of the heterogeneity in the return contribution of the long-short factors.

Finally, in Panel D we redo the analysis for a subsample of pension funds that are in the sample for at least 24 quarters to further reduce the effect of the measurement error. For this group of pension funds, we find a difference in average excess returns of 1.16 percentage points, and this is equivalent to a difference in expected retirement income of 24 percent.

Controversy about the performance of long-short factors exists. However, excluding long-short factors all together, we still find an unexplained difference in the average annual returns of roughly 70 basis points, which is equivalent to a difference in expected retirement income of 16 percent.

2.6.2 Implied beliefs on expected factor returns

The substantial heterogeneity in the average excess returns that is left after the correction for differences in the pension fund characteristics and institutional drivers may also indicate that pension funds differ in their beliefs about factor returns, particularly so for equities. To show this heterogeneity we identify the pension funds' unconditional implied beliefs about expected (excess) factor returns. To do so, we apply the method as described in Shumway et al. (2011). In their work, they assume that fund managers choose portfolio weights such that they maximize their expected returns over a benchmark while minimizing the tracking error volatility. They find true beliefs to be:

$$\mu_i \approx \gamma_i \delta_i \Sigma_i (w_i - q_i) - \lambda \mathbf{1} \qquad \text{for} \qquad i = 1, \ldots, N, \tag{2.24}$$

in which Σ_i is the variance-covariance matrix of returns that is estimated with historical return data and is therefore similar across managers ($\Sigma_i = \Sigma$), w_i are the portfolio weights, q_i are the benchmark portfolio weights, γ_i is the risk aversion parameter of fund manager i, δ_i is the total precision of fund manager i, and λ is the Lagrange multiplier of the borrowing constraint. The total precision parameter measures the informedness of the fund manager about future returns and is the sum of two parts $\delta_i = \tau^{-1} + \tau_i^{-1}$, in which τ^{-1} is the precision of the prior on expected returns, and τ_i^{-1} is the precision of a signal about the expected returns of fund manager i.

The true beliefs are an affine function of the implied beliefs in which the ith fund manager's implied beliefs about the expected returns, $\hat{\mu}_i$, are derived in Shumway et al. (2011) as follows:

$$\hat{\mu}_i = \Sigma_i (w_i - q_i) \qquad \text{for} \qquad i = 1, \ldots, N. \tag{2.25}$$

We can apply this framework to our model in Section 2.2. Because we cannot observe all the parameters required to identify the true beliefs, we assume reasonable parameter values to get estimates of the implied beliefs on the expected factor returns. The results that

Table 2.8. **Remaining heterogeneity of average excess returns**: This table shows the distribution of the average excess return contributions of market factors, long-short factors, and all factors to the overall portfolio returns for unadjusted returns (Panel A), returns corrected for the pension fund characteristics (Panel B), and corrected for both the pension fund characteristics and the institutional factors (Panel C). Panel D uses the same specification as Panel C but for pension funds that are at least 24 quarters in the sample. The overall portfolio contribution of the market factors (long-short factors) (all factors) is calculated as the equity weight times the contribution of market factors (long-short factors) (all factors) for equity, plus the fixed income weight times the contribution of the market factor (long-short factors) (all factors) for fixed income. We report the averages within the 0-20th, 20-40th, 40-60th, 60-80th, and 80-100th percentiles. The last column shows the difference between the 80th-100th and the 0-20th percentile. All values are percentage points and annualized.

Panel A: Unadjusted returns

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	2.21	3.02	3.51	3.93	4.56	2.35
Market factors	2.74	3.24	3.46	3.78	4.04	1.30
Long-short factors	-0.53	-0.21	0.05	0.15	0.51	1.04

Panel B: Returns corrected for pension fund characteristics

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	2.97	3.36	3.65	4.05	4.47	1.50
Market factors	3.22	3.57	3.54	3.82	3.91	0.69
Long-short factors	-0.25	-0.20	0.10	0.23	0.56	0.81

Panel C: Returns corrected for pension fund characteristics and institutional factors

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	3.15	3.58	3.86	4.30	4.65	1.50
Market factors	3.39	3.78	3.73	4.05	4.07	0.68
Long-short factors	-0.24	-0.21	0.13	0.25	0.58	0.82

Panel D: Subsample of pension funds

	0-20th	20-40th	40-60th	60-80th	80-100th	diff.
All factors	2.95	3.42	3.55	3.85	4.11	1.16
Market factors	3.21	3.48	3.60	3.81	3.94	0.73
Long-short factors	-0.26	-0.07	-0.04	0.04	0.17	0.43

follow should therefore be interpreted as approximations of the true beliefs in which we are particularly interested in the magnitude of differences in the expected returns across pension funds.

As in Shumway et al. (2011), to measure implied beliefs, we refrain from private signals and set $\tau_i^{-1} = 0$. We also assume that pension funds have the same overall precision in the prior equal to $\tau = 1$. Together with the assumption of no private signals ($\tau_i^{-1} = 0$), we have $\delta_i = 1$. A precision in the prior equal to $\tau = 1$ means that pension funds have a prior $p(\mu_0)$ that is normally distributed with a mean μ and a variance-covariance Σ, that are, for instance, based on historical returns:

$$p(\mu_0) \sim N(\mu, \Sigma). \tag{2.26}$$

For the benchmark factor exposures q_i, we assume an exposure of one to the global market factor and a zero exposure for all the other factors for equities. For fixed income, we assume an exposure of one to the investment-grade fixed income market factor and zero to all other factors. These weights corresponds to a passive investor who follows the benchmark exactly.

Using our model in Section 2.2 in an unconditional setting and applying the above assumptions to (2.24), we can derive the implied beliefs about the expected factor returns for pension fund i as:

$$\hat{\mathbb{E}}_i[r_{t+1}] = \gamma_i \text{Var}[r_{t+1}](\beta_i - q_i) - \gamma_i \text{Cov}[r^b_{t+1}\iota_N, r_{t+1}]\psi_i \iota_N F_i^{-1} \qquad \text{for} \qquad i = 1, \ldots, N. \tag{2.27}$$

As opposed to Shumway et al. (2011), we do not get rid of γ_i when estimating the implied beliefs as we do have information about the risk aversion coefficient of pension funds. Additionally, compared to (2.25), we correct implied beliefs for the liability hedge demand of pension funds.

As we are interested in the unconditional expectation of returns, we take the average funding ratio over the sample period as the estimate for F_i. We apply the same method for the liability duration and divide it by the typical duration of the fixed income market index of seven years to compute ψ_i. We represent γ_i with $\gamma_i \approx 6 \times \frac{1}{RFR_i}$ in which RFR_i indicates the average required funding ratio for pension fund i. As the average required funding ratio equals 1.15, $\gamma_i = 6 \times \frac{1}{1.15} = 5$ means that there is a risk aversion parameter of five for the average pension fund. Because we are particularly interested in the cross-sectional heterogeneity in implied beliefs across pension funds, the precise magnitude of the average risk aversion coefficient is of less importance.

Table 2.9 shows the results for the annualized implied beliefs (2.27) on the expected factor returns and conditional on all pension funds having the same informedness. For equities, a median pension fund has positive implied beliefs about the European market factor (1.10 percentage points), while they are slightly negative for the global market factor (−0.12 percentage points). This is consistent with a home/currency bias to European countries. For value and low beta, pension funds have positive implied beliefs, while they are negative for momentum and carry. The median implied belief for the value factor equals 0.41 percentage points and equals −0.40 percentage points for momentum, −0.21 for carry, and 0.39 for low beta. This belief means that pension funds on average expect a higher return on value and on low beta of 0.80 percentage points compared to momentum. There is substantial heterogeneity in the implied beliefs about the expected factor returns. For instance, the pension funds with the most pessimistic views on value expect a negative return of 0.34 percentage points on top of the benchmark return, while pension funds with the most optimistic views expect a positive return of 1.30 percentage points.

For fixed income, the median implied beliefs on the investment-grade market factor equals −0.03 percentage points. The heterogeneity in the implied beliefs for the market factor is limited and indicates that when correcting for the hedging demand, pension funds disagree far less about the expected returns on the market factor. For the credit factor, the implied beliefs equal on average −0.19 and have substantial heterogeneity across pension funds. They range from −1.18 to 0.49 percentage points. For the value factor, the implied beliefs equal −0.46, 0.28 for momentum, −0.27 for carry, and 0.45 for low beta. The greatest heterogeneity in the implied beliefs on the expected long-short factor returns exists for low beta in which pension funds with the most pessimistic views on low beta expect a return of zero percentage points, while pension funds with the most optimistic views expect a positive return of 0.81 percentage points, both are on top of the benchmark return.

Other choices for the benchmark exposures q_i may also come to mind, such as the average factor exposures across pension funds. However, the different choices of the benchmark factor exposures result in a shifted distribution to either the right or left from the one in Table 2.9 but does not affect the cross-sectional heterogeneity across pension funds.

2.6.3 The effect via the choice of asset management firms

We next address the question of whether the differences in implied beliefs are intentional choices by the pension funds. We hypothesize that if beliefs are intentional, then they will

Table 2.9. **Implied beliefs on expected factor returns**: Panel A gives the statistics of the implied beliefs on the expected factor returns for equities, and Panel B shows the results for fixed income. Column 1 shows the historical mean of the factor returns over our sample period, and columns 2-6 show the implied beliefs on top of the benchmark return. The results are derived from Equation (2.27). Panel A shows the results for equities and Panel B for fixed income. We report the 10th, 25th, 50th, 75th, and 90th percentiles. All values are percentage points and annualized.

Panel A: Equity	mean	**10th**	**25th**	**50th**	**75th**	**90th**
Benchmark return	4.99					
Global market index	4.99	-1.53	-0.79	-0.12	0.12	0.71
European market index	4.07	-0.18	0.00	1.10	1.86	2.70
Value	4.00	-0.34	0.00	0.41	0.85	1.30
Momentum	5.20	-1.01	-0.70	-0.40	0.00	0.06
Carry	6.49	-0.55	-0.40	-0.21	0.00	0.00
Low beta	11.03	-0.15	0.00	0.39	0.75	1.11
Panel B: Fixed income						
	mean	**10th**	**25th**	**50th**	**75th**	**90th**
Benchmark return	2.55					
Global market index	2.55	-0.33	-0.19	-0.03	0.02	0.17
High yield	6.38	-1.18	-0.78	-0.19	0.08	0.49
Value	1.17	-0.71	-0.59	-0.46	-0.16	0.00
Momentum	1.24	0.00	0.11	0.28	0.39	0.47
Carry	1.84	-0.41	-0.34	-0.27	-0.14	0.00
Low beta	0.86	0.00	0.11	0.45	0.66	0.81

show up in the mandates that pension funds give to external asset management firms.

Pension funds do not necessarily manage assets themselves. In fact, most Dutch pension funds delegate the implementation of their investment strategy to for-profit asset management firms through asset management mandates (e.g. Binsbergen et al., 2008; Blake et al., 2013). Although the information on these mandates is scarce, pension funds do report each quarter the name of the asset management firm that executes at least 30 percent of the total AUM on behalf of the pension fund.[19] These firm names are available for the period from 2009 through

[19]For confidentiality reasons, we cannot disclose the names of the asset management firms.

2017 and facilitate the analyzation of the effect that the choice of the asset management firm has on factor exposures. Furthermore, to extend the supervision data, we manually check the asset management firm as reported in pension funds' annual reports. Some pension funds report multiple asset management firms (roughly 15 percent of the sample). Because we do not observe in either the supervision data or the annual reports the fraction of assets managed by each of those asset management firms, we are not able to clearly identify the changes due to these firms. Thus, apart from the pension funds that have multiple asset management firms, we can now identify whether pension funds switch from one asset management firm to another and in which quarter.

We have two important reasons to look at changes in asset management firms as opposed to those contracted by the pension fund at a specific point in time. First of all, looking at these changes rules out the possibility that we will find effects simply because the asset management firm correlates with unobservable time-invariant pension fund characteristics. Second, pension funds are likely to hire a new asset management firm if they want to implement a change in their beliefs. In the process of contracting a new asset management firm, pension funds typically do a "search" that is supported by specialised consultants (e.g. Del Guercio and Tkac, 2002; Goyal and Wahal, 2008). Once an asset management firm is selected the mandate is agreed upon according to the preferences of the pension fund.

We focus on asset management firms that were newly hired by at least two pension funds during 2009Q2-2017Q4. A new hire means that we observe a different asset management firm from one quarter to the other. These observations result in a total of 10 asset management firms that gained new business from 59 Dutch pension funds of the 350 pension funds that are in our sample over the period from 2009Q2-2017Q4, which is equivalent to 17 percent of the pension funds. We subsequently run the following regression:[20]

$$r_{i,t}^{e} \quad = \quad \delta_0' f_t + \delta_1' (f_t \times \mathrm{AM}_{i,t-1}') \iota_{10} + \epsilon_{i,t}, \tag{2.28}$$

in which $\mathrm{AM}_{i,t-1}$ is a vector of length 10 and equals 1 for each quarter that the corresponding asset management firm is hired by pension fund i after 2009Q1 and zero otherwise; ι_{10} is a vector of ones with length 10.

Table 2.10 shows the results for this regression and indicates that changing asset management firms has an effect on factor exposures in a substantial amount of cases. For equities, pension

[20]For confidentiality reasons, we cannot disclose the names of the asset management firms.

funds that contract asset management firms 3, 4, 5, and 6 get a significantly higher exposure to the global market index. Therefore, it is likely that these asset management firms are deliberately hired to implement a more global allocation to equities. Other pension funds hire asset management firm 9 to lower their global equity allocation and to increase their allocation of European equities. Pension funds switching to asset management firm 1 result in higher low beta exposures. Pension funds that hire asset management firm 8 obtain negative carry exposures, while the ones that hire asset management firms 2, 6, and 8 obtain negative low beta exposures. The economic magnitudes of these changes are substantial. For instance, pension funds that hire asset management firm 1 have an exposure of 0.17 to low beta compared to an average exposure across all pension funds of 0.06. For fixed income, we find that hiring asset management firms 5, 6, and 7 result in lower exposures to the market index. For high yield, asset management firms 5 and 6 result in a substantially higher credit exposure: 0.26 and 0.37 compared to the average of -0.04. Pension funds that hire asset management firms 3, 7, or 8 have higher value exposures. Asset management firms 3, 6, and 8 result in lower carry exposures.

During the sample period, 59 pension funds switch to one of the ten asset management firms, so we do not have a large power for statistical significance. Despite this, we still find statistical significant, and economically sizeable, effects of asset management firms on some of the factor exposures. We therefore argue that these findings support the idea that factor exposures are at least to a reasonable degree driven by choices about beliefs made by pension funds. Pension funds may change asset management firms for multiple reasons, such as low (excess) returns delivered by the old asset management firm, a change in strategic asset allocation, or a change in beliefs. In most cases pension funds that switch to a new asset management firm will select one that can execute the pension funds' investment policy. And at least a fraction of pension funds will change asset management firms because they have a change in beliefs. This is indeed supported by our analysis. This is furthermore consistent with the findings in Del Guercio and Tkac (2002) who show that quantitative performance variables have a much lower explanatory power in explaining flows for pension fund managers as opposed to mutual fund managers. Importantly, they argue that pension funds regularly change asset management firms because they fail to stay within the guidelines of the investment mandate, regardless of their performance.

Table 2.10. **Effect of asset management firm changes on factor exposures**: This table shows the coefficient estimates of Equation (2.28): We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the changes in asset management firms (AM1-AM10) during the period from 2009Q2-2017Q4. Panel A shows the results for equities and Panel B for fixed income. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity

	average	AM1	AM2	AM3	AM4	AM5
$\beta^{M,W}$	0.711***	-0.055	-0.168	0.0890**	0.122**	0.101**
	[0.0063]	[0.0492]	[0.1094]	[0.0352]	[0.0546]	[0.0478]
$\beta^{M,EU}$	0.242***	-0.0075	0.330***	-0.0367	-0.169***	-0.126***
	[0.0057]	[0.0377]	[0.1176]	[0.0321]	[0.0458]	[0.0436]
β^{VAL}	0.0311**	-0.0474	-0.260*	-0.0095	-0.218**	0.0871
	[0.0123]	[0.0728]	[0.1547]	[0.0515]	[0.0952]	[0.0991]
β^{MOM}	-0.0552***	-0.0112	0.139	0.0168	-0.222***	0.0047
	[0.0076]	[0.0506]	[0.1320]	[0.0419]	[0.0708]	[0.0690]
β^{CARRY}	0.0271***	-0.0298	0.218	-0.0388	0.0092	-0.144
	[0.0090]	[0.0689]	[0.1615]	[0.0352]	[0.0803]	[0.1003]
β^{BAB}	0.0551***	0.110**	-0.432***	-0.0336	0.0029	0.0687
	[0.0144]	[0.0550]	[0.1655]	[0.0330]	[0.0530]	[0.0965]
		AM6	AM7	AM8	AM9	AM10
$\beta^{M,W}$		0.132***	-0.0465	0.0585	-0.201***	-0.0727
		[0.0427]	[0.0862]	[0.0415]	[0.0448]	[0.0772]
$\beta^{M,EU}$		-0.141***	-0.0734	-0.0098	0.196***	0.0901
		[0.0351]	[0.0617]	[0.0339]	[0.0401]	[0.0688]
β^{VAL}		-0.0247	-0.175	-0.0069	0.00053	-0.1120
		[0.0659]	[0.1138]	[0.0623]	[0.0953]	[0.0995]
β^{MOM}		-0.0801*	-0.101	-0.00486	-0.0185	-0.001
		[0.0418]	[0.0953]	[0.0420]	[0.0626]	[0.0823]
β^{CARRY}		-0.0263	0.0037	-0.0948**	0.0208	0.126
		[0.0544]	[0.1218]	[0.0460]	[0.0698]	[0.1010]
β^{BAB}		-0.0917**	0.137	-0.109**	0.0607	-0.0452
		[0.0383]	[0.1159]	[0.0510]	[0.0711]	[0.1030]
obs.	9,319	adj. R-sq.	0.867			

Panel B: Fixed income

	average	AM1	AM2	AM3	AM4	AM5
$\beta^{M,EU}$	2.183***	-0.21	-0.787	0.702	0.778	-0.795***
	[0.0550]	[0.3366]	[2.2588]	[0.5028]	[0.7524]	[0.1811]
$\beta^{HY,EU}$	-0.0444***	-0.0351	0.506	-0.124	-0.111	0.306***
	[0.0064]	[0.0813]	[0.7004]	[0.1872]	[0.2772]	[0.0778]
β^{VAL}	-0.175***	0.0537	-0.764	0.273**	0.39	0.104
	[0.0197]	[0.1203]	[1.1188]	[0.1146]	[0.3567]	[0.0893]
β^{MOM}	0.0285**	-0.0906	-0.081	0.250*	-0.0806	0.118
	[0.0120]	[0.0722]	[0.3436]	[0.1394]	[0.1747]	[0.1375]
β^{CARRY}	-0.486***	0.125	0.828	-0.948***	-0.236	-0.126
	[0.0374]	[0.1967]	[1.2438]	[0.2721]	[0.4979]	[0.1491]
β^{BAB}	-0.0585**	0.303	0.761	-0.378*	0.644	0.117
	[0.0278]	[0.2233]	[0.8373]	[0.2253]	[0.4971]	[0.1055]
		AM6	AM7	AM8	AM9	AM10
$\beta^{M,EU}$		-0.816**	-1.055***	0.983	1.102	1.084
		[0.3786]	[0.3360]	[0.7955]	[0.7147]	[0.9558]
$\beta^{HY,EU}$		0.416***	0.12	-0.236	-0.197	-0.144
		[0.1514]	[0.0967]	[0.2169]	[0.2181]	[0.2972]
β^{VAL}		0.125	0.200***	0.486**	0.203	0.00876
		[0.0970]	[0.0727]	[0.2178]	[0.2409]	[0.3613]
β^{MOM}		0.0168	-0.0704	0.0525	0.195	0.112
		[0.0838]	[0.0795]	[0.1485]	[0.1746]	[0.2104]
β^{CARRY}		-0.356*	0.229	-0.870*	-0.695	-0.263
		[0.1984]	[0.1834]	[0.4476]	[0.4285]	[0.5508]
β^{BAB}		-0.32	-0.182	-0.453	-0.136	-0.268
		[0.1958]	[0.1712]	[0.3198]	[0.3482]	[0.4591]
obs.	9,435	adj. R-sq.	0.534			

2.7 Effect of the liability discount rate on factor exposures

Pension funds operate in a highly regulated environment; therefore, we find that regulations affect pension fund investment strategies. Halfway through our sample period, pension funds in the Netherlands experienced an important change with the introduction of risk-based regulation in 2007. The main elements of this framework include the marked-to-market valuation of assets and liabilities and a risk-based minimum required funding ratio. For pension funds, one of the key channels through which regulations affect investment strategies is the liability discount rate (Andonov et al., 2017). Before 2007, pension funds in the Netherlands used a fixed rate of 4 percent to discount liabilities. Under such a discount rule, liabilities artificially contain no interest rate risk. The fixed discount rate was replaced by the full term structure of market interest rates in 2007. Consequently, the present value of liabilities fluctuates significantly with changes in the market interest rates. Furthermore, before 2007 there were no risk-based minimum funding requirements. This lack changed in 2007 and since then the risk-based funding requirement has been implemented. This requirement is derived from a well-known value-at-risk (VaR) concept, whereby risk is measured as the mismatch between the assets and liabilities. Pension funds' investment strategies affect the funding requirement. Pension funds that better match assets and liabilities through investing more in long-term bonds, have a lower required funding ratio, and vice versa.

To show the effect of these regulatory changes, we split the sample period in two and identify the factor exposures prior to and after 2007. Table 2.11 shows the results. We observe a large change in the exposure to the Euro fixed income market index. Prior to 2007, pension funds had an average exposure to the market of 1.02. After 2007 this average exposure increased to 1.23 that reflected that they allocated more to long-term bonds. This finding is consistent with our theoretical framework, because liability hedge demand was nonexistent from a regulatory perspective prior to 2007 but became apparent after 2007. We also observe a decrease in the exposure to the value and carry factors for fixed income. Dutch and German government bonds resemble the risk-free term structure of interest rates better as opposed to Italian and Spanish bonds. Yet, at the same time the former have lower value and carry ranks.[21] These two forces may contribute to a negative exposure to the value and carry factors. For equities, we observe a small shift from global to European stocks.

[21] We obtain these ranks from the construction of the European fixed income factors.

This way pension funds may reduce the exchange rate risk and lower the risk-based funding requirement. Another striking consequence of the change in regulation is the increase to the low beta factor for both equities and fixed income. Because of risk-based regulations, pension funds may aim to decrease the downside risk of their portfolios by investing more in low beta assets. Changes in long-short factor exposures may also result from developments and insights in the literature on factors. We however leave those channels for future research.

2.8 Conclusion

In this study, we provide detailed insight into the investment strategies of defined-benefit pension funds that represent a large fraction of the European market for pension funds' assets. We measure investment strategies through factor exposures within equity and fixed income portfolios. Factor exposures are key to understanding the heterogeneity in the performance and investment strategies of liability-driven investors. We analyse two groups of drivers that influence factor exposures: pension funds' characteristics and institutional factors. These drivers only partially explain investment strategies across pension funds. We attribute the remaining heterogeneity to differences in implied beliefs about factor returns. These differences partially appear through the pension funds' choice of asset management firms to execute their investment policy.

Our results have important policy implications. We suggest that liability-driven investors can use the approach in this study for strategic investment decision-making. Our approach makes a distinction between a liability hedge demand and a speculative demand, that we measure through factor exposures. While the liabilities of a defined benefit pension fund can be measured objectively, a crucial part in the investment strategy is to form beliefs that drive the speculative demand. These are subjective in nature and require careful consideration and decision-making by a pension fund's board of trustees. Further, liability-driven investors should explain this strategy in a clear and transparent way to their stakeholders. This is particularly important because beneficiaries are typically not free to choose their own pension fund as it comes with the job. The exit costs to leave a pension fund if a beneficiary is dissatisfied with the investment strategy are prohibitively high. Employees would need to change jobs to change pension funds and retirees cannot change pension funds whatsoever. Therefore an import fiduciary duty rests on liability-driven investors to invest in the best interest of their beneficiaries.

Table 2.11. **Factor exposures before and after a change in regulations**: This table displays the cross-sectional means and standard deviations of the posterior betas from Equation (2.17) estimated for the period prior to 2007 and the period thereafter. The last column shows the difference between the average posterior betas in the two subsamples and the significance of the difference is based on a t-test; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Panel A shows the results for equities and Panel B for fixed income. M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class.

Panel A: Equity

	full		*prior 2007*		*after 2007*		
	mean	std.dev.	mean	std.dev.	mean	std.dev.	diff. *after - prior*
$\hat{\beta}_i^{M,W}$	0.668	0.179	0.676	0.208	0.645	0.207	-0.031
$\hat{\beta}_i^{M,EU}$	0.273	0.153	0.228	0.165	0.296	0.170	0.068^{***}
$\hat{\beta}_i^{VAL}$	-0.048	0.066	-0.064	0.071	-0.036	0.093	0.029^{***}
$\hat{\beta}_i^{MOM}$	-0.044	0.041	-0.057	0.060	-0.041	0.056	0.016^{***}
$\hat{\beta}_i^{CARRY}$	-0.057	0.126	-0.193	0.400	0.010	0.073	0.203^{***}
$\hat{\beta}_i^{BAB}$	0.075	0.082	0.031	0.071	0.132	0.113	0.101^{***}

Panel B: Fixed income

	full		*prior 2007*		*after 2007*		
	mean	std.dev.	mean	std.dev.	mean	std.dev.	diff. *after - prior*
$\hat{\beta}_i^{M,EU}$	1.107	0.306	1.021	0.115	1.232	0.377	0.211^{***}
$\hat{\beta}_i^{HY,EU}$	0.023	0.061	0.017	0.008	0.023	0.096	0.006
$\hat{\beta}_i^{VAL}$	-0.158	0.147	-0.013	0.008	-0.242	0.181	-0.229^{***}
$\hat{\beta}_i^{MOM}$	0.070	0.007	-0.029	0.004	0.070	0.004	0.099^{***}
$\hat{\beta}_i^{CARRY}$	-0.067	0.087	0.033	0.024	-0.060	0.128	-0.092^{***}
$\hat{\beta}_i^{BAB}$	0.205	0.176	0.033	0.034	0.299	0.213	0.266^{***}

2.9 Appendix

A Model derivation

The mean-variance optimization problem of pension fund i equals:

$$\max_{w_{i,t}} = \max_{w_{i,t}} \mathbb{E}_t \left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}} \right] - \frac{\gamma_i}{2} \text{Var}_{i,t} \left[\frac{A_{i,t+1} - L_{i,t+1}}{A_{i,t}} \right], \tag{A1}$$

subject to

$$w'_{i,t} \iota_M \leq c, \tag{A2}$$

$$w_{i,j,t} \geq 0 \ \ \forall j, \tag{A3}$$

where the assets equal $A_{i,t+1} = \Big(1 + w'_{i,t} r_{t+1}\Big) A_{i,t}$, the liabilities equal $L_{i,t+1} = \Big(1 + \psi_{i,t} r^b_{t+1}\Big) L_{i,t}$, and the funding ratio equals $F_{i,t} = A_{i,t}/L_{i,t}$.

The Lagrange of this optimization problem equals:

$$\begin{aligned} \mathcal{L}(w_{i,t}, \lambda_{i,t}) &= 1 + w'_{i,t} \mathbb{E}_{i,t}[r_{t+1}] - \Big(1 + \psi_{i,t} \mathbb{E}_{i,t}[r^b_{t+1}]\Big) F^{-1}_{i,t} \\ &- \frac{\gamma_i}{2} \Big(w'_{i,t} \text{Var}_t[r_{t+1}] w_{i,t} + \psi^2_{i,t} \text{Var}_t[r^b_{t+1}] F^{-2}_{i,t} - 2 w'_{i,t} \text{Cov}_t[r^b_{t+1} \iota_M, r_{t+1}] \psi_{i,t} \iota_M F^{-1}_{i,t} \Big) \\ &+ \lambda_{i,t} (w'_{i,t} \iota_M - c) + \delta'_{i,t} w_{i,t}. \end{aligned} \tag{A4}$$

Taking the derivative with respect to $w_{i,t}$ and $\lambda_{i,t}$ gives:

$$\begin{aligned} \frac{\partial \mathcal{L}(w_{i,t}, \lambda_{i,t})}{\partial w_{i,t}} &= \mathbb{E}_{i,t}[r_{t+1}] - \gamma_i \text{Var}_{i,t}[r_{t+1}] w_{i,t} + \gamma_i \text{Cov}_t[r^b_{t+1} \iota_M, r_{t+1}] \psi_{i,t} \iota_M F^{-1}_{i,t} \\ &+ \lambda_{i,t} \iota_M + \delta_{i,t} = 0, \end{aligned} \tag{A5}$$

$$\frac{\partial \mathcal{L}(w_{i,t}, \lambda_{i,t})}{\partial \lambda_{i,t}} = w'_{i,t} \iota_M - c = 0. \tag{A6}$$

This results in the optimal weights (2.7):

$$w^*_{i,t} = \underbrace{\frac{\mathbb{E}_{i,t}[r_{t+1}] + \lambda_{i,t} \iota_M + \delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}}_{\text{speculative portfolio}} + \underbrace{\frac{\text{Cov}_t[r^b_{t+1} \iota_M, r_{t+1}] \psi_{i,t} \iota_M}{\text{Var}_t[r_{t+1}]} F^{-1}_{i,t}}_{\text{hedging portfolio}}$$

with $\lambda_{i,t}$:

$$\lambda_{i,t} = \frac{c - \big(\frac{\mathbb{E}_{i,t}[r_{t+1}]+\delta_{i,t}}{\gamma_i \text{Var}_t[r_{t+1}]}\big)' \iota_M - \big(\frac{\text{Cov}_t[r^b_{t+1}\iota_M, r_{t+1}]\psi_{i,t}\iota_M}{\text{Var}_t[r_{t+1}]} F^{-1}_{i,t}\big)' \iota_M}{\big(\frac{\iota_M}{\gamma_i \text{Var}_t[r_{t+1}]}\big)' \iota_M}.$$

B Fixed income factors

Fixed income returns

The universe of European government bond securities that we analyze consists of Austria, Belgium, Denmark, Finland, France Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and the UK. We use constant maturity, zero-coupon bond yields from Bloomberg for all countries on a monthly basis from 1994 to 2017. We complement the missing data points prior to 1998 with zero coupon bond yields from Jonathan Wright's webpage for Norway, Sweden, Switzerland, and the UK. We use the Libor counterpart in each country as a proxy for the risk-free rate. The corresponding Bloomberg ticker numbers are listed in Table 2.13 in the Internet Appendix E. All included countries had investment-grade credit ratings over the entire sample period by Fitch, Moody's, and Standard & Poor's.

We start by deriving the bond returns. Following Koijen et al. (2018), we calculate the price of synthetic $\tau = 1$-month futures on a $T = 10$-year zero-coupon bond each month from the no-arbitrage relation:

$$P^{\tau,syn}_{i,t} = \frac{1}{1 + r^f_{i,t}} \frac{1}{(1 + y_{i,t})^T}, \tag{A7}$$

in which $y_{i,t}$ is the $T = 10$-year zero-coupon bond for country $i = 1, \ldots, J$, and r^f_{it} is the corresponding risk-free rate. At expiration, the price of the $\tau = 1$-month futures contract equals:

$$P^{\tau-1,syn}_{i,t+1} = \frac{1}{(1 + y_{i,t+\tau})^{T-\tau}}, \tag{A8}$$

where we find $y_{i,t+\tau}$ by linear interpolation. The return on a fully-collateralized, currency-hedged, one-month futures contract equals:

$$r^{syn}_{i,t} = \Big(\frac{(1 + r^f_{i,t})(1 + y_{i,t})^T}{(1 + y_{i,t+\tau})^{T-\tau}} - 1\Big) \times \Big(1 + \frac{e_{i,t+1} - e_{i,t}}{e_{i,t}}\Big) \tag{A9}$$

in which $e_{i,t}$ is the time t exchange rate in euros per unit of foreign currency i. Furthermore, the correction term for the exchange rate equals one for all countries in the euro area (Austria, Belgium, Finland, France, Germany, Italy, Netherlands, and Spain).

Factors

We construct value, momentum, carry, and low beta factors for the fixed income portfolios which are zero-cost long-short portfolios that use all the government bonds specified before. For any security $i = 1, \ldots, J$ at time t with signal S_{it} (value, momentum, carry, or low beta), we weight securities in proportion to their cross-sectional rank based on the signal minus the cross-sectional average rank of that signal:

$$w_{it}^{S} = c_t(\text{rank}(S_{it}) - \sum_{i=1}^{J} \text{rank}(S_{it})/J), \quad \text{where } S \in (\text{value, momentum, carry, low beta}). \tag{A10}$$

The weights across all securities sum to zero and represent a dollar-neutral long-short portfolio. The scalar c_t ensures the overall portfolio is scaled one-dollar long and one-dollar short.

The signals are as follows. As in Asness et al. (2013), we define value as the 5-year change in the 10-year yield (5-year $\triangle y$). For momentum, we use the standard measure, namely, the return over the past 12 months but skip the most recent month. The signal for carry is defined as in Koijen et al. (2018):

$$C_{it} = \frac{(1 + y_{i,t}^{T})^{T}}{(1 + r_{i,t}^{f})(1 + y_{i,t}^{T-\tau})^{T-\tau}}. \tag{A11}$$

To construct the low beta factor, we estimate the betas as in Frazzini and Pedersen (2014). The estimated beta for country i is:

$$\hat{\beta}_i = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{A12}$$

in which $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the bond and the market, and $\hat{\rho}$ is their correlation. We estimate the volatilities and correlations with 1- and 5-year windows respectively. The market is defined as the average return of all bonds in our sample. To reduce the effect of outliers, we follow Frazzini and Pedersen (2014) and shrink the time series estimate of beta to one: $\tilde{\beta}_i = 0.6 \times \hat{\beta}_i + 0.4 \times 1$.

The factor returns for value, momentum, and carry are now constructed as:

$$r_t^S = \sum_{i=1}^{J} w_{it-1}^S r_{it}^{syn}, \quad \text{where } S \in (\text{value, momentum, carry}). \tag{A13}$$

The factor return for low beta is constructed as:

$$r_t^{\text{S}} = \frac{1}{\beta_{t-1}^L}(r_t^L - r_t^f) - \frac{1}{\beta_{t-1}^H}(r_t^H - r_t^f), \quad \text{where } S \in (\text{low beta}), \tag{A14}$$

and $\beta_{t-1}^L = w_{Lt-1}'\hat{\beta}_{t-1}$, $\beta_{t-1}^H = w_{Ht-1}'\hat{\beta}_{t-1}$, $r_t^L = w_{Lt-1}'r_t^{syn}$, and $r_t^H = w_{Ht-1}'r_t^{syn}$. The weights w_{Lt-1} (w_{Ht-1}) equal the absolute weights of the long portfolio (short portfolio).

C Total AUM by pension funds in the euro area

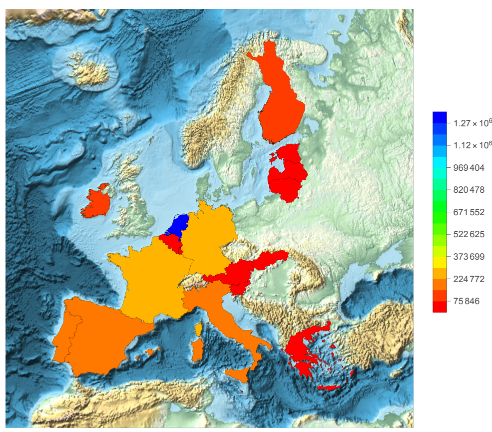


Figure 2.2. Total assets in million EUR in funded and private pension plans (OECD, 2019).

D Random-Coefficients Model

We make the following assumptions when estimating the regression in Equation (2.15):

1. $\alpha_i = \alpha + u_i$ and $u_i \sim N(0, \sigma_\alpha^2)$
2. $\beta_i = \beta + v_i$ and $v_i \sim N(0, G)$, where

$$G = \mathbb{E}(v_k v_j') = \begin{cases} \sigma_{\beta^k}^2 & \text{for} \quad j = k \\ \sigma_{\beta^k \beta^j} & \text{for} \quad j \neq k \end{cases} \tag{A15}$$

3. $\{\epsilon_{it}\}_{i,t=1}^{N,T} \perp\!\!\!\perp \{u_i\}_{i=1}^{N} \perp\!\!\!\perp \{v_i\}_{i=1}^{N}$.

In almost all cases, we assume independence across the random effects of the factor exposures, that is, $\sigma_{\beta^k\beta^j} = 0$, except for the two market factors for equities. Because the Euro Stoxx 50 index is a subset of the MSCI World Index, a higher exposure to the Euro Stoxx 50 Index directly indicates a lower exposure to the MSCI World Index, and vice versa.[22]

The random-coefficients model is estimated using maximum likelihood. We show the derivation here for equities. The procedure works in the same way for fixed income, except that we allow for no correlations between the random coefficients.

To derive the likelihood, we start with writing Equation (2.15) in vector notation:[23]

$$r_i^e = \alpha\iota_T + \beta' f + v_i' f + u_i + \epsilon_i, \tag{A16}$$

in which r_i^e is the $T \times 1$ vector of excess returns for fund i, f is the $T \times k$ matrix of factor returns for the fixed effects $\beta = \begin{bmatrix} \beta^1 \\ .. \\ \beta^K \end{bmatrix}$ and the random effect $v_i = \begin{bmatrix} v_i^1 \\ .. \\ v_i^K \end{bmatrix}$, and u_i is the random intercept.

The $T \times 1$ vector of errors ϵ_i is assumed to be multivariate normal with a mean zero and variance matrix $\sigma_\epsilon^2 \mathbf{I}_T$. We have:

$$\text{Var}\begin{bmatrix} \alpha_i \\ v_i^1 \\ .. \\ v_i^K \\ \epsilon_i \end{bmatrix} = \begin{bmatrix} \sigma_\alpha^2 \iota_T\ \iota_T' & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\beta^1}^2 \iota_T \iota_T' & \sigma_{\beta^1\beta^2}\iota_T\iota_T' & 0 & 0 \\ 0 & \sigma_{\beta^2\beta^1}\iota_T\iota_T' & \ddots & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\beta^K}^2 \iota_T\iota_T' & 0 \\ 0 & 0 & 0 & 0 & \sigma_\epsilon^2 \mathbf{I}_T \end{bmatrix}. \tag{A17}$$

The error term: $v_i^1 f^1 + ... + v_i^K f^K + u_i + \epsilon_i$ has a $T \times T$ variance-covariance matrix

$$V = \text{Var}[r_i^e | f] = \sigma_\alpha^2 \iota_T\ \iota_T' + \sigma_{\beta^1}^2 f^1 f^{1'} + 2\sigma_{\beta^1\beta^2} f^1 f^{2'} + \sigma_{\beta^2}^2 f^2 f^{2'} + ... + \sigma_{\beta^K}^2 f^K f^{K'} + \sigma_\epsilon^2 \mathbf{I}_T. \tag{A18}$$

---

[22]We perform a simulation test to ensure the high correlation between the MSCI World Index and the Euro Stoxx 50 Index does not cause multicollinearity problems. We simulate returns consisting of a mix between the MSCI World Index, the Euro Stoxx 50 Index, and an error term. We then regress the simulated returns on the MSCI World Index and the Euro Stoxx 50 index. We find the exact coefficients with high precision (i.e., low standard errors) that we imposed for the simulated returns.

[23]Here we assume all pension funds have the same T. For pension funds with different T, the T should be replaced by T_i.

The log-likelihood for fund i can now be written as:

$$L_i(\alpha, \beta, \sigma^2_\alpha, \sigma^2_{\beta^1}, ..., \sigma^2_{\beta^K}, \sigma^2_\epsilon | r^e_i) = -\frac{1}{2}\{T\log(2\pi) + \log|V| + (r^e_i - \alpha\iota_T - \beta' f)' V^{-1}(r^e_i - \alpha\iota_T - \beta' f)\}. \quad \text{(A19)}$$

Then, the total log-likelihood equals:

$$\begin{aligned} L(\alpha, \beta, \sigma^2_\alpha, \sigma^2_{\beta^1}, ..., \sigma^2_{\beta^K}, \sigma^2_\epsilon | r^e) &= -\frac{1}{2}\{NT\log(2\pi) + N\log|V| \\ &+ \sum_{i=1}^{N}(r^e_i - \alpha\iota_T - \beta' f)' V^{-1}(r^e_i - \alpha\iota_T - \beta' f)\}. \quad \text{(A20)} \end{aligned}$$

We now turn to a detailed description of the estimation results described in Table 2.16. We begin by analyzing the results for equities. The exposure to the global market factor equals 0.65, and the exposure to the European factor equals 0.30. Both are statistically significant. The positive and significant exposure to the excess European market return displays the existence of a currency bias; that is, Dutch pension funds on average tend to invest more in Europe relative to the global market portfolio. Additionally, sizable cross-sectional variation exists in pension funds' market betas. The exposure to the global market factor varies between 0.28 and 1.02, and the exposure to the European market factor varies between −0.02 and 0.62. Pension funds on average have significantly negative exposures to value (−0.04), momentum (−0.04), and carry (−0.05). Significant cross-sectional variation exists in all three factor exposures. The highest cross-sectional standard deviation equals 0.15 for the carry factor that indicates the range of factor exposures is between −0.35 and 0.24. The exposure to value varies between −0.21 and 0.13, and between −0.14 and 0.05 for momentum. Pension funds on average have a significantly positive exposure to the low beta factor that is equal to 0.09. Again, we find significant and substantial cross-sectional variation in the low beta exposure that ranges from −0.13 to 0.30.

In case of fixed income, pension funds have an average (significant) exposure to the investment-grade market factor that is equal to 1.13. The cross-sectional variation ranges from 0.16 to 2.10. For the fixed income factors we find that pension funds, on average, have a negative exposure to value (−0.21) and carry (−0.08), a positive exposure to momentum (0.07), and a strong positive exposure to low beta (0.27). The exposure to value varies between −0.52 and 0.10, between −0.27 and 0.11 for carry, and between −0.12 and 0.66 for low beta. The cross-sectional heterogeneity is significant at the 1 percent level for the market factors, value, and low beta, and at the 5 percent level for carry. We are unable to statistically detect significant cross-sectional variation in momentum exposures based on the random-coefficients model.

For equities, we also find cross-sectional variation in alphas, or the part of the return that is not explained by the factors. The standard deviation equals 0.0028, and the alphas vary between -0.0064 and 0.0048 on a quarterly basis. For fixed income we do not observe statistically significant variation in the alphas. This finding indicates that pension funds are unable to outperform each other consistently. However, even if pension funds slightly vary in their alphas, our sample might not have enough observations to say something statistically meaningful about the alphas. This finding is expected, because first moments can be estimated less accurately than second moments (Merton, 1980).

E Additional tables

Table 2.12. **Glossary of symbols**: This table summarizes the main symbols in this study.

Symbol	*Description*
A	Asset value
AM	Vector of asset management firms
AUM	Total asset under management for the corresponding asset class
B	Pension benefits
D	Liability duration
F	Funding ratio
K	Total number of factors
L	Present discounted value of future pension benefits
M	Total number of assets
N	Total number of pension funds
RFR	Required funding ratio
Type	Pension fund type
f_t^a	Vector of factor returns for asset class a
r	Vector of asset returns
r^a	Pension fund return for asset class a
r^b	Return on the risk-free bonds traded in the market
r^e	Pension fund excess return (relative to short-term risk-free rate)
r^f	Short-term risk-free rate
r^h	Regulatory discount rate for time-to-maturity h
r^L	Liability return
w	Vector of portfolio weights
q	Benchmark factor exposures
$se(\beta_i^k)$	Standard error of the time-series OLS factor exposures for factor k
v	Vector of random-effect coefficients
β^a	Vector of factor exposures for asset class a
$\hat{\beta}^k$	Fixed-effect estimator for factor k (prior mean)
$\tilde{\beta}^k$	Posterior factor exposure for factor k
$\hat{\beta}_i^k$	Time-series OLS factor exposures for factor k
$\tilde{\beta}_{adj}^k$	Posterior factor exposures adjusted for pension fund characteristics
γ	Risk aversion coefficient
δ	Kuhn-Tucker multipliers for the short-sale constraints
ι	Vector of ones
λ	Lagrange multiplier for the borrowing constraint
λ^k	Historical average return for factor k
μ	Expected (excess) returns
Σ	Variance-covariance matrix of returns
$\hat{\sigma}_{\beta^k}^2$	Variance estimator of the random effects for factor k (prior variance)
$\tilde{\sigma}_{\beta^k}^2$	Posterior variance for factor k
ψ	Duration of the liabilities over the duration of the risk-free bonds

Table 2.13. **Bloomberg ticker list**: The Bloomberg ticker numbers used to construct the European fixed income factors described in Appendix B. The x in each ticker number should be replaced by the corresponding maturity: x=10 years, x=09 years, and x=03 months; and y by the corresponding unit of time: y=y for years and y=m for months.

Country	Ticker
Austria	F908xy Index
Belgium	F900xy Index
Denmark	F267xy Index
Finland	F919xy Index
France	F915xy Index
Germany	F910xy Index
Italy	F905xy Index
Netherlands	F920xy Index
Norway	F266xy Index
Spain	F902xy Index
Sweden	F259xy Index
Switzerland	F256xy Index
U.K.	F110xy Index

Table 2.14. **Correlation table of factor returns**: This table provides the correlation matrix of the factor returns. MSCI-W is the excess MSCI World Total Return Index, EU-50 is the excess Euro Stoxx 50 Total Return Index, VAL-S is the global value factor for stocks, MOM-S is the global momentum factor for stocks, Carry-S is the global carry factor for stocks, and BAB-S is the global low beta factor for stocks. FI-EU is the excess Bloomberg Barclays Euro Aggregate Total Return Bond Index, HY-EU is the Bloomberg Barclays Euro High Yield Index, VAL-FI is the European value factor for fixed income, MOM-FI is the European momentum factor for fixed income, CARRY-FI is the European carry factor for fixed income, and BAB-FI is the European low beta factor for fixed income. All returns are converted into euro returns.

Correlation matrix

	MSCI-W	EU-50	VAL-S	MOM-S	CARRY-S	BAB-S	FI-EU	HY-EU	VAL-FI	MOM-FI	CARRY-FI	BAB-FI
MSCI-W	1											
EU-50	0.87	1										
VAL-S	−0.22	−0.11	1									
MOM-S	−0.18	−0.24	−0.68	1								
CARRY-S	−0.15	−0.26	0.03	−0.01	1							
BAB-S	−0.32	−0.30	0.25	0.13	0.14	1						
FI-EU	−0.15	−0.13	0.11	−0.07	0.08	0.04	1					
HY-EU	0.64	0.63	0.04	−0.41	0.15	−0.10	0.09	1				
VAL-FI	0.18	0.26	0.17	−0.19	−0.03	0.13	0.06	0.37	1			
MOM-FI	−0.12	−0.11	−0.08	0.20	−0.05	−0.06	0.05	−0.34	−0.51	1		
CARRY-FI	0.16	0.27	0.12	−0.17	−0.03	0.10	0.33	0.30	0.66	−0.34	1	
BAB-FI	−0.29	−0.34	0.21	−0.01	0.00	0.10	0.37	−0.25	−0.29	0.31	−0.29	1

Table 2.15. **OLS factor exposures**: This table displays the cross-sectional mean and standard deviation of the estimated betas from the time-series regression presented in Equation (2.14). The cross-sectional mean and standard deviation of the R-squared from the time-series regressions are also provided. 10%-level and 5%-level sign. indicate the number of pension funds for which the corresponding factor is statistically different from zero at the 5% and 10% significance level, respectively, by using the Newey-West adjusted standard errors. M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class.

	mean	std.dev.	5%-level sign.	10%-level sign.
Equity returns				
$\hat{\beta}_i^{M,W}$	0.656	0.297	531	537
$\hat{\beta}_i^{M,EU}$	0.270	0.311	429	455
$\hat{\beta}_i^{VAL}$	−0.060	0.230	131	182
$\hat{\beta}_i^{MOM}$	−0.056	0.244	143	192
$\hat{\beta}_i^{CARRY}$	−0.106	0.549	139	196
$\hat{\beta}_i^{BAB}$	0.088	0.240	221	269
R^2	0.928	0.092		
Fixed income returns				
	mean	std.dev.	5%-level sign.	10%-level sign.
$\hat{\beta}_i^{M,EU}$	1.139	0.564	553	559
$\hat{\beta}_i^{HY,EU}$	0.019	0.111	206	256
$\hat{\beta}_i^{VAL}$	−0.146	0.402	218	274
$\hat{\beta}_i^{MOM}$	0.024	0.623	93	119
$\hat{\beta}_i^{CARRY}$	−0.037	0.552	101	132
$\hat{\beta}_i^{BAB}$	0.253	0.508	249	310
R^2	0.760	0.185		

Table 2.16. **Prior factor exposures**: This table shows the coefficient estimates and corresponding standard errors for the random-coefficients model in Equation (2.15) that is used as a prior to compute the posterior betas. The estimates $\hat{\alpha}$ and $\hat{\beta}^k$ indicate the fixed effects, and $\hat{\sigma}^2_\alpha$, and $\hat{\sigma}^2_k$ indicate the random effects of the random-coefficients model. M,W indicates the excess global market index for equities, M,EU indicates the excess European market index for the corresponding asset class, HY-EU indicates the excess high yield index for fixed income, VAL, MOM, CARRY, and BAB indicate the value, momentum, carry, and low beta factor for the corresponding asset class. Standard errors are clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. The significance for each random coefficient is determined by performing a LR-test. The LR-test compares the full random-coefficients model with a random-coefficients model that assumes the factor exposure of interest to be fixed.

Equity returns			Fixed income returns		
	Coefficient	std. error		Coefficient	std. error
$\hat{\alpha}$	-0.001^{**}	0.0003	$\hat{\alpha}$	0.001^{***}	0.0002
$\hat{\beta}^{M,W}$	0.649^{***}	0.0096	$\hat{\beta}^{M,EU}$	1.126^{***}	0.0226
$\hat{\beta}^{M,EU}$	0.299^{***}	0.0083	$\hat{\beta}^{HY,EU}$	0.024^{***}	0.0046
$\hat{\beta}^{VAL}$	-0.043^{***}	0.0051	$\hat{\beta}^{VAL}$	-0.208^{***}	0.0093
$\hat{\beta}^{MOM}$	-0.041^{***}	0.0042	$\hat{\beta}^{MOM}$	0.071^{***}	0.0081
$\hat{\beta}^{CARRY}$	-0.054^{***}	0.0102	$\hat{\beta}^{CARRY}$	-0.079^{***}	0.0122
$\hat{\beta}^{BAB}$	0.087^{***}	0.0063	$\hat{\beta}^{BAB}$	0.271^{***}	0.0117
$\hat{\sigma}^2_\alpha$	0.00001^{*}	0.0000	$\hat{\sigma}^2_\alpha$	0.0000005	0.0000
$\hat{\sigma}^2_{M,W}$	0.0338^{***}	0.0049	$\hat{\sigma}^2_{M,EU}$	0.235^{***}	0.0904
$\hat{\sigma}^2_{M,EU}$	0.0256^{***}	0.0043	$\hat{\sigma}^2_{HY,EU}$	0.007^{***}	0.0012
$\hat{\sigma}^2_{VAL}$	0.0073^{***}	0.0026	$\hat{\sigma}^2_{VAL}$	0.024^{***}	0.0052
$\hat{\sigma}^2_{MOM}$	0.0023^{***}	0.0011	$\hat{\sigma}^2_{MOM}$	0.001	0.0028
$\hat{\sigma}^2_{CARRY}$	0.0218^{***}	0.0057	$\hat{\sigma}^2_{CARRY}$	0.009^{**}	0.0068
$\hat{\sigma}^2_{BAB}$	0.0115^{***}	0.0029	$\hat{\sigma}^2_{BAB}$	0.038^{***}	0.0204
$\hat{\sigma}_{M,WM,EU}$	-0.0259^{***}	0.0042			
Wald chi2(6)	47,345		Wald chi2(6)	4,192	
obs.	25,434		obs.	25,839	

Table 2.17. **Effect of model parameters on the equity allocation**: This table shows the coefficient estimates of a regression of the equity allocation on pension fund characteristics from 2009Q1-2017Q4. The equity allocation is computed as the total AUM in equities divided by the total AUM in fixed income and equities. The pension fund characteristics are the funding ratio, the risk aversion coefficient that we represent with the inverse of the required funding ratio, and the liability duration. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	Equity allocation		
Funding ratio	0.0756***	0.0748***	0.0772***
	[0.0106]	[0.0106]	[0.0106]
Risk aversion	-1.865***	-1.866***	-1.853***
	[0.0401]	[0.0391]	[0.0397]
Liability duration	-0.0015***	-0.0015***	-0.0015***
	[0.0003]	[0.0003]	[0.0003]
Size			0.0038*
			[0.0021]
Corporate			-0.0081**
			[0.0035]
Professional			-0.0200***
			[0.0063]
Constant	0.360***	0.360***	0.367***
	[0.0013]	[0.0013]	[0.0030]
time FE	No	Yes	Yes
obs.	8,648	8,648	8,648
adj. R-squared	0.246	0.275	0.277

Table 2.18. **Impact of pension fund's characteristics on factor exposures - proxy**: We regress the pension funds' excess returns on the factor returns and the factor returns interacted with the funding ratio, the risk aversion coefficient that we represent with the inverse of the required funding ratio, and the ratio of actives relative to total participants during the period from 2009Q1-2017Q4, where the total equals the active participants and the retirees. Standard errors are in parentheses and clustered at the pension fund level; $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Panel A: Equity returns

	average	funding ratio	risk aversion	% active participants
$\beta^{M,W}$	0.713***	-0.0166	-0.482***	0.0243
	[0.0061]	[0.0513]	[0.1683]	[0.0266]
$\beta^{M,EU}$	0.253***	0.0518	0.208	-0.0027
	[0.0063]	[0.0437]	[0.1644]	[0.0256]
β^{VAL}	0.0263**	-0.0583	0.477	0.0616
	[0.0116]	[0.0929]	[0.3415]	[0.0482]
β^{MOM}	-0.0487***	-0.0064	0.274	0.001
	[0.0080]	[0.0599]	[0.2059]	[0.0330]
β^{CARRY}	0.0165*	0.0794	-0.385	0.0053
	[0.0091]	[0.1146]	[0.2909]	[0.0427]
β^{BAB}	0.0838***	0.0275	-0.0616	-0.0744**
	[0.0153]	[0.0569]	[0.2126]	[0.0330]
obs.	8,851	adj. R-sq.	0.860	

Panel B: Fixed income returns

	average	funding ratio	risk-aversion	% active participants
$\beta^{M,EU}$	2.204***	-0.977***	9.394***	1.561***
	[0.0505]	[0.2358]	[1.3144]	[0.2362]
$\beta^{HY,EU}$	-0.0371***	0.0714*	-0.776***	-0.130***
	[0.0065]	[0.0424]	[0.1504]	[0.0267]
β^{VAL}	-0.157***	0.0261	-0.682	-0.0426
	[0.0187]	[0.0893]	[0.4933]	[0.0789]
β^{MOM}	0.015	-0.0351	1.081***	0.0749
	[0.0118]	[0.0606]	[0.3158]	[0.0518]
β^{CARRY}	-0.557***	0.360**	-3.770***	-0.733***
	[0.0341]	[0.1709]	[0.9128]	[0.1582]
β^{BAB}	-0.0821***	0.142	-1.964***	-0.406***
	[0.0260]	[0.1220]	[0.7088]	[0.1205]
obs.	8,954	adj. R-sq.	0.558	

Chapter 3

The Liquidity Premium Across Asset Classes[1]

3.1 Introduction

Illiquid assets increasingly have a role in investors' portfolios. The illiquid assets of large US endowment funds comprised 55% of the total portfolios in 2015 (Dimmock et al., 2019). Moreover, the seven largest pension funds in the world have increased their average allocations of illiquid assets from 4% in 1997 to 25% in 2017 (Willis Towers Watson, 2019). One potential reason for investing in illiquid assets is to capture liquidity premiums (OECD, 2014; Watson, 2019). In other words, investing in illiquid assets might compensate the investor for bearing this cost. Yet, there is no consensus in the empirical literature that justifies which asset classes should have first-order liquidity premiums. In this study, we aim to give more guidance to its opposing findings by modeling illiquid assets and heterogeneous investor types in four different asset classes: private equity, real estate, corporate bonds, and stocks.

Studies have either modeled illiquidity as proportional transactions costs, for example, Constantinides (1986); Vayanos (1998), or as the inability to trade illiquid assets for random time periods, for example, Ang et al. (2014). We combine these two dimensions of illiquidity here for two reasons. First, several asset classes show both aspects of illiquidity simultaneously. For instance, traders of corporate bonds face transaction costs, yet sometimes specific bonds

[1]This chapter is based on joint work with Bas Werker. We thank Jules van Binsbergen, Marie Brière, Dirk Broeders, Joost Driessen, Esther Eiling, Frank de Jong, Ralph Koijen, Olivia Mitchell, Theo Nijman, Antoon Pelsser, Patrick Tuijp, seminar participants at Tilburg University, the Wharton School, Maastricht University, Netspar Pension Day, Ortec Finance Canada, Ortec Finance Rotterdam, Achmea Investment Management, Robeco, and conference participants of the Market Microstructure & High Frequency Data Stevanovich Center University of Chicago, SoFiE, and the International Pension Workshop for very useful comments. Kristy gratefully acknowledges financial support from Instituut Gak.

may not trade for several days. Similarly, selling real estate may take several years, and it obviously carries transaction costs as well. Second, combining both sources of illiquidity allows us to capture the heterogeneity across asset classes by adjusting the prominence of both effects.

We solve for liquidity premiums in a partial equilibrium power utility framework. We propose that the cost of illiquidity involves two aspects: suboptimal asset allocation and suboptimal consumption. If the cost of liquidating the illiquid asset is too high and the investor prefers not to trade the illiquid asset, or the illiquid asset cannot be traded at all; then the illiquidity leads to suboptimal portfolio allocations. Yet, deviating from the optimal asset allocation generally only leads to small utility costs (Constantinides, 1986). At the same time, illiquidity may hamper the possibility of smoothing consumption after negative wealth shocks. If the investor is unable to sell the illiquid asset or only at high costs, they may face an even stronger negative consumption shock compared to the case where the illiquid asset can always be traded without costs. Shocks to consumption generally carry a high utility cost and hence illiquidity does generate first-order liquidity premiums.

Our model's flexibility allows us to quantify the magnitude of the liquidity premium in four markets. This flexibility is important as the effects of liquidity highly depend on the characteristics of illiquid assets such as the frequencies of trade and potential income returns on illiquid assets as well as the characteristics of the investor types that operate in those markets. For each asset classes we calculate the premium different investor types are willing to pay for the illiquid asset to become liquid. We find that this willingness-to-pay is larger for short-term investors, investors who face substantial liquidity shocks, and investors who desire to allocate over 60% of their wealth to illiquid assets if that same asset would otherwise be liquid. Thus, in equilibrium, the liquidity premiums depend on the relative prevalence of different investor types. For instance, Amihud and Mendelson (1986), Longstaff (2003), and Chen et al. (2020) find investor heterogeneity in which short-term investors hold liquid assets and long-term investors hold illiquid assets. The heterogeneity in investor types across asset classes enables us to relate to the empirical evidence about liquidity premiums for each market.

We make several contributions. Even though private equity is the most illiquid asset that we analyze, we find an average annual liquidity premium no larger than 5-15 basis points. Private equity investors have to lockup their money for long periods of time; and mainly for that reason, only long-term investors are present in this market: approximately 20% is held by endowments and 60% by pension funds (Harris et al., 2014). For these investors illiquidity is unlikely to substantially harm investors' consumption patterns. Moreover, the non-trading period is typically fixed at 10 years, so by and large investors know when the position will be liquidated. For direct real estate, we find an average annual liquidity premium equal to 15-35 basis points. Direct real estate can often not be traded for a substantial amount of time, the timing of the trading opportunities are uncertain, and the transaction costs are high. Yet, the threat of illiquidity is dampened because of the liquid return component (rents) of real estate investments and the large share of long-term investors in this market. We find the largest liquidity premiums for stocks and corporate bonds; the average annual liquidity premium for corporate bonds equals 30-50 basis points. For corporate bonds, the transaction costs are small, but uncertainty in trading opportunities and its high price of risk amplify liquidity premiums. For stocks we find an average annual liquidity premium equal to 20-45 basis points. Even though stocks trade very often, liquidity premiums do not disappear: short-term investors are the largest group of investors in these markets (84%), and they demand first-order liquidity premiums even at relatively low transaction costs.

A potential shortcoming of our approach is that we are not able to model investors' preferences perfectly. However, we make two assumptions that are more likely to overestimate rather than to underestimate the liquidity premium. First, we assume that the investors cannot borrow against the illiquid assets. This caveat may be a realistic assumption for some asset classes, but not in others. For instance, real estate investors are typically able to borrow a substantial amount using the property as collateral. However, taking this borrowing into account decreases liquidity premiums because the investors can partially undo the illiquidity of the asset. Second, we allow for liquidity shocks as large as 50% of the investors' total wealth. Even though larger wealth shocks are in practice possible, our model shows that investors avoid risky assets all together if faced with such shocks. As a result, large liquidity shocks do not necessarily amplify liquidity premiums.

Our study contributes to the empirical literature on liquidity premiums. The early empirical literature found significant effects of illiquidity on stock prices. For instance, Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) show that a 1% higher transaction cost means a 1.5% to 2% higher expected return for stocks. Yet, some recent studies have challenged the empirical evidence for liquidity premiums in stocks.[2] For instance, Ben-Rephael et al. (2015) show that liquidity premiums have become insignificant

[2]Note that we refer here to the *level* of the liquidity premium. There are also studies on the liquidity *risk* premium, for example, Pastor and Stambaugh (2003).

in recent decades for public US equities, except for very small stocks. Our findings show that a 1% higher transaction cost means a 0.20-0.45% higher expected return for stocks, which is substantially lower than the estimates from the early literature and more in favor with the recent evidence of a small liquidity premium for stocks. First-order liquidity premiums also exist for corporate bonds (e.g. Chen et al., 2007; Bao et al., 2011; Bongaerts et al., 2017). In particular, Bongaerts et al. (2017) find an average (level) liquidity premium equal to 0.54% for corporate bonds that carry 0.52% transaction costs. Yet, Palhares and Richardson (2019) find only limited evidence for liquidity premiums for corporate bonds after using illiquidity-factor portfolios, that is, a strategy that goes long in illiquid bonds and short in the liquid ones. Our model indicates that liquidity premiums are below, yet fairly close to the estimates in Bongaerts et al. (2017). However, in our model the liquidity premium is not only driven by transaction costs but also by the inability to trade corporate bonds for several weeks. This may mean that empirical estimates indirectly incorporate the inability to trade as part of the liquidity premium.

Similarly, for private equity there is no clear consensus regarding the existence of a liquidity premium, although the evidence is more indirect. Franzoni et al. (2012) report no out-performance of private equity relative to public equity, while Harris et al. (2014) finds a substantial out-performance of 3% annually. Our findings point in the direction of second-order liquidity premiums for private equity. Finally, opposing indirect evidence also exists for real estate investments. Qian and Liu (2012) find a somewhat higher expected return for direct compared to indirect real estate, while Ang et al. (2013a) find comparable performance for direct and indirect real estate investments. Our range of model implied liquidity premiums for real estate is consistent with the dearth of empirical evidence for liquidity premiums in real estate markets.

Our study also contributes to the theoretical literature on liquidity premiums. The early theoretical literature did not find evidence for the existence of liquidity premiums. Constantinides (1986) and Vayanos (1998) show that transaction costs only have a second-order effect on prices, that is, a 1% higher transaction cost increases the liquidity premiums by only roughly 10 basis points per year. After their work, a great deal of literature was developed that studies illiquidity or transactions costs by using assumptions more in line with real-world investment problems. This work finds that illiquidity can have first-order effects on prices. For instance, theoretical work from Huang (2003) and Gârleanu (2009) show that illiquidity may arise when investors face borrowing constraints. Jang et al. (2007) add return predictability to the investor's problem in a market with transactions costs and find a slight increase in liquidity premiums. Lynch and Tan (2011) solve a model that comprises labor income, wealth shocks, return predictability, and transaction costs and are able to generate liquidity premiums for stocks in the same order of magnitude as the early empirical literature. The main goal of these studies is to understand the mechanism behind the effect of illiquidity in equilibrium. By contrast, we focus on explaining the observed variation in the magnitude of the liquidity premium for different asset classes using heterogeneity in the illiquidity source and investors' preferences.

The remainder of the study is organized as follows: Section 3.2 shows the theoretical framework of the model and describes the corresponding optimal strategies and the partial equilibrium implications for the liquidity premiums. We link our theoretical findings to the empirical literature on liquidity premiums in Section 3.3. Section 3.4 concludes.

3.2 Optimal consumption and investment with illiquid assets

In this section, we model illiquidity as the inability to trade an asset frequently and by the cost that occurs when trading. This is formalized in Section 3.2.1. In Section 3.2.2 we describe the optimization problem of the investor and the solution of this optimization problem is presented in Section 3.2.3. Section 3.2.4 shows how we derive model implied liquidity premiums and Section 3.2.5 reveals magnitudes of model implied liquidity premiums depending on different parameter values.

3.2.1 Financial market

The financial market consists of three assets: a risk-free asset B, a liquid risky asset S, and an illiquid risky asset denoted by X. The risk-free asset has a constant (annual) rate of return r_f. The liquid risky asset earns a nominal return r_t^S over the period $(t-1, t]$, while we denote the nominal return on the illiquid asset over the same period by r_t^X. All returns are continuously compounded. Further, we assume that the price of the illiquid asset is observed, even though it cannot be traded every period.

The prices of risk of the liquid and illiquid assets are denoted by λ_S and λ_X, respectively. Their volatilities are similarly denoted by σ_S and σ_X; their correlation by ρ_{SX}. The returns r_t^S and r_t^X are jointly normally distributed:

$$\begin{bmatrix} r_t^S \\ r_t^X \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} r_f + \lambda_S\sigma_S - \frac{1}{2}\sigma_S^2 \\ r_f + \lambda_X\sigma_X - \frac{1}{2}\sigma_X^2 \end{bmatrix}, \begin{bmatrix} \sigma_S^2 & \rho_{SX}\sigma_S\sigma_X \\ \rho_{SX}\sigma_S\sigma_X & \sigma_X^2 \end{bmatrix} \right). \tag{3.1}$$

The differences between the liquid and the illiquid risky asset are the trading opportunities and transaction costs. While the investor can always trade the liquid risky asset S at no cost, the illiquid asset X can only be traded at random points in time and at a cost. We denote the trading indicator for time t with $\mathbf{1}_t^p$ and interpret $\mathbf{1}_t^p = 1$ as the trading opportunity that arises for illiquid asset X, while $\mathbf{1}_t^p = 0$ indicates that the illiquid asset cannot be traded that period. We assume throughout that the trading indicators are i.i.d. Bernoulli random variables with trading probability $p = \mathbb{P}\{\mathbf{1}_t^p = 1\}$. If a trading opportunity occurs ($\mathbf{1}_t^p = 1$) and the investor decides to trade, then the proportional transaction costs ϕ must be paid, $0 \leq \phi \leq 1$. We allow for two types of return components on the illiquid asset: income return and capital gains. That is, we separate r_t^X into a liquid part d_t (income return) and an illiquid part $r_t^X - d_t$ (capital gains).

3.2.2 The investors' consumption and investment problem

The investor has an investment horizon equal to T. We assume that the illiquid asset can be traded (and thus liquidated) against transaction costs ϕ at the final date T. Notice that under the assumption that the illiquid asset might not be liquidated at T, the liquidity premiums are amplified. We do not consider this because, in that case, the investor is better off postponing the liquidation of the illiquid asset until a trading opportunity arises. We introduce the following notation to distinguish liquid and illiquid wealth. We denote liquid wealth as available at time t by W_t. This wealth consists of investments in both the risk-free asset B and the risky liquid asset S. The value of the investment in the illiquid asset at time t is denoted by X_t. Therefore, total wealth equals $W_t + X_t$.

Furthermore, we assume that the investor may face a liquidity shock L_t that is assumed to be fraction l_t of the previous period's total wealth $W_{t-1}+X_{t-1}$. The liquidity shock indicator is denoted by $\mathbf{1}_t^s$ and follows an i.i.d. Bernoulli process with probability $q = \mathbb{P}\{\mathbf{1}_t^s = 1\}$. Various causes of such a liquidity shock arise. For individual investors, examples are health care costs, unforeseen expenditures, or extreme weather events. For institutional investors a possible cause for liquidity shocks are margin calls on derivative positions. For long-term investors, such as pension funds and life insurers, shocks to the mortality rate can increase the temporary need for liquidity.

We denote the fraction of liquid wealth W_t that is invested in the liquid risky asset S by

θ_t, and $1-\theta_t$ is invested in the risk-free asset B. Consumption at time t is denoted by C_t and must be financed with liquid wealth W_t. Preferences are represented by a standard constant relative risk aversion (CRRA) expected utility function with risk-aversion parameter γ.

Illiquid wealth X_t can only be converted into liquid wealth (and, if desired, immediately consumed) if a trading opportunity arises, that is, if $\mathbf{1}_t^p = 1$. We denote the transfer from liquid to illiquid wealth by $\triangle X_t$. Thus, $\triangle X_t > 0$ means that at time t, an additional amount $\triangle X_t$ of the illiquid asset is bought, and thus liquid wealth W_t decreases by $\triangle X_t + \phi|\triangle X|$. If no trading opportunity arises, then $\mathbf{1}_t^p = 0$; and we automatically have $\triangle X_t = 0$.

The investor optimizes its utility of a stream of consumption levels C_t over a horizon $t = 0, \ldots, T$. Thus, the criterion function is:

$$\mathbb{E}_0 \left[\sum_{t=0}^{T} \beta^t \frac{C_t^{1-\gamma}}{1-\gamma} \right], \tag{3.2}$$

where β denotes the time-preference discount factor, and $\gamma > 1$ is the risk-aversion parameter.

The investor faces two budget constraints: one for liquid wealth W_t and one for illiquid wealth X_t. Formally, we have:

$$\begin{aligned} W_t &= (W_{t-1} - \triangle X_{t-1} - \phi|\triangle X_{t-1}| - C_{t-1}) \left(\exp(r_f) + \theta_{t-1} \left[\exp(r_t^S) - \exp(r_f)\right]\right) \\ &+ (X_{t-1} + \triangle X_{t-1}) \exp(d_t) - L_t && (3.3) \\ X_t &= (X_{t-1} + \triangle X_{t-1}) \left(\exp(r_t^X) - \exp(d_t)\right). && (3.4) \end{aligned}$$

We assume that the investor cannot borrow against the illiquid investments. The effect of illiquidity would be strongly reduced if this borrowing was possible, as the investor could always undo the illiquidity by borrowing against the illiquid asset if needed. Thus, we impose:

$$C_t \leq W_t, \quad t = 0, \ldots, T. \tag{3.5}$$

The optimal consumption problem can now be stated as follows:

Problem 3.2.1. *The investor maximizes*

$$\max_{\{\theta_t, \triangle X_t, C_t\}_{t=0}^{T-1}} \mathbb{E}_0 \left[\sum_{t=0}^{T} \beta^t \frac{C_t^{1-\gamma}}{1-\gamma} \right] \tag{3.6}$$

subject to the budget constraints (3.3) and (3.4) and the borrowing constraint (3.5). Moreover, when $\mathbf{1}_t^p = 0$*, we must have* $\triangle X_t = 0$.

The decision variables θ_t, $\triangle X_t$, and C_t are non-anticipative. Formally, $\{\theta_t, \triangle X_t, C_t\}$ are adapted to the filtration $\mathbb{F} = \{\mathcal{F}_t\}_{t=0}^{T}$, where $\{\mathcal{F}_t\}$ is the filtration generated by $\{r_t^S, r_t^X, \mathbf{1}_t^p, \mathbf{1}_t^s\}$.

To summarize, illiquidity limits the investor's consumption and investment decisions in three ways compared to the case where the illiquid asset is fully liquid, that is, the two risky asset Merton case (Merton, 1969): the inability to trade the illiquid assets for uncertain periods of time; transaction costs of the illiquid asset when a trading opportunity arises; and the investor cannot borrow against the illiquid assets. All three assumptions are important characteristics of (most) illiquid assets.

3.2.3 Optimal strategies

Because of incomplete markets, the optimization in Problem 3.2.1 cannot be solved analytically, so we resort to numerical methods. For these, the numerical complexity is well-known to strongly increase with the dimension of the endogenous state variables. In the formulation of Problem 3.2.1 there are two: W_t and X_t. Yet, in line with Ang et al. (2014), a simple transformation leads to a partly analytical result due to the homogeneity of the CRRA utility function we consider, see Theorem 3.2.2 below.

More precisely, we consider as endogenous state variables the total wealth $W_t + X_t$ and the fraction of total wealth invested in the illiquid asset, that is,

$$\xi_t = \frac{X_t}{W_t + X_t}. \tag{3.7}$$

With this reparametrization we define the value function using the Bellman principle as:

$$V_t\left(W_t + X_t, \xi_t\right) = \max_{\theta_t, \triangle X_t, C_t} \beta^t \frac{C_t^{1-\gamma}}{1-\gamma} + \mathbb{E}_t V_{t+1}(W_{t+1} + X_{t+1}, \xi_{t+1}), \tag{3.8}$$

with the boundary condition at time T given by:

$$V_T\left(W_T + X_T, \xi_T\right) = \beta^T \frac{\left(W_T + (1-\phi)X_T\right)^{1-\gamma}}{1-\gamma}. \tag{3.9}$$

The boundary condition means that we assume that all assets can be traded (and thus liquidated) at time T against transaction costs ϕ. With the above introduced change of variables, that is, the pair (W_t, X_t) is replaced by the pair $(W_t + X_t, \xi_t)$, then the solution to the investor's problem satisfies the following theorem.

Theorem 3.2.2. *There are time-dependent (deterministic) functions α_t, θ_t, and H_t such that the optimal solution $\{C_t^*, \triangle X_t^*, \theta_t^*\}$ to Problem 3.2.1 can be written as:*

$$
\begin{aligned}
V_t\left(W_t + X_t, \xi_t\right) &= \beta^t \frac{\left(W_t + X_t\right)^{1-\gamma}}{1-\gamma} H_t\left(\xi_t\right), && (3.10) \\
C_t^* &= \alpha_t(\xi_t)\left(W_t + X_t\right), && (3.11) \\
\theta_t^* &= \theta_t\left(\xi_t\right), && (3.12) \\
\xi_t^* &= \arg\min_{\xi_t} H_t(\xi_t). && (3.13)
\end{aligned}
$$

The proof of Theorem 3.2.2 is provided in Appendix A. Moreover, the optimal investment decision concerning illiquid wealth, that is, $\triangle X_t^*$, is determined by the choice ξ_t^*; but only when trading is allowed, that is, when $\mathbf{1}_t^p = 1$:

$$
\triangle X_t^* = \begin{cases} (\xi_t^* - \xi_t)(W_t + X_t) & \text{if} \quad \mathbf{1}_t^p = 1 \\ 0 & \text{if} \quad \mathbf{1}_t^p = 0, \end{cases} \tag{3.14}
$$

where $\xi_t^* = \xi_t$ if the transaction costs do not outweigh the benefit of rebalancing back to the optimal illiquid asset allocation ξ_t^*.

The advantage of Theorem 3.2.2 is that the dependence of the value function on total wealth $W_t + X_t$ is known analytically. The fact that the value function is proportional to $(W_t + X_t)^{1-\gamma}$ simplifies the numerical optimization to a one dimensional grid search over ξ_t only. Details are provided in Appendix B.

We posit that the function $H_t(\xi_t)$ can be viewed as a penalty function which is minimized at the optimal fraction of total wealth invested in the illiquid asset ξ_t^*. If the investor is able to trade the illiquid asset at time t, then they will rebalance their portfolio towards the optimal ratio of illiquid wealth to total wealth ξ_t^*, if the decrease in the penalty function is sufficient to outweigh the transaction cost ϕ. Thus, in line with Constantinides (1986), there is a no trading region where the investor will not rebalance their portfolio. We depict the no trading region in Appendix C. As opposed to Constantinides (1986), the no trading region in our model is not symmetric and the upper bound is more stringent than the lower bound; an over-investment in the illiquid asset relative to the optimal amount may prevent the investor from smoothing consumption due to the borrowing constraints and/or potential liquidity shocks. In order to avoid these states of the world, they rebalance back to the optimal illiquid asset allocation more quickly as opposed to under investing in the illiquid asset.

Theorem 3.2.2 furthermore indicates that the optimal consumption choice and the optimal investment strategy in the liquid risky asset depend on the fraction of total wealth invested in the illiquid asset ξ_t. If illiquid wealth is substantial relative to liquid wealth, for instance after a liquidity shock L_t occurs; then the investor might have to cut their consumption relative to the case where the illiquid asset can always be traded. Moreover, to compensate for the increased risk exposure that results from the high fraction invested in illiquid wealth, the investor reduces their allocation to the liquid risky asset. The optimal consumption and asset allocation decisions are depicted in Appendix C.

3.2.4 Willingness to pay for liquidity: theory

To understand why liquidity premiums exist in some asset classes but not in others, we analyze the willingness to pay for liquidity. We define the investor's willingness to pay δ_t as the decrease in the expected return on the illiquid asset over period t that they are willing to pay to convert the illiquid asset into a liquid one. In other words, δ_t is the compensation the investor demands for holding the illiquid asset. To formalize the willingness to pay, denote the value function for Problem 3.2.1 by assuming that the asset X is actually also liquid by $V_t^{LIQ}\left(W_t + X_t\right)$. In other words, we solve Problem 3.2.1 subject to the budget constraints (3.3) and (3.4), where $p = 1$, $\phi = 0$. This value function factorizes as:

$$V_t^{LIQ}\left(W_t + X_t\right) = \beta^t \frac{\left(W_t + X_t\right)^{1-\gamma}}{1-\gamma} H_t^{LIQ}, \tag{3.15}$$

for a deterministic constant H_t^{LIQ}, where H_t^{LIQ} no longer depends on ξ_t as the illiquid asset is tradeable as well.

The value function V_t^{LIQ} depends on the expected return $r_f + \lambda_X \sigma_X - 0.5\sigma_X^2$ of asset X. Subtracting δ_t from this expected return leads to a (lower) value function that we denote by $V_t^{LIQ}\left(W_t + X_t | \delta_t\right)$. We then define the willingness to pay as that value of δ_t that solves:

$$V_t^{LIQ}\left(W_t + X_t | \delta_t\right) = V_t\left(W_t + X_t, \xi_t\right). \tag{3.16}$$

Given (3.10) and (3.15), we can find δ_t by solving:

$$H_t^{LIQ}(\delta_t) = H_t(\xi_t), \tag{3.17}$$

where $H_t^{LIQ}(\delta_t)$ denotes the value function when the illiquid asset is actually liquid at a risk premium reduced by δ_t. This willingness to pay depends on the actual allocation to the illiquid asset: ξ_t. To determine the liquidity premium, we assume that an investor with horizon T chooses the optimal allocation to the illiquid asset when entering the investment, so the actual allocation at time $t = 0$ equals $\xi_{t=0}^{T} = \xi_{t=0}^{T,*}$.

3.2.5 Willingness to pay for liquidity: comparative statics

In this subsection we show how the model implied liquidity premiums depend on different parameter values. We use a range of realistic parameter values and show how the results change depending on the assumptions.[3] With respect to the investor's preferences we assume the investor faces a liquidity shock with probability $q = 10\%$ equal to $l = 20\%$ of the previous period's total wealth, (i.e., the liquidity shock occurs on average once in 10 years), has a risk-aversion parameter equal to $\gamma = 5$ and the time-preference discount factor equals $\beta = 0.91$.[4] With respect to the financial market, we assume the liquid asset has a price of risk $\lambda_S = 38\%$ and volatility $\sigma_S = 18.5\%$, and the risk-free rate is $r_f = 2\%$. These parameter values result in an optimal risky asset allocation of approximately 40% and a risk-free bond allocation of 60%.

The parameter values of the illiquid asset are set equal to the parameter values of the liquid risky asset: $\lambda_X = 38\%$ and $\sigma_X = 18.5\%$. In this way, we isolate the effect of illiquidity instead of relying on a higher Sharpe ratio for the illiquid asset. In line with this reasoning, we also assume no correlation between the liquid and illiquid risky assets in the baseline model; $\rho_{SX} = 0$. We also assume no income return for the illiquid assets, that is, $d_t = 0$. For the illiquidity parameters, we assume that the investor can trade the illiquid asset on average once in two years, or in other words $p = 50\%$. If the investor decides to trade the illiquid asset when a trading opportunity arises, then the proportional transactions costs equal $\phi = 1\%$. At the final date, the investor has to pay transaction costs $\phi = 1\%$ in all states of the world. Table 3.1 summarizes the parameter values.

[3] In the next section, when linking our model to empirical evidence on liquidity premiums in different asset classes, we motivate the choice of the parameter values more thoroughly.

[4] A lower value for the time-preference discount factor has a negligible effect on liquidity premiums.

Table 3.1. **Parameter values**
This table summarizes the parameter values of our baseline model.

Parameters	*Symbol*	*Value*
Liquidity shock	l	20%
Probability liquidity shock	q	10%
Risk aversion parameter	γ	5
Time-preference discount factor	β	0.91
Risk-free rate	r_f	2%
Price of risk liquid risky asset	λ_S	38%
Volatility liquid risky asset	σ_S	18.5%
Price of risk illiquid asset	λ_X	38%
Volatility illiquid asset	σ_X	18.5%
Correlation coefficient	ρ	0
Income return	d	0
Trading probability illiquid asset	p	50%
Transaction costs illiquid asset	ϕ	1%

Liquidity premium and investment horizon

Perhaps the most straightforward, but nevertheless important result, is that the willingness to pay depends on the investment horizon. Figure 3.1 shows that the shorter the investor's investment horizon amplifies the liquidity premium. Illiquidity is typically a bigger threat for short-term investors as they want to consume or payout a large part of their total wealth compared to long-term investors. Under the baseline parameters, the liquidity premium demanded by the short-term investors ($T = 1$) equals 42 basis points, while this premium converges to only a few basis points as the horizon T becomes large.

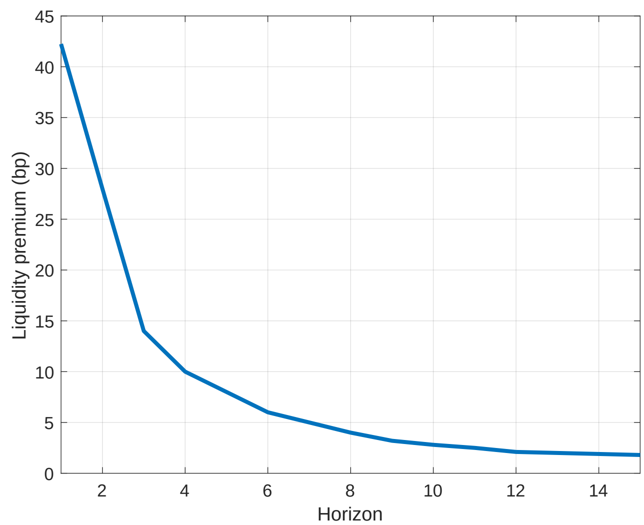
Liquidity premium and trading opportunities

Higher trading opportunities decrease the willingness to pay for illiquidity. Figure 3.2 shows that for the short-term investors ($T = 2$) the liquidity premium equals 32 basis points if the investor is unable to trade the illiquid asset before the final date and decreases to 20 basis points when the probability of trading is high.[5] For long-term investors ($T = 10$), the liquidity premium equals 13 basis points if the investor is unable to trade the illiquid

[5]Because the transaction costs of investors with a horizon equal to $T = 1$ are the only component of illiquidity that affects liquidity premiums, we typically refer in the comparative statistics to the short-term investor as the investor with a horizon equal to $T = 2$ instead of $T = 1$ years.

Figure 3.1. **The liquidity premium as a function of the investment horizon**

This graph shows the liquidity premium as a function of the investment horizon T that assumes the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income return $d = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.



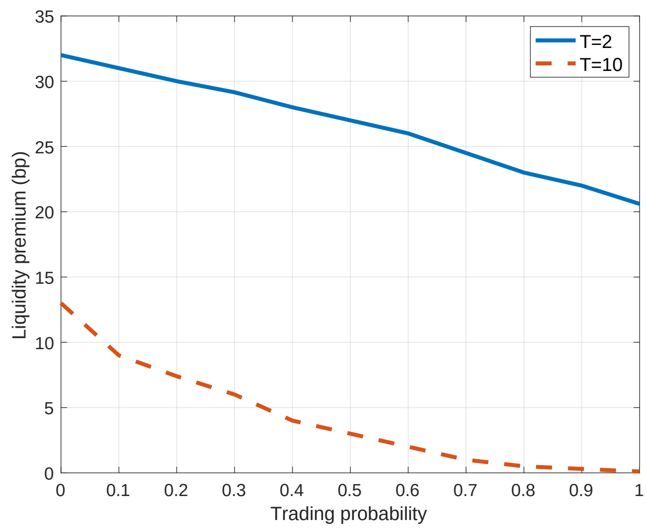
asset before the final date and converges to zero if the probability of trading is high. The relation between the trading probability and the liquidity premium is approximately linear for the short-term investors but decreases exponentially for the long-term investor. The short-term investor knows for sure that they are able to trade in two periods from now on, so the trading probability only affects trading one period from now. However, the inability to trade lengthens with a lower trading probability for the long-term investor. As a result, the probability of scenarios where illiquid wealth grows too fast relative to liquid wealth increases more rapidly at low trading probabilities for the long-term investor compared to the short-term investor.

Liquidity premium and transaction costs

Figure 3.3 shows that rising transaction costs increase the willingness to pay for both short-term ($T = 2$) and long-term ($T = 10$) investors. Nevertheless, the increase is much more substantial for the short-term investor, such that a 1 percentage point increase in transaction costs increases the liquidity premium demanded by approximately 18 basis points. Short-

Figure 3.2. **The liquidity premium as a function of the trading probability**

This graph shows the liquidity premium as a function of the trading probability p for the investor at horizons $T = 2$ and $T = 10$ that assumes the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income return $d = 0$, and the transactions costs $\phi = 1\%$.



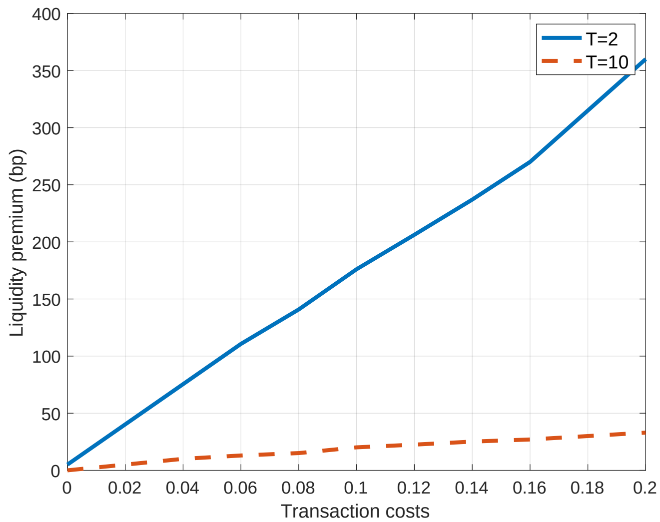
term investors always liquidate their illiquid wealth two periods from now, and they can only do so at cost ϕ. Long-term investors only liquidate their illiquid wealth at proportional cost ϕ if the realized illiquid asset allocation is too far from the optimal level. As a result, the liquidity premium increases by 2 basis points when transaction costs increase by 1 percentage points. This increase confirms earlier results from Constantinides (1986), where the investor has an infinite horizon and transactions costs endogenously decrease their trading frequency. The larger the transaction costs, the larger the investor's no-trading region. As the investor's value function is insensitive to some deviations from the optimal (non-transaction) portfolio allocation, the transaction costs lead to second-order effects on prices.

Liquidity premium and liquidity shocks

Figure 3.4 shows that the liquidity premium is hump-shaped in the level of the liquidity shock. This hump-shaped relation means that the liquidity premium is amplified when the level of the liquidity shock increases up to a shock of $l = 70\%$ for the short-term investors

Figure 3.3. **The liquidity premium as a function of the transaction costs**

This graph shows the liquidity premium as a function of the transaction costs ϕ for the investor at horizons $T = 2$ and $T = 10$ that assumes the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income return $d = 0$, and the trading probability of the illiquid asset $p = 50\%$.



and $l = 50\%$ for the long-term investors, but decreases again for larger shocks.[6] Because a liquidity shock can only be financed out of liquid wealth, a shock increases the probability that liquid wealth becomes insufficient to fulfill consumption needs. In order to prevent these states of the world, the investor reduces their optimal allocation to the illiquid asset substantially as compared to the liquid case. However, when the liquidity shock gets too severe, the allocation to the illiquid asset if it where fully liquid also gets closer to zero. Such large liquidity shocks make risky assets unattractive also in the fully liquid case, and as a result, liquidity premiums drop.

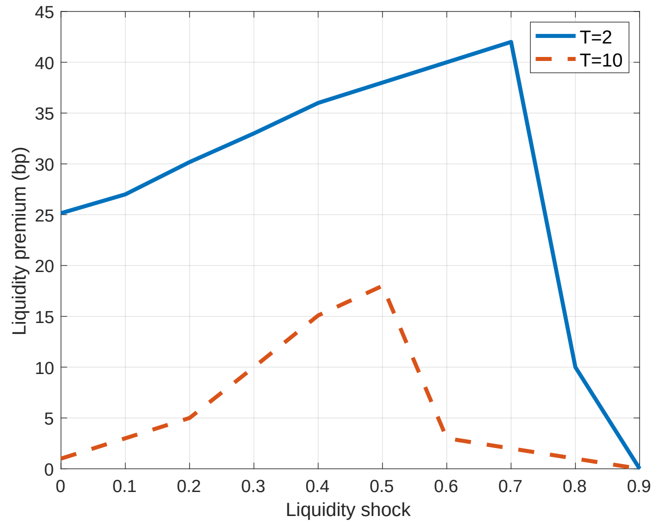
Liquidity premium and income return

The liquidity premium is also hump-shaped in the level of income return. On the one hand, the income return on the illiquid asset may diverge the optimal fraction allocated to liquid

[6]We find a similar hump-shaped relation between the liquidity premium and the probability of a liquidity shock. Also, the turning point of the hump-shaped pattern depends on the choice of the other parameter values.

Figure 3.4. **The liquidity premium as a function of the level liquidity shock**

This graph shows the liquidity premium as a function of the level liquidity shock l for the investor at horizon $T = 2$ and $T = 10$ that assumes the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a probability liquidity shock $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income return $d = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.



versus illiquid wealth. On the other hand, the income return on the illiquid asset can be used to smooth consumption and dampen the effect of liquidity shocks. Figure 3.5 shows both effects. The liquidity premium increases when the level of the income return increases up to $d = 3\%$ for the short-term investors and $d = 4\%$ for the long-term investors, but decreases again thereafter.[7]

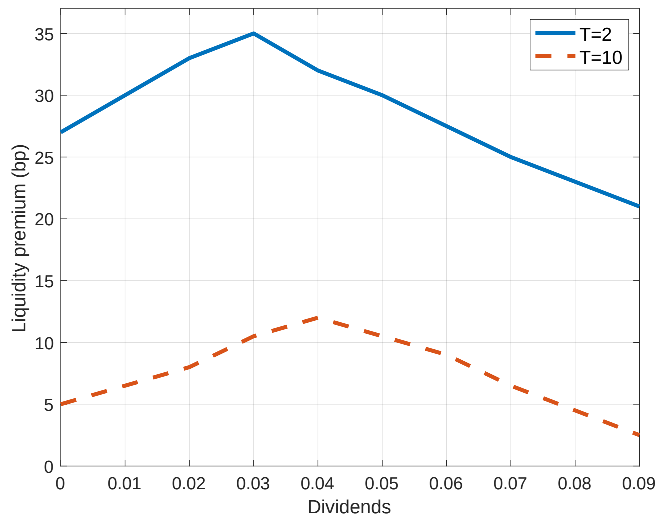
Liquidity premium and price of risk

Figure 3.6 shows that a higher price of risk strongly amplifies liquidity premiums. A higher price of risk increases the illiquid asset's attractiveness so that the optimal fraction of wealth allocated to it increases in case the illiquid asset becomes fully liquid. The higher the fraction of total wealth that the investor optimally wants to invest in the illiquid asset, the stronger the threat of illiquidity. Because the investor cannot borrow against the illiquid asset and to remain able to smooth consumption, the gap between the optimal allocation to the illiquid

[7]The turning point of the hump-shaped pattern depends on the choice of the other parameter values.

Figure 3.5. **The liquidity premium as a function of income return**

This graph shows the liquidity premium as a function of the income return d for the investor at horizon $T = 2$ and $T = 10$ that assumes the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.

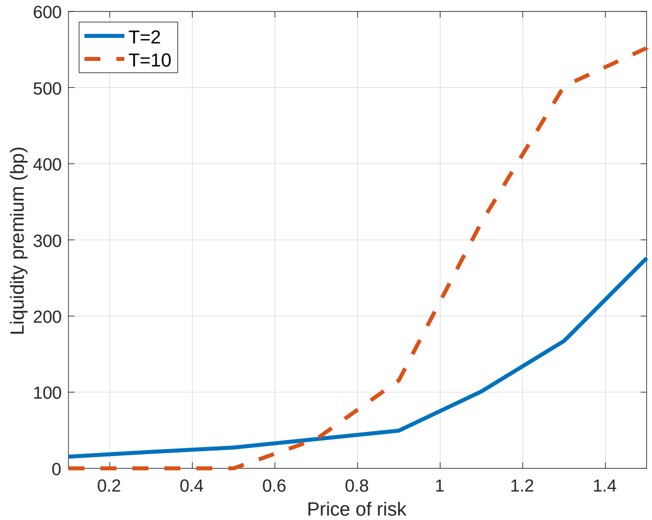


asset compared to when it is fully liquid widens as the illiquid asset becomes more attractive. These findings are consistent with Kahl et al. (2003) and Longstaff (2003) who show that the welfare effects of illiquidity are much larger when more wealth is tied up in the illiquid asset. For the long-term investor, illiquidity starts to pose a challenge for the investor's portfolio when the price of risk exceeds 0.55, which is equivalent to a 60% allocation to the illiquid asset.

Further, the threat of illiquidity gets more severe for the long-term investors as opposed to short-term ones at very high prices of risk. The reason is that the short-term investors know for sure that they will be able to liquidate illiquid wealth in two years and can therefore allocate a substantial amount to the illiquid asset. However, for the long-term investors there is uncertainty in the next trading opportunity. A substantial allocation to the illiquid asset therefore increases the likelihood of scenarios of insufficient liquid wealth to smooth consumption due to liquidity shocks or the poor performance of liquid relative to illiquid wealth.

Figure 3.6. **The liquidity premium as a function of the price of risk**

This graph shows the liquidity premium as a function of the price of risk of the illiquid asset for the investor at horizon $T = 2$ and $T = 10$ that assumes the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid risky asset $\mu_S = 9\%$, the volatility of the liquid risky asset $\sigma_S = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income return $d = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.



3.3 Liquidity premium in four asset classes

Next, we link our theoretical findings to the empirical evidence for liquidity premiums in several asset classes. Section 3.3.1 describes the implications of our theoretical findings in an equilibrium setting. In subsequent sections we relate these findings to the empirical evidence for liquidity premiums in four asset classes. The asset classes we consider are: private equity, real estate, corporate bonds, and stocks. We focus on US markets.

3.3.1 Implications equilibrium

So far we have analyzed the willingness to pay for a single investor. The next question to ask is: what does the willingness to pay mean for the liquidity premium in a general equilibrium setting? Under market clearing conditions the total amount of illiquid assets in the market should equal the sum of all current investors' holdings of the illiquid asset:

$$X_{mt} = \sum_{i=1}^{N} X_{it} \tag{3.18}$$

The N individual investors will demand illiquid assets depending on the illiquidity source, their preferences, and their total wealth. The liquidity premium in each asset class will subsequently depend on the composition of their investors. Suppose all investors in a certain asset class have low liquidity needs, then a positive liquidity premium would generate excessive demand for the illiquid asset and therefore push down the liquidity premium. In that case, the liquidity premium will converge to zero in equilibrium. On the other hand, if liquidity matters for a substantial portion of the investors, the demand for those who are less liquidity constrained might not be enough to push down the liquidity premium.

To quantify the liquidity premium demanded by different types of investors for each asset class, we choose parameter values representative of that asset class. Throughout, we assume that the liquid risky asset S represents a liquid stock index. We use the annualized mean and the standard deviation of the S&P500 Index to model the diversified liquid stock index. Calibrated over the last 25 years, the average return is $\mu_S = 11.3\%$ and the standard deviation $\sigma_S = 17.8\%$. Moreover, we use as the risk-free rate the annualized 1-year Treasury yield over the last 25 years that gives us $r_f = 2.8\%$. Appendix D provides details on the indexes.

The preferences of investors in each market are less well-known, as researchers only have a very rough idea about investors' investment horizons and their liquidity needs that are usually represented as holdings periods (e.g. Atkins and Dyl, 1997) or investors' funding constraints (e.g. Chen et al., 2020). These measures are generally incomplete as these proxies do not measure other liquidity risks such as margin calls on derivative positions or rare disasters that investors potentially face. For this reason, we provide qualitative indicators of investors' preferences for each asset class. The main goal of this section is therefore not to model investors perfectly but to give a rough indication of the average preferences of the investors in each market.

Despite this drawback, we argue that our findings can be interpreted as upper bounds on the liquidity premiums. We make two assumptions that are more likely to overestimate rather than to underestimate the liquidity premium. First, we assume that the investors cannot borrow against the illiquid assets. This constraint may be a realistic assumption for some asset classes but not for others. For instance, real estate investors are typically able to borrow a substantial amount using the property as collateral. However, taking this borrowing into account decreases liquidity premiums because the investors can partially undo the illiquidity of the asset. Second, we allow for liquidity shocks as large as 50% of the investors' total wealth. Even though larger wealth shocks are in practice possible, our model shows that investors avoid risky assets all together if faced with such shocks. As a result, large liquidity shocks do not necessarily have a positive effect on liquidity premiums (Figure 3.4).

3.3.2 Private equity

The evidence on liquidity premiums in private equity markets is mixed, mostly because there is only indirect evidence of the potential existence or non-existence of liquidity premiums. For instance, Franzoni et al. (2012) show that adding a liquidity risk factor to the traditional three-factor model of Fama and French leads to an alpha that is statistically insignificant from zero. This is indirect evidence of no liquidity (level) premium. By contrast, Harris et al. (2014) find an out-performance of private equity versus the S&P500 Index of 3% annually. They use the compensation for illiquidity as a potential explanation for this out-performance. Here we find an average liquidity premium of around 5-15 basis points on an annual basis when using both calibrated parameters values and realistic assumptions about investors' preferences.

To assess the liquidity premium for private equity, we specify model parameters such that the illiquid asset has properties similar to private equity investments. We use the mean and standard deviation of the S&P500 Index to model the liquid counterpart of the illiquid private equity investment in our model, as the S&P500 Index is generally taken as the benchmark for private equity, see, for example, Franzoni et al. (2012) and Harris et al. (2014). This benchmark means that $\mu_X = 11.3\%$ and $\sigma_X = 17.8\%$. We do not take a stance on the correlation between private equity and the S&P500 Index. The performance of private equity varies substantially across private equity investments, as noted by Phalippou and Gottschalg (2009) for example, and as a result the correlation coefficient varies across the specifications as well. Nevertheless, Ang et al. (2014) show a correlation between the S&P500 and private equity of 0.63, S&P500 and buyouts of 0.27, and the S&P500 and venture capital of 0.57. We therefore analyze the results for the correlation coefficients of $\rho_{SX} = 0.25$ and $\rho_{SX} = 0.60$.

Private equity investments have two distinctive features. First, private equity contracts generally run for 10 years, and trading is unusual before a contract expires (Metrick and Yasuda, 2010). Therefore, we set $p = 0$ over the first 10 years of the investment horizon.

Second, private equity usually involves capital commitment agreements. The investor agrees to provide a preset amount of capital over the first three to five years of the project. Yet, the capital commitment is preset, so we treat it as an upfront investment in our model. We furthermore assume that the transaction cost at exiting the contract is $\phi = 1\%$. A study by Dechert and Preqin (2011) shows that transaction fees at completion of a private equity contract vary between 0.84%-1.25% depending on the size of the private equity investment.

Turning to investors' preferences in the private equity market, we posit that they likely have a low demand for liquidity, as the lock-up period of private equity is long and known beforehand. Unfortunately, as opposed to stocks and bonds, there is no public holdings data available for private equity. However, Harris et al. (2014) report that for the Burgiss database that covers $1 trillion of committed capital to private equity over 20% is held by endowment funds and 60% by pension funds. Phalippou and Gottschalg (2009) also report endowments and pension funds as the main investors in private equity for the Thomson Venture Economics database. These findings support the assumption that only long-term investors are present in private equity markets. We then assess the liquidity premium for long-term investors who face different liquidity shocks.

Table 3.2 shows that liquidity premiums are lower for a positive correlation between the liquid and illiquid assets. The reasoning is that the effect of illiquidity is smaller because of lower diversification benefits when the correlation coefficient is larger. The liquidity shock, as shown before, amplifies liquidity premiums. Nevertheless, taking the results of Table 3.2 together indicates an average liquidity premium for private equity of 5-15 basis points only. Our findings therefore point in the direction of second-order liquidity premiums for private equity.

3.3.3 Real estate

Similar mixed evidence exists for liquidity premiums in real estate markets. Qian and Liu (2012) show that a 10% increase in their illiquidity measure decreases the contemporaneous real estate prices by $0.3 - 0.5\%$ and increases future returns by 25 basis points over the next quarter. On the other hand, Ang et al. (2013a) show comparable performance of direct and indirect real estate investments that indicates no liquidity premium. We find an average liquidity premium of 15-35 basis points on an annual basis by using both calibrated parameters values and realistic assumptions about the investors' preferences.

To model a direct investment in real estate, we use the first two moments of the S&P US REIT Index to model the liquid counterpart of a direct real estate investment. We calibrate

Table 3.2. **Liquidity premiums for private equity**
This table shows the liquidity premium in basis points for investors who face liquidity shock l and the correlation coefficient equal to ρ_{SX}. Further, we use the following parameter values: investment horizon $T = 10$, risk-aversion parameter $\gamma = 5$, time-preference discount factor $\beta = 0.91$, return on the risk-free rate $r_f = 2.8\%$, average and standard deviation of the return on the liquid risky asset $\mu_S = 11.3\%$ and $\sigma_S = 17.8\%$, average and standard deviation of the return on the illiquid asset $\mu_X = 11.3\%$ and $\sigma_X = 17.8\%$, the income return $d = 0$, the trading probability of the illiquid asset $p = 0$, and the transaction costs equal to $\phi = 1\%$.

	Correlation coefficient ρ_{SX}	
	0.25	0.6
Liquidity shock l		
0.0	6	5
0.2	8	7
0.5	17	9

the annualized average return on the REIT index as $\mu_X = 12.22\%$ and the corresponding standard deviation as $\sigma_X = 18.31\%$. The correlation coefficient between the liquid and illiquid assets is calibrated as the correlation between the S&P500 Index and S&P US REIT Index, which equals $\rho_{SX} = 0.4$.

The return on real estate includes both the income return and capital gains. The income return refers to the rent on properties, so the real estate returns are partially liquid. Following Hardin III et al. (2002) we assume that the income return or rent payments explain the majority of the total investment returns for REITs. In the model, we therefore set the income return equal to $d = \mu_X - r_f$. The volatility is instead largely defined by the volatility in the capital gains, and we therefore assume that the volatility relates to volatility in capital gains only.[8]

To describe the illiquidity parameters for real estate, we point out that the transaction costs consist of various main components: registration costs, legal fees, and sales and transfer taxes. On average, the total transaction costs lie in the range of $5\%-8\%$, and we therefore set transaction costs equal to $\phi = 6\%$ (Ommeren, 2008). The typical time between transactions for residential housing is 4-5 years and 8-11 years for institutional real estate, see, for example, Hansen (1998) and Miller et al. (2011). We thus assume trading probabilities p in the range

[8]The last two assumptions lead to similar results if we slightly alter them, that is, the findings are robust to a 1% higher or lower income return and/or a positive volatility for the income return.

of 10% − 20%. Unfortunately, we are not aware of public holdings data on real estate. However, pension funds are large investors in real estate markets worldwide (Willis Towers Watson, 2019). We therefore conjecture that the majority of investors are either medium term ($T = 5$) or long term ($T = 10$). We again assess the liquidity premium for various liquidity shocks.

Table 3.3 shows the model implied liquidity premiums for real estate. The liquidity premium for real estate is diminished mainly by the large share of long-term investors and the large income return component of the real estate returns (Figure 3.1 and 3.5). The substantial transaction costs increase the no trading region resulting in similar liquidity premiums demanded for various magnitudes of the liquidity shock. Taking the average of Table 3.3, we find a liquidity premium equal to 15-35 basis points over the past 25 years. Our range of model implied liquidity premiums is consistent with the dearth of empirical evidence for liquidity premiums in real estate markets.

Table 3.3. **Liquidity premiums for real estate**
This table shows the liquidity premium in basis points demanded by investors at horizon T that face liquidity shock l and trading probability p. Further, we use the following parameter values: risk-aversion parameter $\gamma = 5$, time-preference discount factor $\beta = 0.91$, return on the risk-free rate $r_f = 2.8\%$, average and standard deviation of the return on the liquid risky asset $\mu_S = 11.3\%$ and $\sigma_S = 17.8\%$, average and standard deviation of the return on the illiquid asset $\mu_X = 12.2\%$ and $\sigma_X = 18.3\%$, the correlation coefficient $\rho_{SX} = 0.4$, the income return $d = 9.4\%$, and the transaction costs $\phi = 6\%$.

	Investment horizon $T = 5$		Investment horizon $T = 10$	
	Trading probability p			
	10%	20%	10%	20%
Liquidity shock l				
0.0	33	31	14	13
0.2	34	32	15	14
0.5	38	35	19	18

3.3.4 Corporate bonds

In the corporate bond market, several studies have found empirical evidence for a first-order level liquidity premium (e.g. Chen et al., 2007; Bao et al., 2011; Bongaerts et al., 2017). In particular, Bongaerts et al. (2017) show that transaction costs of 0.54% lead to a 0.56% liquidity level premium. Yet, Palhares and Richardson (2019) find only limited evidence for liquidity premiums of corporate bonds using illiquidity-factor portfolios. We find an average annual liquidity premium around 30-50 basis points by using both calibrated parameter values and realistic assumptions about the investors' preferences.

To assess the liquidity premiums of corporate bonds we again choose parameter values representative of the US corporate bond market. We use the first two moments of the Bloomberg Barclays US Corporate Bond Index to model the liquid counterpart of corporate bonds. We calibrate the annualized average return as $\mu_X = 7.0\%$ and the corresponding standard deviation as $\sigma_X = 6.6\%$. We calibrate the correlation coefficient as the correlation between the Bloomberg Barclays US Corporate Bond Index and the S&P500 Index, which equals $\rho_{SX} = 0.35$. Finally, we assume fixed coupon payments, and as for real estate, we assume that the income return equals $d = \mu_X - r_f$.

Turning to the illiquidity parameters, we see that Bongaerts et al. (2017) find average transaction costs for corporate bonds of 0.52% that range between 0.46% and 0.58% from the most liquid to the least liquid corporate bond. As the spread in transaction costs is rather low, we analyze the liquidity premium for transaction costs equal to $\phi = 0.46\%$ and $\phi = 0.58\%$. Corporate bonds are not traded as often as public equities, but the period between trades differs across bonds. For instance, Bao et al. (2011) show an annualized turnover of corporate bonds that varies between 25%-35% and Bongaerts et al. (2017) show that 15% to 25% of corporate bonds are not traded in a given week. We translate these no trading periods in trading probabilities that vary between 92% and 95% that means trades occur on average once a month to once every two weeks, so we set $p = 0.935$.[9]

Table 3.4 reveals that the liquidity premium demanded by short- and long-term investors are relatively close to each other. This result is driven by the high price of risk of corporate bonds ($\lambda_X = 0.64$): Figure 3.6 shows that for this price of risk the liquidity premium demanded by short and long-term investors gets close to each other. A high price of risk also leads to a liquidity premium that is decreasing in the liquidity shock: a liquidity shock decreases the optimal allocation to the illiquid asset if it where fully liquid, diminishing the threat of illiquidity (Figure 3.4).

The Financial Accounts of the United States (Fed, 2020) reports the holdings of several asset classes within the US by investor type. We define long-term investors as the insurance companies, pension funds, and the government. The short-term investors are the banks,

[9] The results are in the same order of magnitude using $p = 0.92$ or $p = 0.95$ instead.

broker-dealers, households, and mutual funds. The Fed (2020) reports that for 2019, 38% of corporate bonds were held by long-term investors, (26% by insurance companies, 11% by pension funds, and 1% by the government), and 34% by short-term investors (7% by households, 5% by banks, 1% by broker-dealers, and 21% by mutual funds that include ETFs). The remaining 28% of the holdings are unspecified. Assuming that the distribution over long- and short-term investors is similar for the unspecified holdings, this assumption means that 53% of the corporate bonds are held by long-term investors and 47% by short-term investors. Taking the weighted average between short- and long-term investors, we expect a liquidity premium equal to 30-50 basis points over the past 25 years. This finding is below, yet fairly close to the empirical estimates found in Bongaerts et al. (2017). This may mean that empirical estimates indirectly incorporate the inability to trade as part of the liquidity premium.

Table 3.4. **Liquidity premiums for corporate bonds**
This table shows the liquidity premium in basis points demanded by investors at horizon T that face liquidity shock l and transaction costs ϕ. Further, we use the following parameter values: risk-aversion parameter $\gamma = 5$, time-preference discount factor $\beta = 0.91$, return on the risk-free rate $r_f = 2.8\%$, average and standard deviation of the return on the liquid risky asset $\mu_S = 11.3\%$ and $\sigma_S = 17.8\%$, average and standard deviation of the return on the illiquid asset $\mu_X = 7.0\%$ and $\sigma_X = 6.6\%$, the correlation coefficient $\rho_{SX} = 0.35$, the income return $d = 4.2\%$, and the trading probability of the illiquid asset $p = 0.935$.

	Investment horizon $T = 1$		Investment horizon $T = 10$	
	Transaction costs ϕ			
	0.46%	0.58%	0.46%	0.58%
Liquidity shock l				
0.0	51	56	46	51
0.2	40	46	29	33
0.5	29	32	25	26

3.3.5 Stocks

Several early studies have reported significant liquidity premiums for US equities. For instance, Amihud and Mendelson (1986) find that a 1% increase in the bid-ask spread increased the expected return by 2.4% per year. Acharya and Pedersen (2005) also show a liquidity premium of 4.5% for the most illiquid stocks versus the most liquid stocks. Ben-

Rephael et al. (2015) have challenged the existence of the liquidity premium in US stocks. They show that the liquidity premium almost disappeared over the 1997-2008 period due to lower transaction costs. For instance, for stocks listed on the NYSE, the liquidity premium for an average liquid stock was 16 basis points per month in the period from 1964-1974 but was in fact zero for the period from 1997-2008. The liquidity premium only survived for very small stocks. We find an average liquidity premium of 20-45 basis points on an annual basis using both calibrated parameters values and realistic assumptions about the investors' preferences.

For our model we again use the first two moments of the S&P500 Index to model the liquid counterpart of the illiquid stock, so $\mu_X = 11.3\%$ and $\sigma_X = 17.8\%$. Equity asset classes, such as small-growth stocks, value stocks, and mid cap stocks are highly correlated with the US stock market. For instance, the correlation between small-growth stocks and the S&P500 Index is approximately 0.9. We therefore set the correlation coefficient equal to $\rho_{SX} = 0.9$. Given the improved liquidity of US equities, we assume that the trading probability equals $p = 100\%$; in other words, the investor can always trade the illiquid stock. The transaction costs for stocks range from 0.25% for the most liquid stocks to 8% for the least liquid stocks (Beber et al., 2020). The average transaction costs across 25 liquidity sorted portfolios equals 1.14%. We therefore assess the liquidity premium for transaction costs equal to 0.30%, 1%, 4%, and 8%.

Table 3.5 shows that the short-term investors demand substantially higher liquidity premiums than long-term investors, consistent with Figure 3.3. The liquidity premium demanded by short-term investors is bounded, because the short-term investors do not invest in the illiquid asset at all when transaction costs exceed 2%.[10]

The Fed (2020) reports that for 2019, 13% of US corporate equity is held by long-term investors (2% by insurance companies and 11% by pension funds), and 70% by short-term investors (38% by households, 4% by non-financial corporations, and 28% by mutual funds (including ETFs)). The remaining 17% of the holdings are unspecified. Assuming that the distribution over long- and short-term investors is similar for the unspecified holdings, this assumption means that 16% of the equities are held by long-term investors and 84% by the short-term investors. Given the average transaction costs equal to 1.14% and taking the weighted average between short and long-term investors, we expect liquidity premiums for stocks to be 20-45 basis points on average over the past 25 years. Our findings are therefore

[10]Recall that our model does not allow the investors to short the illiquid asset.

substantially lower than the estimates from the early literature and more in favor with the recent evidence of a small liquidity premium for stocks.

Table 3.5. **Liquidity premiums for stocks**
This table shows the liquidity premium in basis points demanded by investors at horizon T that face liquidity shock l, and transaction costs ϕ. Further, we use the following parameter values: risk-aversion parameter $\gamma = 5$, time-preference discount factor $\beta = 0.91$, return on the risk-free rate $r_f = 2.8\%$, average and standard deviation of the return on the liquid risky asset $\mu_S = 11.3\%$ and $\sigma_S = 17.8\%$, average and standard deviation of the return on the illiquid asset $\mu_X = 11.3\%$ and $\sigma_X = 17.8\%$, the correlation coefficient $\rho_{SX} = 0.9$, the income return $d = 0$, and the trading probability of the illiquid asset $p = 1$.

Panel A: Investment horizon $T = 1$	Transaction costs ϕ			
	0.30%	1%	4%	8%
Liquidity shock l				
0.0	15	48	105	105
0.2	11	37	98	98
0.5	6	20	85	85

Panel B: Investment horizon $T = 10$	Transaction costs ϕ			
	0.30%	1%	4%	8%
Liquidity shock l				
0.0	0	1	4	7
0.2	0.5	2	7	13
0.5	0	0.5	1	2

3.4 Conclusion

In this study, we investigate the liquidity premium demanded by different investor types. The cost of illiquidity may be twofold: suboptimal asset allocation and suboptimal consumption smoothing. We show that only the illiquidity that results in suboptimal consumption smoothing is able to generate a substantial liquidity premium, while the illiquidity that leads to suboptimal asset allocations does not. From this we conclude that, in equilibrium, the liquidity premiums depend on the source of illiquidity and the relative prevalence of investor types in the market. This heterogeneity across asset classes enables us to relate to the empirical evidence about the liquidity premiums in those markets.

We make several contributions. First, although private equity is the most illiquid asset that we analyze, we only find a liquidity premium of 5-15 basis points that point in the direction of second-order liquidity premiums for this market. Private equity investors have to lockup their money for a long period of time, and mainly for that reason only long-term investors are present in this market. For these investors illiquidity is unlikely to substantially harm their consumption patterns. Moreover, the non-trading period is fixed so that investors know by and large when the position is liquidated. Second, for direct real estate we find an average liquidity premium of 15-35 basis points. Direct real estate can often not be traded for a substantial amount of time, and the timing of the trading opportunities are uncertain. Yet, the liquidity premium substantially dampens because of the large share of long-term investors and the liquid return component (rents) in real estate markets. This finding is consistent with the scare empirical evidence on liquidity premiums for real estate markets. Third, the average liquidity premium for corporate bonds equals 30-50 basis points. This finding gets close to the majority of the empirical literature on liquidity premiums for corporate bonds. Finally, for stocks we find an average liquidity premium of 20-45 basis points. This finding is in line with the recent literature that shows a diminishing liquidity premium in US equity markets.

3.5 Appendix

A Proof of optimal consumption and investment strategies

Proof of Theorem 3.2.2. Instead of the endogenous variables (W_t, X_t), we use the pair $(W_t + X_t, \xi_t)$ as endogenous state variables. That is, we write:

$$C_t = \alpha_t(W_t + X_t, \xi_t)(W_t + X_t),$$

$$\theta_t = \theta_t(W_t + X_t, \xi_t).$$

Now, rewrite the evolution of total wealth $W_t + X_t$ using budget constraints (3.3)-(3.4) as:

$$\begin{aligned} W_t + X_t &= (W_{t-1} + X_{t-1}) \\ &\times [(1 - \xi_{t-1} - \alpha_{t-1} - \phi|\triangle\xi_{t-1}|) \times \left(\exp(r_f) + \theta_{t-1}(\exp(r_t^S) - \exp(r_f))\right) \\ &+ \xi_{t-1}\exp(d_t) - l_t + \xi_{t-1}\left(\exp(r_t^X) - \exp(d_t)\right)], \end{aligned} \tag{A1}$$

$$\xi_t = \frac{\xi_{t-1}\left(\exp(r_t^X) - \exp(d_t)\right)}{\begin{array}{r}(1 - \xi_{t-1} - \alpha_{t-1} - \phi|\triangle\xi_{t-1}|) \times \left(\exp(r_f) + \theta_{t-1}(\exp(r_t^S) - \exp(r_f))\right) \\ + \xi_{t-1}\exp(d_t) - l_t + \xi_{t-1}\left(\exp(r_t^X) - \exp(d_t)\right)\end{array}}. \tag{A2}$$

where $\triangle\xi_{t-1} = \xi^*_{t-1} - \xi_{t-1}$.

The proof is by backward induction. At the final horizon $t = T$, the claim is obviously correct with $\alpha_T \equiv 1$ and $H_T \equiv (1 - \phi\xi_T)^{1-\gamma}$. At time T, θ_T is irrelevant. Now, for the induction argument, assume that (3.10)-(3.13) holds at time t. Then, we need to show that (3.10)-(3.13) also holds at time $t-1$. From the value function (3.8), evaluated at time $t-1$

and substituting (3.10), we find:

$$
\begin{aligned}
& V_{t-1}(W_{t-1}+X_{t-1},\xi_{t-1}) \\
&= \max_{\alpha_{t-1},\theta_{t-1},\xi_{t-1}} \beta^{t-1}\frac{C_{t-1}^{1-\gamma}}{1-\gamma}+\mathbb{E}_{t-1}V_t(W_t+X_t,\xi_t) \\
&= \max_{\alpha_{t-1},\theta_{t-1},\xi_{t-1}} \beta^{t-1}\frac{(\alpha_{t-1}(W_{t-1}+X_{t-1}))^{1-\gamma}}{1-\gamma} \\
&+ \mathbb{E}_{t-1}[\beta^{t}\frac{(W_t+X_t)^{1-\gamma}}{1-\gamma}H_t(\xi_t)] \\
&= \max_{\alpha_{t-1},\theta_{t-1},\xi_{t-1}} \beta^{t-1}\frac{(W_{t-1}+X_{t-1})^{1-\gamma}}{1-\gamma} \\
&\times \Big(\alpha_{t-1}^{1-\gamma}+\beta\mathbb{E}_{t-1}[\{(1-\xi_{t-1}-\alpha_{t-1}-\phi|\triangle\xi_{t-1}|)\times \\
&\quad \big(\exp(r_f)+\theta_{t-1}(\exp(r_t^S)-\exp(r_f))\big)+\xi_{t-1}\exp(d_t)-l_t \\
&+ \xi_{t-1}\big(\exp(r_t^X)-\exp(d_t)\big)\}^{1-\gamma}H_t(\xi_t)]\Big) \\
&= \max_{\alpha_{t-1},\theta_{t-1},\xi_{t-1}} \beta^{t-1}\frac{(W_{t-1}+X_{t-1})^{1-\gamma}}{1-\gamma}H_t(\xi_t) \qquad \text{(A3)}
\end{aligned}
$$

At time $t-1$, the penalty function $H_{t-1}(\xi_{t-1})$ equals

$$
\begin{aligned}
H_{t-1}(\xi_{t-1}) &= \alpha_{t-1}^{1-\gamma}+\beta\mathbb{E}_{t-1}[\{(1-\xi_{t-1}-\alpha_{t-1}-\phi|\triangle\xi_{t-1}|) \\
&\times \big(\exp(r_f)+\theta_{t-1}(\exp(r_t^S)-\exp(r_f))\big) \\
&+ \xi_{t-1}\exp(d_t)-l_t+\xi_{t-1}\big(\exp(r_t^X)-\exp(d_t)\big)\}^{1-\gamma}H_t(\xi_t)] \qquad \text{(A4)}
\end{aligned}
$$

Therefore, the function $H_{t-1}(\xi_{t-1})$ is a function of $t-1$ and ξ_{t-1} only and hence (3.10) from (3.10)-(3.13) hold for all t. We continue with proving (3.11)-(3.12) at time $t-1$. The first-order conditions of the decision variables α_{t-1} and θ_{t-1} equal:

$$\alpha_{t-1}^{UC*}=\arg\max_{\alpha_{t-1}}\frac{(\alpha_{t-1}(W_{t-1}+X_{t-1}))^{1-\gamma}}{1-\gamma}+\mathbb{E}_{t-1}V_t(W_t+X_t,\xi_t), \qquad \text{(A5)}$$

$$\theta_{t-1}^{*}\arg\max_{\theta_{t-1}}\frac{(\alpha_{t-1}(W_{t-1}+X_{t-1}))^{1-\gamma}}{1-\gamma}+\mathbb{E}_{t-1}V_t(W_t+X_t,\xi_t), \qquad \text{(A6)}$$

where α_{t-1}^{UC*} is the solution if the investor were unconstrained, i.e. when constraint (3.5) does not bind. Because we assume that the investor cannot borrow against the illiquid asset the constrained solution becomes:

$$\alpha_{t-1}^{C*} = \begin{cases} \alpha_{t-1}^{UC*} & \text{if} \quad \alpha_{t-1}^{UC*} \leq 1-\xi_{t-1} \\ 1-\xi_{t-1} & \text{if} \quad \alpha_{t-1}^{UC*} > 1-\xi_{t-1} \end{cases} \tag{A7}$$

We can now rewrite (A5) and (A6) as:

$$\begin{aligned} \frac{\partial V_{t-1}}{\partial \alpha_{t-1}} &= \beta^{t-1}(\alpha_{t-1}(W_{t-1}+X_{t-1}))^{-\gamma} \\ &- \mathbb{E}_{t-1}[\frac{\partial V_t}{\partial W_t + X_t}\Big(\exp(r_f)+\theta_{t-1}(\exp(r_t^S)-\exp(r_f))\Big)] \\ &+ \mathbb{E}_{t-1}[\frac{\partial V_t}{\partial \xi_t}\xi_t\frac{1}{W_t+X_t}\Big(\exp(r_f)+\theta_{t-1}(\exp(r_t^S)-\exp(r_f))\Big)] = 0, \quad \text{(A8)} \\ \frac{\partial V_{t-1}}{\partial \theta_{t-1}} &= \mathbb{E}_{t-1}[\frac{\partial V_t}{\partial W_t + X_t}\Big(\exp(r_t^S)-\exp(r_f)\Big)] \\ &+ \mathbb{E}_{t-1}[\frac{\partial V_t}{\partial \xi_t}\xi_t\frac{1}{W_t+X_t}\Big(\exp(r_t^S)-\exp(r_f)\Big)] = 0. \quad \text{(A9)} \end{aligned}$$

To see that both α_{t-1}^* and θ_{t-1}^* depend only on ξ_{t-1}, we solve (A8) and (A9) and substitute (A1) into (A8) and (A9), we get:

$$\begin{aligned} \frac{\partial V_{t-1}}{\partial \alpha_{t-1}} &= \alpha_{t-1}^{-\gamma} + \beta\mathbb{E}_{t-1}[\{(1-\xi_{t-1}-\alpha_{t-1}-\phi|\triangle\xi_{t-1}|)(\exp(r_f)+\theta_{t-1}(\exp(r_t^S)-\exp(r_f))) \\ &+ \xi_{t-1}\exp(d_t) - l_t + \xi_{t-1}\left(\exp(r_t^X)-\exp(d_t)\right)\}^{-\gamma} \times \Big(\frac{H_t'(\xi_t)}{1-\gamma}\xi_t - H_t(\xi_t)\Big)\exp(r_f)], \\ &= 0 \quad \text{(A10)} \\ \frac{\partial V_{t-1}}{\partial \theta_{t-1}} &= \mathbb{E}_{t-1}[\{(1-\xi_{t-1}-\alpha_{t-1}-\phi|\triangle\xi_{t-1}|)(\exp(r_f)+\theta_{t-1}(\exp(r_t^S)-\exp(r_f))) + \xi_{t-1}\exp(d_t) \\ &- l_t + \xi_{t-1}\left(\exp(r_t^X)-\exp(d_t)\right)\}^{-\gamma} \times \Big(H_t(\xi_t) - \frac{H_t'(\xi_t)}{1-\gamma}\xi_t\Big)\Big(\exp(r_t^S)-\exp(r_f)\Big)] \\ &= 0. \quad \text{(A11)} \end{aligned}$$

The first-order conditions ($A10$) and ($A11$) depend only on time $t-1$ and the fraction invested in the illiquid asset ξ_{t-1}. In this way, the optimal consumption and the fraction invested in the liquid risky assets can indeed be written as in (3.11) and (3.12), so (3.11)-(3.12) from (3.10)-(3.13) holds for all t. We finish the proof by showing that (3.13) also holds at time $t-1$. When a trading opportunity arises at $t-1$, the investor chooses ξ_{t-1} such that the value function at $t-1$ is optimized:

$$\begin{aligned}\xi^*_{t-1} &= \arg\max_{\xi_{t-1}} V_{t-1}(W_{t-1}+X_{t-1},\xi_{t-1}) = \arg\max_{\xi_{t-1}} \beta^{t-1}\frac{(W_{t-1}+X_{t-1})^{1-\gamma}}{1-\gamma}H_{t-1}(\xi_{t-1}) \\ &= \arg\min_{\xi_{t-1}} H_{t-1}(\xi_{t-1}). \qquad \text{(A12)}\end{aligned}$$

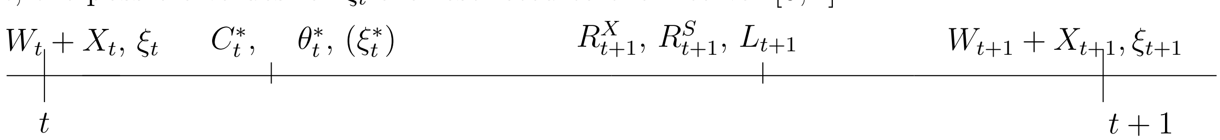
□

B Numerical implementation

This appendix provides an outline of the numerical method to solve the baseline model. First, we describe the sequence of making decisions. Second, we explain the numerical solution technique to solve for the decision variables.

Sequence of decision making

Figure B depicts the sequence of making decisions. The endogenous variables, liquid wealth W_t and illiquid wealth X_t, are defined as total wealth before consumption, liquidity shocks, and returns earned in period $(t, t+1]$. Based on the actual fraction allocated to the illiquid asset ξ_t, the investor chooses the optimal fraction of total wealth to be consumed in period $(t, t+1]$, $\alpha_t(\xi_t)$, and the optimal allocation towards the liquid risky asset, $\theta_t(\xi_t)$. If a trading opportunity arises at time t, the investor chooses simultaneously ξ^*_t, $\alpha_t(\xi^*_t)$ and $\theta_t(\xi^*_t)$. Further, by the assumption $X_t \geq 0$ and the inability to borrow against the illiquid asset, the possible values for ξ_t are restricted to the interval $[0, 1]$.



Numerical solution technique

The baseline model is solved by means of backward induction, where we start solving the problem at the final date $t = T$ and solve the model backwards for each period until arriving at time $t = 0$. At the final horizon $t = T$, we have $\alpha_T \equiv 1$ and $H_T \equiv (1-\phi\xi_T)^{1-\gamma}$. To solve for ξ^*_{T-1}, $\alpha_t(\xi_{T-1})$ and $\theta_t(\xi_{T-1})$, we construct a grid for $\xi_{T-1} \in [0, 1]$. We simulate $M = 100,000$ trajectories for the exogenous state variables, the returns on the liquid and illiquid risky asset in the periods $(T-1,T]$, R_T^S, and R_T^X from a multi-normal distribution with means and variance-covariance matrix, as described in Section 3.2.1. We also simulate $M = 100,000$ trajectories for the liquidity shock L_T from a Bernoulli distribution as described in Section 3.2.2.

For each grid point by using a nonlinear least squares, we solve the first order conditions with respect to consumption (A10) and the allocation towards the liquid risky asset (A11) by using $H_T(\xi_T) \equiv (1-\phi\xi_T)^{1-\gamma}$, R_T^S, R_T^X, and l_T to find $\alpha_{T-1}(\xi_{T-1})$ and $\theta_{T-1}(\xi_{T-1})$. Then we are able to compute $H_{T-1}(\xi_{T-1})$ and solve for $\xi_{T-1}^* = \arg\min_{\xi_{T-1}} H_{T-1}(\xi_{T-1})$ with the corresponding consumption level $\alpha_{T-1}(\xi_{T-1}^*)$ and the allocation to the liquid risky asset $\theta_{T-1}(\xi_{T-1}^*)$. This gives us the optimal solution at time $T-1$.

We then solve for the optimal solution at time $T-2$ in the same way, except that we also simulate $M = 100,000$ trajectories for the trading probability p_{T-1} from a Bernoulli distribution as described in Section 3.2.2. In the scenarios the investor is able to trade ($\mathbf{1}_{T-1}^p = 1$), we use $H_{T-1}(\xi_{T-1}^*)$ and in the scenarios the investor is unable to trade ($\mathbf{1}_{T-1}^p = 0$), we use $H_{T-1}(\xi_{T-1})$. Together with R_{T-1}^S, R_{T-1}^X, and l_{T-1} we find $\alpha_{T-2}(\xi_{T-2})$ and $\theta_{T-2}(\xi_{T-2})$. We again compute $H_{T-2}(\xi_{T-2})$ and solve for $\xi_{T-2}^* = \arg\min_{\xi_{T-2}} H_{T-2}(\xi_{T-2})$ with the corresponding consumption level $\alpha_{T-2}(\xi_{T-2}^*)$ and the allocation to the liquid risky asset $\theta_{T-2}(\xi_{T-2}^*)$. We can continue this approach until we arrive at $t = 0$.

C Optimal consumption and asset allocation baseline model

This appendix shows the optimal consumption pattern and asset allocation decisions for the baseline model described in Section 3.2. Both consumption (Figure 3.7) and the allocation to the liquid risky assets (Figure 3.8) are functions of the investment horizon and the fraction invested in the illiquid asset, as derived in Theorem 3.2.2. These graphs show that the larger the actual allocation to illiquid assets, the lower the consumption and allocation to the liquid risky asset. The optimal allocation to the illiquid asset is in Figure 3.9 and found by minimizing the penalty function $H_t(\xi_t)$ (Theorem 3.2.2). We compare this allocation to the case where the illiquid asset is fully liquid, that is, the two risky asset Merton case (Merton, 1969). The shorter the investment horizon, the lower the optimal allocation to the illiquid asset relative to the Merton case.

The no-trade region induced by transaction costs is in Figure 3.10. As long as the illiquid asset allocation is within the no-trade region, that is, the area within the two dashed lines, the investor does not trade if a trading opportunity arises, while the investor re-balances back to the optimal allocation when outside of the no-trade region. Compared to Constantinides

(1986), the upper bound of the no-trading region is lower in our model; an over-investment in the illiquid asset relative to the optimal amount may prevent the investor from smoothing consumption due to the borrowing constraints and/or potential liquidity shocks. In order to avoid these states of the world, they re-balance back to the optimal illiquid asset allocation more quickly as opposed to under-investment in the illiquid asset.

Figures

Figure 3.7. **Optimal consumption**

This graph shows the optimal consumption as a function of the investment horizon T and fraction invested in the illiquid asset that uses the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, income return $d = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.

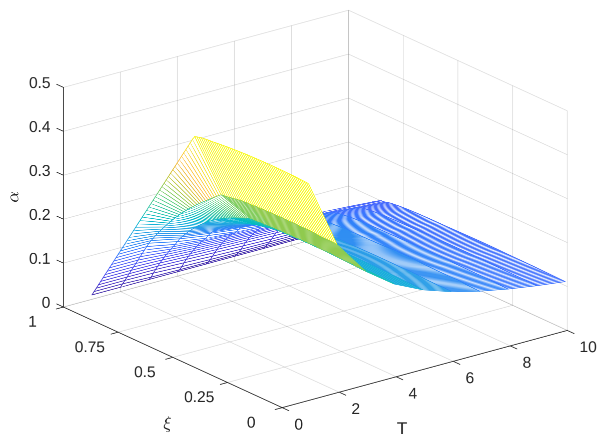


Figure 3.8. **Optimal liquid risky asset allocation**

This graph shows the optimal liquid risky asset allocation as a function of the investment horizon T and fraction invested in the illiquid asset that uses the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income return $d = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.

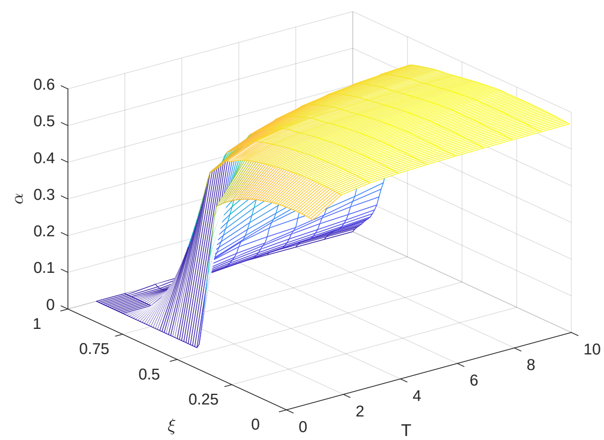


Figure 3.9. **Optimal illiquid asset allocation**

This graph shows the optimal illiquid asset allocation as a function of the investment horizon T that uses the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income return $d = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.

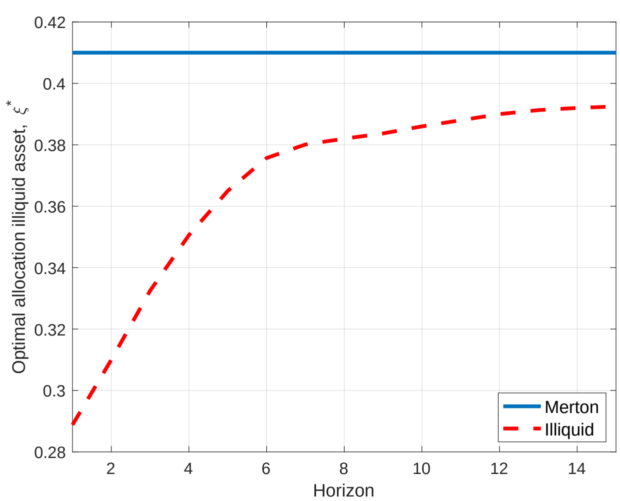
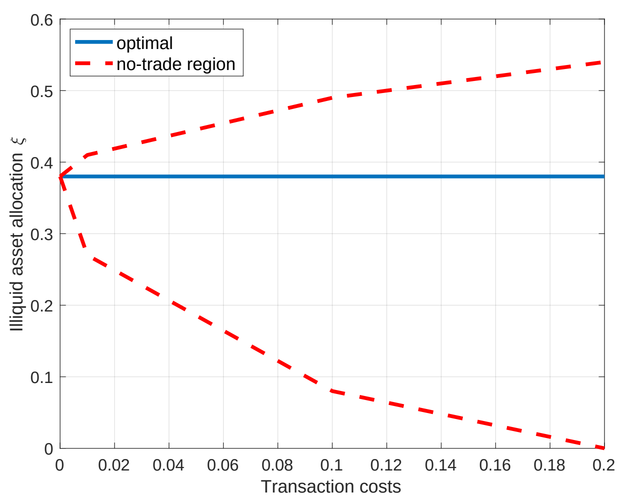


Figure 3.10. **No-trading region**

This graph shows the no-trading region of the investor with an investment horizon $T = 10$ that uses the following parameter values: the risk-aversion parameter $\gamma = 5$, the time-preference discount factor $\beta = 0.91$, a liquidity shock $l = 20\%$ with probability $q = 10\%$, the return on the risk-free rate $r_f = 2\%$, the average return on the liquid and illiquid risky asset $\mu_S = \mu_X = 9\%$, the volatility of the liquid and illiquid risky asset $\sigma_S = \sigma_X = 18.5\%$, the correlation coefficient $\rho_{SX} = 0$, the income $d = 0$, the trading probability of the illiquid asset $p = 50\%$, and the transactions costs $\phi = 1\%$.



D Market Indexes

Here we list the market indexes used to calibrate the four different asset classes: private equity, real estate, corporate bonds, and stocks.

Table 3.6. **Market Indexes calibration**
This table lists the indexes used to calibrate the four different asset classes described in Section 3.3 as well as the source for the risk-free rate.

Risk-free rate	*1-year Treasury yield*
Stocks	*S&P500 Index* The index includes 500 leading companies publicly traded in the US stock market.
Corporate bonds	*Bloomberg Barclays US Corporate Bond Index* The index measures the investment grade, fixed-rate taxable corporate bond market. It includes USD denominated securities publicly issued by US and non-US industrial, utility and financial issuers.
Real estate	*S&P United States REIT Index* The index includes the invest-able universe of publicly traded real estate investment trusts domiciled in the US.
Private Equity	*S&P500 Index*

Chapter 4

Pension Fund's Illiquid Assets Allocation under Liquidity and Capital Requirements[1]

4.1 Introduction

Pension funds are important investors in illiquid asset classes such as real estate, mortgages, private equity, hedge funds, and infrastructure. The annual OECD survey of large pension funds reveals an average illiquid assets allocation of 15 percent in 34 countries.[2] According to the 2018 Willis Towers Watson Global Pension Asset Study the 7 largest pension markets in the world (Australia, Canada, Japan, the Netherlands, Switzerland, UK, and US) have increased their average illiquid assets allocation from 4 percent in 1997 to 25 percent in 2017.[3] Illiquid assets may offer pension plans benefits in terms of a liquidity premium e.g., Sadka (2010), Franzoni et al. (2012), and Qian and Liu (2012), portfolio diversification (Jacobs et al., 2014) and liability hedging (Hoevenaars et al., 2008). Their long investment horizon

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[2]www.oecd.org/daf/fin/private-pensions/2015-Large-Pension-Funds-Survey.pdf

[3]https://www.willistowerswatson.com/-/.../Global-Pension-Asset-Study-2018-Japan.pdf

makes pension funds well placed to invest in illiquid asset classes (Attig et al., 2012).

Several papers study investment risk-taking by pension funds, e.g. Sharpe (1976), Jin et al. (2006), Rauh (2009), An et al. (2013), and Andonov et al. (2017). These papers typically focus on the allocation to risk-free assets (such as government bonds) on the one hand versus risky assets (such as equities) on the other hand. In this paper we address the investment policy of pension funds regarding illiquid asset classes. So far, little is known about the factors that influence how much they invest in illiquid asset classes. The main purpose of this paper is to show how liquidity and capital requirements affect the appetite of pension funds towards investing in illiquid assets. Several papers provide indeed evidence that regulations have a significant impact on pension fund's investment decisions, e.g., Sias (2004), An et al. (2013), and Andonov et al. (2017). We, therefore, build our paper on a theoretical model of liquidity and capital requirements. Based on that model we link pension funds' characteristics to their investments in illiquid assets. We test this in an empirical study using unique and unbiased data on Dutch pension funds.

First, we assess the aggregate illiquid assets allocation as a fraction of the risky assets allocation, following the typical top-down decision-making process of a pension fund. Second, we study the implications for the following illiquid asset classes separately: real estate, mortgages, private equity, and hedge funds. While we do the empirical analysis on defined benefit pension plans in this paper, our theoretical framework also applies to different types of institutional investors. For instance, insurers with guaranteed products take into account both liquidity and capital requirements in choosing their optimal asset allocation (Niedrig, 2015). Also banks are exposed to liquidity and capital requirements in their asset allocation decision (Khan et al., 2017).

The *liquidity requirements* of pension funds consist of two components: short-term pension payments and collateral requirements following margin calls on derivative contracts. The cash required for pension payments over the next year is well predictable. However, the cash needed for collateral requirements is much less predictable. If the market value of a derivative contract declines, a pension fund must transfer cash or highly liquid short-term bonds to a margin account in order to limit the risk the counterparty faces. Margining on derivatives can become quite substantial, especially during financial crises.

We also consider *capital requirements* as a source of variation in illiquid assets holdings by pension funds. Regulations often require defined benefit plans to have sufficient capital to manage the risks they are exposed to, such as financial market risks and longevity risk.[4] In choosing its strategic asset allocation, a pension fund optimizes the trade-offs between different risk factors for a given level of required capital. As a result, a pension fund may be constrained to increase their exposure to illiquid assets. If a certain risk factor consumes a larger part of the available capital, less capital remains to be allocated to illiquid assets.

Liquidity and capital requirements interact in two ways. First, they interact through the liability duration as a measure of a pension fund's average investment horizon. On the one hand, a pension fund with a high liability duration is less liquidity constrained as it will have to pay less pensions in the short-term. This allows for a higher allocation to illiquid assets. On the other hand, a high liability duration also implies more exposure to interest rate risk through the present value of its liabilities. This restricts the opportunity to invest in illiquid assets as more of the available capital is required for interest rate risk. Second, liquidity and capital requirements also interact through derivatives. For instance, hedging interest rate risk increases the liquidity requirement as a result of higher collateral requirements. However, by hedging interest rate risk, a pension fund frees up capital to invest more in illiquid assets. Our theoretical model in Section 4.2 precisely disentangles these effects.

We empirically test the predictions from our theoretical model using the investment decisions of Dutch occupational pension funds from 2012 to 2017. The Dutch pension system is particularly well suited to study the effect of liquidity and capital requirements on the illiquid assets allocation for multiple reasons. First, Dutch pension funds have mandatory reporting requirements to the prudential supervisor, De Nederlandsche Bank (DNB). This gives us unbiased data. Second, the Dutch pension system is large in terms of size. The total assets under management (AUM) of Dutch pension funds' is approximately 1.3 trillion euro or 1.5 times the GDP of the Netherlands. Third, Dutch pension funds do not face quantitative investment restrictions. Regulation allows them to invest in any asset class in any country, as long as a pension fund complies with the capital requirements and the well-known prudent person principle. Dutch pension funds invest in a broad range of asset classes. In fact, over two-thirds of them invest in illiquid assets. Fourth, Dutch pension funds mainly have defined benefit pension liabilities. This means that they have a clear asset-liability perspective in making strategic investment decisions. Liabilities are valued marked-to-market by discounting accrued benefits against the prevailing term structure of

[4] In Section 4.2.2 we explain that a pension fund's capital is the difference between the market value of assets and liabilities. The term capital requirements is synonymous to funding requirements.

market interest rates. As a result, we can analyze the impact of liability interest rate risk on the illiquid assets allocation.

In short, these are our key findings. First, in line with our theoretical framework, we find a hump-shaped impact of liability duration on the fraction of risky assets invested in illiquid assets. Up to 18 years, liability duration positively affects this allocation. For higher durations the effect reverses. Second, we do not find evidence that interest rate risk hedging impacts the fraction of risky assets allocated to illiquid assets. Currency risk hedging, by contrast, creates the opportunity to allocate more to illiquid assets. A one standard deviation increase in currency risk hedging leads to an increase in the fraction of risky assets allocated to illiquid assets of approximately 0.71 percentage points. This implies a relative increase in the fraction of risky assets allocated to illiquid assets of 5.5 percent. Third, we find that, next to liability duration, also other pension fund characteristics impact strategic asset allocation decisions. Size positively affects the fraction of risky assets allocated to illiquid assets, which is in line with Andonov (2014) and Dyck and Pomorski (2016). A pension fund that is ten times larger in terms of assets under management has a 7.4 percentage points higher fraction of risky assets allocated to illiquid assets. Furthermore, corporate pension funds invest 7.6 percentage points less in illiquid assets as fraction of risky assets compared to industry-wide and professional group pension funds. Finally, pension funds with a lower funding ratio invest a larger fraction of risky assets in illiquid assets, supporting the results found in Basak and Shapiro (2001). A one standard deviation decrease in the funding ratio increases the fraction of risky assets allocated to illiquid assets by 0.89 percentage points.

The remainder of this paper is organized as follows. Section 4.2 explains the liquidity and capital requirements of pension funds and in which way these requirements affect the illiquid assets allocation in a theoretical framework. The data description is given in Section 4.3. The model and results are discussed in Section 4.4. The robustness check is in Section 4.5. Section 4.6 describes the implications of our theoretical framework for pension funds in different regulatory frameworks and Section 4.7 concludes.

4.2 Illiquid assets allocation: theory

A key responsibility of a pension fund is to optimize the asset allocation given its liability structure. This is known as Asset Liability Management (ALM). Here, we focus on a specific part of the ALM process: the strategic allocation to illiquid assets. For our theoretical framework the focus is on the aggregate illiquid assets allocation. In the empirical section we, however, also consider individual illiquid asset classes.

In deriving their strategic allocation to illiquid asset classes, pension funds assess the benefits and costs imposed by these investments. Important drivers of the investment decision are the risk-return trade-offs, the portfolio diversification benefits, and the ability of illiquid assets to hedge liability risk. Other drivers of investment decisions are constraints. We focus on liquidity and capital requirements and conjecture that these impact investment decisions. We, therefore, first formally introduce the liquidity and capital requirements. Next, we show in a theoretical model how the two requirements interact and affect investment decisions.

4.2.1 Liquidity requirements

A pension fund must have sufficient liquidity available to fulfill its immediate obligations. Liquidity requirements consist mainly of two components: short-term pension payments and collateral requirements on interest rate and currency derivatives. The cash required for pension payments in the foreseeable future is generally well predictable. The number of retirees and their benefits are known. However, the cash needed for collateral requirements, is much less predictable. If the market value of a derivative declines, the pension fund is required to transfer cash or highly liquid short-term bonds to a margin account. Margining on derivatives can become quite substantial, especially during financial crises. Pension payments can be seen as the expected liquidity requirement, whereas collateral requirements present liquidity risk. Liquidity problems arise when a pension fund lacks the resources to fulfill its immediate obligations.[5]

An investor facing liquidity risk should reduce the allocation to illiquid assets in order to avoid states of the world in which it would be short liquidity. Theoretical studies from for instance Gârleanu (2009) and Ang et al. (2014) show this formally. From a theoretical perspective we, therefore, predict that higher liquidity requirements restrict investments in illiquid assets. We will now discuss liquidity requirements in more detail.

[5]Salary payments to pension fund's staff, administrative expenses and investment costs are also sources that require short-term liquidity, but are generally small compared to the size of the pension fund and therefore outside the scope of this paper.

Liquidity requirement for pension payments

We start with the short-term pension payments and denote these by LR_P. We define this as the ratio of pension payments in the first year to the present value of total liabilities. To formalise this, suppose we have an homogeneous group of participants with mortality rate λ that receive annual pension payments of A at the beginning of each year. The pension payments in year t are then given by

$$A \exp(-\lambda t). \tag{4.1}$$

Assuming a flat term-structure of interest rates r, the present value of all future pension payments equals

$$V = \int_0^\infty A \exp(-(r+\lambda)t)dt = \frac{A}{r+\lambda}. \tag{4.2}$$

Then, in relative terms, the short-term pension payments equal

$$LR_P = \frac{A}{A(r+\lambda)^{-1}} = r + \lambda. \tag{4.3}$$

The duration of the present value of future pension payments V equals

$$D_V = -\frac{1}{V}\frac{dV}{dr} = \frac{1}{r+\lambda}. \tag{4.4}$$

Using (4.3) and (4.4) we rewrite the liquidity requirement from pension payments as

$$LR_P = \frac{1}{D_V}. \tag{4.5}$$

Equation (4.5) has an intuitive interpretation. The liability duration is the weighted average time to maturity of all pension payments. In other words, it measures a pension fund's average investment horizon. A high liability duration D_V implies less short-term payments as only a small fraction of the liabilities has to be paid out in the near future. In line with the findings in Ang et al. (2014), a high liability duration, therefore, creates opportunities to invest in illiquid assets. The inability to frequently trade illiquid assets is less of a restriction for a pension fund with a high liability duration.

Liquidity requirement for interest rate derivatives

Next to short-term pension payments, liquidity requirements also arise to meet margin requirements on derivatives. We consider margin requirements on interest rate swaps in this section and on currency forwards in the next section. For model tractability we refer to the interest rate derivates portfolio as a position in a single receiver swap. Pension funds mainly use receiver swaps to hedge the interest rate risk embedded in the present value of the pension liabilities. In a receiver swap a pension fund pays a counterparty a floating rate and receives, in return, a fixed rate over a certain notional amount. We denote the notional of the receiver swap by N and the duration of its fixed leg by D_R. The fraction of interest rate risk hedged with the receiver swap, again relative to the total value of liabilities V, is given by the following swap hedge ratio

$$\phi^R = \frac{N}{V}\frac{D_R}{D_V}.$$

We model the liquidity requirement on the swap through a margin call. In case of a receiver swap an increase in the interest rate dr^+ leads to a margin call because it lowers the value of the fixed leg of the swap. As a first-order approximation, the margin calls on the swap then equals

$$MC_R = \frac{ND_R dr^+}{V} = \phi^R D_V dr^+. \tag{4.6}$$

We could add a second-order, convexity, effect to (4.6). However, this has only a small effect on the quantitative results of the model and is, therefore, excluded here to keep the model simple.

Liquidity requirement for foreign exchange derivatives

The liquidity requirement on foreign exchange derivatives also results from margin calls in case the value of the derivative portfolio decreases. Pension funds generally hedge exchange rate risk using currency forwards. We assume that the pension funds in our model each have a position in a single forward contract. We consider an increase in the foreign exchange rate dFX^+ because this lowers the value of the forward contract and, thus, results in a margin call. The liquidity requirement from margin calls on foreign exchange derivatives then equals

$$MC_{FX} = w^{FX}\phi^{FX} dFX^+, \tag{4.7}$$

where w^{FX} is the fraction of V invested in foreign assets and ϕ^{FX} is the foreign exchange hedge ratio relative to V.

We can now determine the total liquidity requirement by adding together (4.5)-(4.7). This gives us the total liquidity requirement LR, relative to the value of the pension liabilities V, as

$$LR = \frac{1}{D_V} + \phi^R D_V dr^+ + w^{FX} \phi^{FX} dFX^+. \tag{4.8}$$

4.2.2 Capital requirements

Next to liquidity requirements the pension funds in our sample also face capital requirements to be able to absorb financial markets risks and longevity risk. In contrast to a bank or an insurer, a pension fund generally does not have shareholders that provide capital. Instead, a pension fund's capital is the difference between the value of the assets and the value of the liabilities. In the Netherlands, the capital requirement is risk-based and calculated as a Value-at-Risk risk measure (Broeders and Pröpper, 2010). In fact, the level of the required capital is calculated such that the probability that the funding ratio falls below 100 percent on a one-year horizon equals 2.5 percent. This level is pension fund specific. Pension funds determine the capital requirement by applying a method prescribed by law that takes the following risk factors into account: interest rate risk, equity and real estate risk, currency risk, commodity risk, credit risk, and longevity risk. The capital required for each of these risk factors is determined by simulating the impact on a pension fund's capital of a prescribed shock in the risk factor. The total capital requirement follows from aggregating the individual requirements using a correlation matrix. In practice a pension fund does not always have sufficient capital. If that is the case a pension fund gets a 10 year recovery period to become compliant again. The Dutch setting is unique and allows us study the effect of capital requirements on the illiquid assets allocation. For the purpose of our paper we only consider the capital requirement for interest rate risk and for currency risk. Pension funds also have a capital requirement for equity risk. But this requirement is only related to the equity allocation and does not depend on the liability structure, which is the core risk driver in our model.

Capital requirement for interest rate risk

The root cause of interest rate risk is embedded in the present value of the future pension payments. Pension funds can hedge this liability interest rate risk not only with receiver swaps but also with bonds. In the Dutch regulations, the capital requirement is therefore based on the part of the liability interest rate risk that is not hedged with swaps and bonds. We already introduced the swap hedge ratio ϕ^R. The bond hedge ratio, or the fraction of interest rate risk hedged with bonds, is denoted by ϕ^B. If a pension fund invests fraction B/V in bonds with a duration of D_B then ϕ^B is defined as

$$\phi^B = \frac{B}{V}\frac{D_B}{D_V}.$$

Next we consider a decrease in the interest rate dr^-. An interest rate decrease typically lowers the funding ratio because it increases the value of the liabilities more than the value of the swaps and bonds. The first-order approximation of the capital requirement for interest rate risk is given by[6]

$$CR_R = -(1 - \phi^R - \phi^B)D_V dr^-. \tag{4.9}$$

To keep the capital requirement for interest rate risk in (4.9) positive, we assume that pension funds never over-hedge their interest rate risk exposure, so that $\phi^R + \phi^B \leq 1$.[7]

Capital requirement for foreign exchange rate risk

Pension funds hedge foreign exchange rate risk typically with currency forwards. Exchange rate risk occurs when the liabilities are dominated in one currency and the investments in another currency. The capital requirement depends on the part of the exchange rate risk that is not hedged with forwards. We consider a decrease in the foreign exchange rate dFX^- because this lowers the value of the assets in the local currency. The capital requirement for

[6]We again exclude the convexity effect here as it only has a small second-order effect on the quantitative results.

[7]This assumption is realistic as the value-weighted average interest rate risk hedging across Dutch pension funds equals 40 percent, meaning that $\phi^R + \phi^B = 0.40$.

exchange rate risk equals

$$CR_{FX} = -w^{FX}(1 - \phi^{FX})dFX^{-}. \tag{4.10}$$

Adding (4.9) and (4.10) together gives us the total capital requirement CR, again relative to V, as

$$CR = -(1 - \phi^{R} - \phi^{B})D_V dr^{-} - w^{FX}(1 - \phi^{FX})dFX^{-}. \tag{4.11}$$

4.2.3 Overall liquidity and capital requirements

To derive the overall impact of liquidity and capital requirements on investment policy we will combine them. In order to do that we make the following three assumptions. First, we assume that capital and margin requirements are interchangable. If a pension fund hedges risks with derivatives it will have a lower capital requirement but it will be more exposed to margin calls. Second, we assume that a positive and negative shocks in a risk factor are equally likely and that the changes are identical in absolute value. The latter means for interest rate risk that $dr^{+} = -dr^{-} = dr$ and for exchange rate risk that $dFX^{+} = -dFX^{-} = dFX$. This is reasonable as a pension fund cannot ex ante know whether an increase or decrease in the underlying risk factor occurs. Third, we assume that the capital requirements and the margin calls are calibrated with the same probability on the same horizon. We believe this to be reasonable because from a risk management perspective it is logical to measure risk independent of how to manage the risk (via capital or via derivatives).

Under these assumptions we can combine (4.8) and (4.11) to obtain the following total requirement

$$TR = \frac{1}{D_V} + (1 - \phi^{B})D_V dr + w^{FX}dFX. \tag{4.12}$$

Equation (4.12) shows that the total requirement is a non-linear function of the liability duration and a linear function of the foreign exchange risk exposure. The reader may notice that Equation (4.12) does not depend on the swap hedge ratio ϕ^{R}. The intuition behind this is that in our model a margin call on the swap cancels against the capital requirement. The more a pension fund hedges it's interest rate risk with swaps, the higher the liquidity requirement and equally lower the capital requirement.[8] For the same reason, ϕ^{FX} also does not appear in the total requirement (4.12).

Based on the analysis above we can derive for which pension funds the total requirement TR is least constraining to invest in illiquid assets. For that we examine how the liability duration of a pension fund impacts the total requirement. We equate the first-order derivative of TR with respect to the liability duration D_V to zero, to get

$$\frac{dTR}{dD_V} = -\frac{1}{D_V^2} + (1-\phi^B)dr = 0. \tag{4.13}$$

If we solve this, we find the liability duration for which the total requirement TR is least constraining to be

$$D_V^* = \frac{1}{\sqrt{(1-\phi^B)dr}}. \tag{4.14}$$

Based on this we expect pension funds with a liability duration of around D_V^* to have the highest exposure to illiquid assets. Pension funds with a higher or a lower liability duration are more constrained by capital and liquidity requirements to invest in illiquid assets.

We illustrate how liability duration impacts the total requirement TR in a stylized, but representative, example. We take the following shocks to calculate the liquidity and capital requirement to be equal to $dr = 0.5\%$ and $dFX = 25\%$. These values are comparable to the ones in Dutch pension funds' regulations and to the calibration in Solvency II regulation. Next we take a continuum of pension funds that are equal except for their liability duration. We use the following parameter values that match with the average Dutch pension fund: $\phi^R = 20\%$, $\phi^B = 20\%$, $\phi^{FX} = 25\%$, and $w^{FX} = 50\%$. Figure 4.1 shows how, all else equal, the liquidity, capital, and total requirement depend on the liability duration. From this figure it follows that the liquidity requirement is a convex decreasing function of D_V, whereas the capital requirement is a linearly increasing function of D_V. The total requirement TR is therefore first increasing and then decreasing depending on a pension fund's liability duration. A low total requirement implies that a pension fund has more opportunities to invest in illiquid assets. Thus, our model predicts that the impact of D_V on the illiquid assets allocation follows the inverse shape of the total requirement in Figure 4.1. In other words, D_V creates a hump-shaped effect on the illiquid assets allocation. We will see in Section 4.4

[8]This is not exactly true in practice, because the total capital requirement takes into account a diversification effect between interest rate risk and other risk factors. This diversification effect however only has a marginal second order effect on the numerical solution of the model.

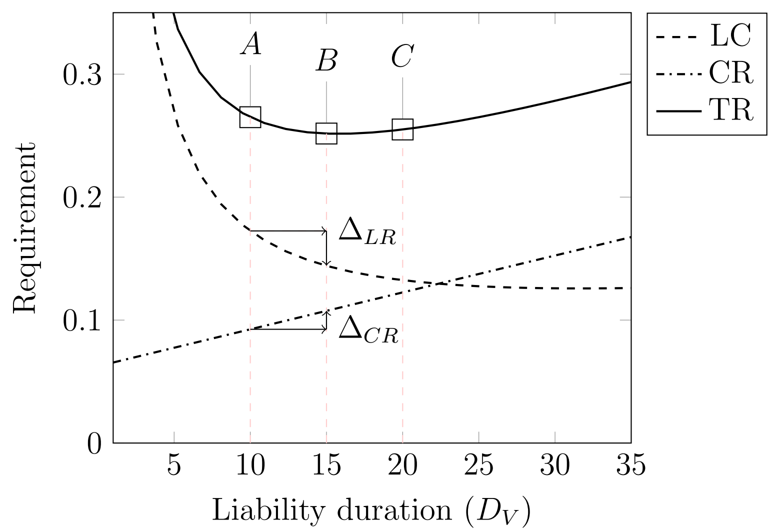

Figure 4.1. **Liquidity requirement, capital requirement, and total requirement as a function of liability duration**
We use the following parameter values $dr = 0.5\%$, $\phi^R = 20\%$, $\phi^B = 20\%$, $dFX = 25\%$, $\phi^{FX} = 50\%$, and $w^{FX} = 50\%$.

that our empirical analysis confirms this.

The economic interpretation of Figure 4.1 is as follows. If we compare pension fund A with a liability duration of 10 years, with pension fund B with a liability duration of 15 years, we see that pension fund B has a lower total requirement. The lower liquidity requirement of pension fund B (Δ_{LR}) is not fully compensated by a higher capital requirement (Δ_{CR}) compared to A. The higher liability duration of B thus creates more opportunities to invest in illiquid assets compared to pension fund A. If we compare pension fund C with a liability duration of 20 years, with pension fund B, we see the reverse effect. The total requirement of pension fund C is higher in comparison to pension fund B. Although pension fund C has a lower liquidity requirement, this is more than fully compensated by a higher capital requirement relative to pension fund B. In Figure 4.1 the reflection point is at $D_V = 15.8$. This reflection point will be different for other parameter configurations.

4.2.4 Summary of the hypotheses

In this section we summarize the hypotheses that follow from our theoretical framework. We expect a hump-shaped impact of liability duration on the illiquid assets allocation and we assess this by adding the square of the liability duration to the regression model. Based on the total requirement in (4.12) we expect that the swap hedge ratio and the foreign exchange hedge ratio have no effect on the fraction of risky assets invested in illiquid assets. Both the swap and foreign exchange hedge ratios do not appear in the total requirement because the liquidity and capital requirement cancel out against each other. Following (4.12) we do however expect that the bond hedge ratio will positively impact the illiquid assets allocation. If a pension fund hedges more interest rate risk with bonds it will unlock some of its capital. This can be used to invest a larger fraction of risky assets in illiquid assets. Further, we expect that pension funds that invest more in non-euro dominated assets will allocate less to illiquid assets. A higher exposure to currency risk will seize a larger part of the capital that therefore is less available to invest in illiquid assets.

In the empirical section we will focus on three regression specifications. The main regression uses the fraction of risky assets invested in illiquid assets as dependent variable. We explain in detail why we use the fraction of risky assets allocated to illiquid assets as dependent variable in Section 4.4. In addition to that, we will also assess the impact of liability duration and hedging on the allocation to illiquid assets and on the allocation to risky assets.

4.3 Data

We use quarterly data on N=219 Dutch pension funds including their asset allocations, interest rate derivatives, currency derivatives, and other characteristics such as size and pension fund type. The data are free from reporting biases because pension funds report mandatory, following strict reporting requirements, to De Nederlandsche Bank the prudential supervisor in the Netherlands. The sample runs from the beginning of 2012 to the end of 2017, or 24 quarters. Following a change in the reporting requirements in 2015, we carefully merge the data before and after 2015 to ensure consistency.[9] We only consider defined benefit pension funds because those are subject to capital requirements. Because Dutch pension funds cannot go bankrupt, there is no survivorship bias.[10] We do however exclude pension funds that are "liquidated" during the sample period. A liquidation means that the

[9]From 2015 onwards the reporting requirements are more granular in order to improve the knowledge on pension fund investment behavior.

[10]As a measure of last resort to prevent bankruptcy pension funds in the Netherlands can reduce accrued pension benefits.

pension fund will gradually transfer assets and liabilities to either another pension funds or to an insurance company for cost efficiency reasons. Because such a gradual transfer of assets may result in non-representative asset allocations we exclude these pension funds. Table 4.1 shows that in terms of total AUM we only exclude a minor fraction of pension funds this way, about 2 percent.

Table 4.1. **Total assets under management**

This table shows the total assets under management in billions of all pension funds (left column) and of the pension funds selected for the analysis (right column) at the end of each year. The total number of pension funds is denoted by N. In the analysis, we leave out pension funds that are liquidated during the sample period.

year	**AUM all**	**AUM selected**
2012	904.15	894.33
2013	945.98	936.50
2014	1,131.74	1,124.42
2015	1,146.66	1,118.72
2016	1,262.54	1,233.41
2017	1,326.07	1,297.67
N	330	219

A - Assets

Our data distinguishes between the following 12 assets classes: government bonds, stocks in mature markets, credits, stocks in emerging markets, inflation index-linked bonds, cash and short-term receivables, listed indirect real estate, commodities, non-listed real estate, mortgages, private equity, and hedge funds.[11] One minus the allocation to government bonds, inflation-index bonds, cash and short-term receivables is defined as the allocation to risky assets (w^{RISKY}).[12]

To distinguish between illiquid and liquid asset classes we need to define the concept of

[11]Credits contain all credit related products, e.g. corporate bonds, bank loans, and syndicated loans.

[12]Privately issued inflation-index bonds constitute only a small portion of the market. As a result, we assume that all inflation-index bonds are issued by governments.

liquidity. An asset is considered less liquid if the investor cannot quickly sell a significant quantity of the asset at a price near its fundamental value. Asset classes such as private equity require buyers to have significant capital and particular knowledge about the asset class, which are both often limited in supply. Therefore, transactions costs of illiquid assets can become substantial. For some illiquid assets, legal impediments make it impossible to trade for a particular time period at all, such as lock-up periods that some hedge funds and private equity funds impose. Certainly, each asset or asset class has some time-varying degree of liquidity. Trading volume in a corporate bond may, e.g., drop to nil if the company runs into a bankruptcy. During the Great Financial Crisis trading in mortgage backed securities came to a stop. As a result, no clear distinction can be made between liquid and illiquid assets. However, some asset classes are substantially more illiquid than others in terms of the three dimensions (time, quantity and price) mentioned above. As pension funds are long term investors, we use immediacy as the key criterion to distinguish between liquid and illiquid asset classes. We classify the sum of non-listed real estate, private equity, mortgages, and hedge funds allocations as the total allocation to illiquid assets (w^{ILLIQ}). Private equity includes both listed and non-listed private equity, infrastructure investments and micro finance investments. The allocation to private equity contains only the commitments already made, so future commitments are not included. Mortgages contains mortgage-backed securities and direct mortgage lending.

The sum of allocations to stocks in mature markets, credits, stocks in emerging markets, listed indirect real estate and commodities is defined as total allocation to liquid risky assets (w^{LIQ}). We define the allocation to risky assets equal to the sum of the allocation to risky illiquid assets and the allocation to risky liquid assets

$$w^{RISKY} = w^{ILLIQ} + w^{LIQ}.$$

Pension funds report both strategic and actual asset allocations. We focus on the strategic asset allocations because those better reflect the decisions made by pension funds. The actual asset allocation, by contrast, is less useful for our research question because it is influenced by market fluctuations and imperfect portfolio rebalancing (Bikker et al., 2010).

Table 4.2 presents the summary statistics. Panel A highlights the strategic asset allocations. The averages are equally weighted over pension funds and time. Government bonds, stocks mature markets and credits are the most important asset classes, with average allocations of 33, 29 and 18 percent respectively. Concerning the illiquid asset classes, non-listed real estate is the largest asset class with an average allocation of 4 percent. The 90th percentile

Table 4.2. **Descriptive statistics**

Panel A provides summary statistics of pension funds' strategic asset allocation. The means and standard deviations of the actual asset allocation are shown between brackets. Panel B provides the summary statistics of the variables specified in Section 4.3: allocation to illiquid assets (w^{ILLIQ}), allocation to risky assets (w^{RISKY}), fraction of risky assets allocated to illiquid assets (w^{ILLIQ}/w^{RISKY}), liability duration (D_V), collateral requirements on interest rate derivatives (CRr), collateral requirements on currency derivatives ($CRfx$), bond hedge ratio (ϕ^B), fraction of investments outside euro area (w^{FX}), log of total AUM ($Size$), required funding ratio (Rfr), and one period lag of the actual funding ratio (Fr). The summary statistics are computed as the equally weighted average over all pension funds and all quarters in the 2012-2017 period.

Panel A: asset allocations	**mean**	**std. dev.**	**p10**	**p50**	**p90**	**obs.**
Liquid assets						
Government bonds	0.33 [0.31]	0.20 [0.21]	0.05	0.33	0.60	4,956
Stocks mature markets	0.29 [0.30]	0.13 [0.13]	0.16	0.27	0.43	4,956
Credits	0.18 [0.19]	0.12 [0.11]	0.00	0.17	0.34	4,956
Stocks emerging markets	0.05 [0.05]	0.04 [0.04]	0.00	0.05	0.10	4,956
Inflation index-linked bonds	0.02 [0.02]	0.05 [0.05]	0.00	0.00	0.08	4,956
Listed real estate	0.02 [0.03]	0.03 [0.04]	0.00	0.00	0.05	4,956
Commodities	0.01 [0.01]	0.02 [0.02]	0.00	0.00	0.05	4,956
Cash and short-term receivables	0.01 [0.03]	0.07 [0.08]	0.00	0.00	0.03	4,956
Illiquid assets						
Non-listed real estate	0.04 [0.04]	0.05 [0.05]	0.00	0.03	0.12	4,956
Mortgages	0.02 [0.02]	0.04 [0.04]	0.00	0.00	0.07	4,956
Private equity	0.01 [0.01]	0.02 [0.02]	0.00	0.00	0.05	4,956
Hedge funds	0.01 [0.01]	0.02 [0.02]	0.00	0.00	0.04	4,956

Panel B: variables	**mean**	**std. dev.**	**p10**	**p50**	**p90**	**obs.**
Allocation to illiquid assets	0.08	0.08	0.00	0.06	0.20	4,956
Allocation to risky assets	0.64	0.18	0.40	0.65	0.90	4,956
Fraction illiquid in risky assets	0.13	0.12	0.00	0.11	0.30	4,904
Liability duration	18.90	3.98	14.60	18.60	23.90	4,978
CR on interest rate derivatives	0.05	0.04	0.00	0.04	0.10	4,973
CR on currency derivatives	0.05	0.04	0.00	0.05	0.10	4,991
Bond hedge ratio	0.25	0.14	0.09	0.22	0.45	4,940
Foreign investments	0.22	0.22	0.00	0.20	0.51	3,682
Log of total AUM	5.84	0.81	5.00	5.79	6.86	4,997
Required funding ratio	1.16	0.07	1.10	1.16	1.23	4,992
Funding ratio (t-1)	1.09	0.13	0.96	1.07	1.22	4,992

shows that 10 percent of the pension funds invest more than 12 percent in this asset class. Pension funds on average invest 2 percent in mortgages. The other two illiquid asset classes have a strategic allocation of around 1 percent on average. Panel A also shows the mean and standard deviation of the actual asset allocations between brackets. The differences between the strategic and actual asset allocations are small suggesting that pension funds on average rebalance their portfolios accurately.

Turning to Panel B, we see that the average allocation to the illiquid assets equals 8 percent. Approximately one-third of Dutch pension funds do not invest in illiquid assets at all. The 90th percentile however shows that 10 percent of the pension funds allocate over 20 percent of their total AUM to illiquid assets.

Table 4.3 shows that the strategic illiquid assets allocation is not fixed and varies over the sample period. This holds for both the aggregate illiquid assets allocation and the illiquid asset classes separately. Pension funds generally review their strategic asset allocation every 3 years. This implies that pension funds on average reviewed there illiquid assets allocation twice during the sample period.

Table 4.3. **Time variation in the strategic illiquid assets allocation**

This table shows the cross-sectional average time variation of pension fund's illiquid assets allocation over the period 2012–2017. The average time variation is computed as the cross-sectional average of the standard deviation of pension funds' strategic illiquid assets allocations over time.

Illiquid asset class	**time variation**
Total illiquid assets	0.0251
Non-listed real estate	0.0146
Mortgages	0.0153
Private equity	0.0040
Hedge funds	0.0048

B - Liability duration

Pension funds report the modified duration of their liabilities (D_V). The liability duration is summarized in Panel B of Table 4.2. The average liability duration equals 18.9 years. However, 10 percent of the pension funds have a liability duration below 14.6 years and 10 percent have a liability duration in excess of 23.9 years. This shows there is quite some variation in the average investment horizon of pension funds.

C - Collateral requirements

Unfortunately, pension funds do not report on their swap hedge ratio or their foreign exchange hedge ratio. However, the data do allow us to calculate the collateral requirements in case of an adverse event in the underlying risk factor, which we argue are good proxies for the swap hedge ratio and the foreign exchange hedge ratio.[13] We will, therefore, explain in detail how we measure the collateral requirements.

Pension funds report the market value of the total interest rate derivatives and currency derivatives that they have entered into. In addition, they also report the expected values of these positions after some predefined shocks in the underlying risk factors. For interest rate risk these shocks are an increase (decrease) in the term structure of market interest rates of 1 percentage points and for foreign exchange risk an appreciation (depreciation) of foreign currencies with respect to the euro of 25 percent.

The collateral requirement on interest rate derivatives (CRr) is the absolute difference between the market value of the portfolio of derivatives after a predetermined shock, MVr_s, minus its current market value, MVr_c. We divide the absolute value of this difference by the total assets under management (AUM)

$$CRr = \frac{|MVr_s - MVr_c|}{AUM}.$$

We define the collateral requirements on currency derivatives ($CRfx$) as the absolute difference between the market value of the portfolio of derivatives after a predetermined shock, $MVfx_s$, minus its current market value, $MVfx_c$. We express the absolute value of the change relative to the total AUM

$$CRfx = \frac{|MVfx_s - MVfx_c|}{AUM}.$$

We determine the collateral requirements by using an increase in the interest rate of 1 percentage points and an increase of the foreign currency relative to the euro of 25 percent.

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[13]As of 2015, pension funds do report the swap hedge ratio. The correlation between the reported swap hedge ratio and our computation of the collateral requirement on interest rate derivatives equals 0.75. This shows that our approximation of the swap hedge ratio is not far off.

The collateral requirements on interest rate derivatives and on currency derivatives are summarized in Panel B of Table 4.2. The averages of both are of the same order of magnitude and equal 5 percent of AUM. The 10th percentiles are in both cases equal to zero, revealing that some pension funds do not hedge these risks with derivatives at all.

D - Bond hedge ratio and foreign investments

Our theoretical model in (4.12) shows that the bond hedge ratio (ϕ^B) and the fraction invested outside the euro area (w^{FX}) affect the illiquid assets allocation. Table 4.2 shows that pension fund on average hedge 25 percent of their liability interest rate risk with bonds. About 10 percent of the pension funds in the sample have a bond hedge ratio in excess of 45 percent. The fraction investments outside the euro area equals 22 percent on average and 51 percent in the 90th percentile. In our theoretical model we express all results relative to the liabilities. Here we take both the bond hedge ratio and the foreign investments as a fraction of total AUM to make the quantities easier to interpret. Expressing the quantities in either AUM or liabilities does however not materially affect our empirical analysis.

E - Control variables

As control variables we include the log of total assets under management ($Size$), pension fund type ($Type$), the required funding ratio (Rfr) and the actual funding ratio at the end of the previous period (Fr). We distinguish between three types of pension funds. There are 55 industry-wide pension funds, 10 professional group pension funds and 154 corporate pension funds in the sample. Industry-wide pension funds are generally mandatory pension funds and organize pensions for a specific industry or sector, e.g., civil servants or hospital staff. Professional group pension funds provide pensions for a single profession such as hairdressers or pharmacists. Corporate pension funds arrange pensions for a particular company.

The level of the required funding ratio to comply with regulations depends on the specific risk profile of a pension fund.[14] Including the required funding ratio in the regression model, therefore, controls for differences in risk appetite. For instance, a "young" pension fund (with a high liability duration) could substantially differ in its risk appetite compared to an "old" pension fund (with a low liability duration), potentially driving the impact of liability duration on the illiquid assets allocation. Furthermore, pension funds that hedge only a

[14]The risk profile is measured by the "mismatch" between assets and liabilities.

small part of their interest rate risk or currency risk, could be the ones that take more risk in general, potentially driving the effect of hedging on the illiquid assets allocation.

The actual, previous period, funding ratio is also included in the analysis. From the literature on risk-taking behavior of pension funds, the actual funding ratio could either have a positive or a negative effect on the illiquid assets allocation. Basak and Shapiro (2001) show that, compared to normal circumstances, investors take more risk in worst case scenarios when they are subjected to a VaR requirement. On the other hand, Rauh (2009), using US corporate defined benefit pension funds data, finds that poorly funded pension plans allocate a larger share of their assets to government bonds.

Size, required funding ratio and actual funding ratio are summarized in Panel B, Table 4.2. The 10th and 90th percentile of the log of total AUM reveals that the size distribution is right skewed: the largest pension funds in our sample are considerably larger compared to the mean pension fund. The average required funding ratio equals 116 percent and varies from 110 to 123 percent. The actual funding ratio equals 109 percent on average, which is substantially below the required funding ratio of pension funds.

Table 4.4 splits the sample in pension funds that invest and that do not invest in illiquid assets. The latter group takes less risk in general, having on average a 10 percentage points lower risky assets allocation. The table also reveals that the average size of pension funds that do not invest in illiquid assets is considerably smaller. On other dimensions, however, the subsamples are comparable.

4.4 Allocation to illiquid assets: empirical results

To measure the impact of liquidity and capital requirements on the illiquid assets allocation, we estimate a static random effects Tobit model.[15] The Tobit model controls for left-censoring of the allocation to illiquid assets at zero. This is necessary as a substantial number of pension funds does not invest in illiquid assets. Asset allocation decisions are typically first made to very broad asset classes such as safe assets (bonds) and risky assets (stocks). In a second step, asset allocations are determined within each broad asset class (Binsbergen et al., 2008). Following this top-down decision-making process, we first analyze the aggregate illiquid assets allocation. Because illiquid asset classes differ in their degree of

[15]A random effects structure corrects for time-invariant pension funds' characteristics that we do not observe but potentially play a role in investment decisions.

Table 4.4. **Descriptive statistics - subsamples**

This table specifies the summary statistics of the variables specified in Section 4.3 for pension funds that *do invest in illiquid assets (Panel A) and pension funds that do not invest in illiquid assets (Panel B)*: allocation to illiquid assets (w^{ILLIQ}), allocation to risky assets (w^{RISKY}), fraction of risky assets allocated to illiquid assets (w^{ILLIQ}/w^{RISKY}), liability duration (D_V), collateral requirements on interest rate derivatives (CRr), collateral requirements on currency derivatives ($CRfx$), bond hedge ratio (ϕ^B), fraction of investments outside euro area (w^{FX}), log of total AUM ($Size$), required funding ratio (Rfr), and the one period lag of the actual funding ratio (Fr). The summary statistics are computed as the equally weighted average over all pension funds and all quarters in the 2012-2017 period.

Panel A: pension funds that invest in illiquid assets

	mean	**std. dev.**	**p10**	**p50**	**p90**
Allocation to illiquid assets	0.12	0.08	0.03	0.11	0.22
Allocation to risky assets	0.67	0.16	0.47	0.67	0.90
Fraction illiquid in risky assets	0.18	0.10	0.05	0.16	0.32
Liability duration	18.61	3.50	15.00	18.00	23.00
CR on interest rate derivatives	0.05	0.04	0.00	0.04	0.09
CR on currency derivatives	0.06	0.04	0.00	0.05	0.10
Bond hedge ratio	0.24	0.12	0.10	0.22	0.40
Foreign investments	0.23	0.22	0.00	0.23	0.53
Log of total AUM	6.05	0.77	5.19	5.98	7.00
Required funding ratio	1.17	0.07	1.11	1.17	1.24
Funding ratio (t-1)	1.09	0.12	0.96	1.08	1.22

Panel B: pension funds that do not invest in illiquid assets

	mean	**std. dev.**	**p10**	**p50**	**p90**
Allocation to illiquid assets	0.00	0.00	0.00	0.00	0.00
Allocation to risky assets	0.57	0.22	0.30	0.56	0.91
Fraction illiquid in risky assets	0.00	0.00	0.00	0.00	0.00
Liability duration	20.00	4.88	14.00	20.00	26.00
CR on interest rate derivatives	0.05	0.05	0.00	0.05	0.12
CR on currency derivatives	0.04	0.04	0.00	0.03	0.09
Bond hedge ratio	0.28	0.18	0.08	0.23	0.58
Foreign investments	0.18	0.19	0.00	0.12	0.44
Log of total AUM	5.28	0.62	4.65	5.30	6.03
Required funding ratio	1.15	0.06	1.08	1.14	1.22
Funding ratio (t-1)	1.10	0.16	0.95	1.07	1.24

immediacy, we look at individual illiquid asset classes separately in the next section.

We will however not assess the illiquid assets allocation directly. Instead we will take the fraction of risky assets invested in illiquid assets as our key dependent variable. The main reason to take this fraction is to circumvent mechanical effects. The following two examples show these mechanical effects. First, suppose that a pension fund decides to invest more in bonds, this mechanically results in a lower allocation to risky assets and therefore, potentially, also a lower allocation to illiquid assets. Second, Dutch pension funds invest the majority of their bond portfolio in the euro area, whereas the risky assets are generally invested more globally. Currency hedging is thus directly related to the risky assets allocation. A positive effect of currency hedging on the illiquid assets allocation could therefore be mechanical.

In alternative model specifications we nonetheless also use the allocation to illiquid assets (w^{ILLIQ}) and to risky assets (w^{RISKY}) as dependent variables. In the latter case we estimate a standard random effects model as there is no censoring around zero.

The general model specification is

$$\frac{w_{it}^{ILLIQ}}{w_{it}^{RISKY}} = \beta_0 + \beta_1 D_{V,it} + \beta_2 D_{V,it}^2 + \beta_3 CRr_{it} + \beta_4 CRfx_{it} + \beta_5 \phi_{it}^B + \beta_6 w_{it}^{FX} \qquad (4.15)$$

$$+ \beta_7 Size_{it} + \beta_8 Type_i + \beta_9 Rfr_{it} + \beta_{10} Fr_{it-1} + \lambda_t + \epsilon_{it}$$

where w_i indicates the allocation of pension fund $i = 1, ..., N$ at the end of the quarter $t = 2012Q1, ..., 2017Q4$. The main explanatory variables are the liability duration (D_V), the square of the liability duration (D_V^2), the collateral requirements on interest rate derivatives (CRr), the collateral requirements on currency derivatives ($CRfx$), the bond hedge ratio ϕ^B, and the fraction of total foreign investments w^{FX}. To link the main regression specification directly to our theoretical framework, we recall from the previous section that CRr proxies for the swap hedge ratio ϕ^R and $CRfx$ proxies for the foreign exchange hedge ratio ϕ^{FX}. The control variables are the log of total AUM ($Size$), the pension fund type ($Type$), the required funding ratio (Rfr) and the lag of the actual funding ratio (Fr). We include dummies for the pension fund type, where the reference group consists of industry-wide pension funds. A professional group pension fund is denoted by dummy $Prof$ and a corporate pension fund by dummy $Corp$. The fall in market interest rates over our sample period may have caused pension funds to increase their allocation towards illiquid assets in a search for yield (Boubaker et al., 2017). Therefore, we control for time-fixed effects (λ) in all our model specifications.

Another potential concern is that pension funds with a high liability duration are more likely to hedge interest rate risk using swaps. The reason for this is that there are not sufficient long-term government bonds available to match with the duration of long-term pension liabilities. This issue is more severe for pension funds with a high liability duration. Therefore, liability duration D_V and collateral requirement for interest rate risk CRr may be correlated. Table 4.5 shows that there is indeed a positive correlation between D_V and CRr, however, given a value of 0.40 collinearity should not be an issue. This implies that the results for D_V and CRr can be interpreted separately.[16]

Table 4.5. **Correlation table of key variables**

This table provides the correlation matrix of the key variables: liability duration (D_V), collateral requirements on interest rate derivatives (CRr), collateral requirements on currency derivatives ($CRfx$), bond hedge ratio (ϕ^B), fraction of investments outside euro area (w^{FX}), log of total AUM ($Size$), required funding ratio (Rfr), and the one period lag of the actual funding ratio (Fr).

Correlation matrix	D_V	CRr	$CRfx$	ϕ^B	w^{FX}	$Size$	Rfr	Fr
D_V	1							
CRr	0.40	1						
$CRfx$	0.02	0.12	1					
ϕ^B	−0.29	−0.40	−0.24	1				
w^{FX}	0.20	0.01	0.27	−0.17	1			
$Size$	0.04	0.06	0.21	−0.15	0.28	1		
Rfr	0.12	−0.17	0.13	−0.24	0.29	0.16	1	
Fr	−0.33	−0.19	−0.08	0.06	−0.07	−0.15	−0.02	1

[16] We also run our models to test for a possible interaction between liability duration and collateral requirements. The interaction term between both variables is, however, statistically indifferent from zero in all of the model specifications. These results are available upon request. Further, the liability duration (D_v) is negatively correlated with bond hedge ratio (ϕ^B) as well as the lagged funding ratio (Fr). The variance inflation factor for liability duration equals $\frac{1}{1-R^2} = 1.15$, which is far below the threshold for multicollinearity issues (10), and hence multicollinearity is not an issue here.

A - Liability duration

Table 4.6 shows the results for the main model specification in (4.15). The first column shows that liability duration has a positive effect on the fraction of risky assets allocated to illiquid assets, whereas the square of the liability duration has a negative impact. Both coefficients are statistically significant at the 1 percent significance level. This means that there is indeed a hump-shaped relationship. Up to a liability duration of 18 years ($\frac{\partial w^{ILLIQ}/w^{RISKY}}{\partial D_V} = \beta_1 + 2\beta_2 D_V = 0 \rightarrow D_V = -\frac{\beta_1}{2\beta_2}$), the effect of liability duration is positive. After this point however, the effect reverses. The fraction of illiquid assets for a pension fund with a liability duration of 11 years is 1.07 percentage points higher compared to a pension fund with a liability duration of 10 years. A pension fund with a liability duration of 26 years allocates 1.02 percentage points less to illiquid assets compared to a pension funds with a 25 year duration.[17] Figure 4.2 shows the estimated hump-shaped impact of liability duration on the fraction of the risky assets allocated to illiquid assets.

The results are in line with our theoretical predictions. Up to a liability duration of 18 years, the liquidity requirement decreases faster than the capital requirement increases. A pension fund with a high liability duration has less short-term liabilities relative to a pension fund with a low liability duration. A high liability duration implies that it is less of a constraint for a pension fund not being able to trade frequently in illiquid assets. Beyond a liability duration of 18 years however, the capital requirement increases faster than the liquidity requirement decreases. This lowers the opportunity to invest in illiquid assets.

As an alternative specification we use the allocation to illiquid risky assets w^{ILLIQ} (Table 4.6, Column (2)). Again, a hump-shaped impact of liability duration on the illiquid assets allocation appears. We also assess the allocation to risky assets w^{RISKY}. Table 4.6, Column (3) shows a negative impact of liability duration on the risky assets allocation, while the of duration squared is positive. Figure 4.3 plots the combined impact on the allocation to risky assets. The increase in the risky asset allocation on the right-hand side of this figure coincides with the findings in Andonov et al. (2017), who find that the investment policy of public and private European and Canadian pension funds and private US pension funds is more aggressive for less mature pension funds. A study by Alestalo and Puttonen (2006)

[17] Notice that the coefficients are estimates based on the uncensored latent variable, not the observed outcome. The coefficients are the right interpretation for all observations on the dependent variable, w^{ILLIQ}/w^{RISKY}, above zero. In order to get the effect on the actual observed dependent variable, the coefficient estimates have to be multiplied by the probability of the dependent variable being above zero.

Table 4.6. **Main results - total illiquid assets allocation**

In this table, we show the random effects estimators based on the regression (4.15). The dependent variable in the first column is the strategic fraction of risky assets allocated to illiquid assets (w^{ILLIQ}/w^{RISKY}), the dependent variable in the second column is the strategic allocation to illiquid assets (w^{ILLIQ}) and the third column uses the strategic risky assets allocation as dependent variable (w^{RISKY}). The fourth column uses actual rather than strategic allocations. The independent variables include the liability duration (D_V), the liability duration squared (D_V^2), the collateral requirements on interest rate derivatives (CRr), the collateral requirements on currency derivatives ($CRfx$), bond hedge ratio (ϕ^B), fraction of foreign investments (w^{FX}), the log of total AUM ($Size$), $Corp$ indicates a corporate pension fund, $Prof$ indicates a professional pension fund, Rfr is the required funding ratio, and Fr the one period lag of the actual funding ratio. Standard errors are between parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
Dependent variable	w^{ILLIQ}/w^{RISKY}	w^{ILLIQ}	w^{RISKY}	w^{ILLIQ}/w^{RISKY}
D_V	.0254***	.0126***	−.0404***	.0120**
	(0056)	(.0039)	(.0062)	(.0050)
D_V^2	−.0007***	−.0004***	.0009***	−.0004***
	(.0001)	(.0001)	(.0002)	(.0001)
CRr	−.0124	−.0141	−.0208	.0355
	(.0576)	(.0405)	(.0713)	(.0517)
$CRfx$	.1784***	.1371***	.4104***	.0151
	(.0363)	(.0255)	(.0481)	(.0325)
ϕ^B	.0204	−.0761***	−.4038***	.0127
	(.0181)	(.0127)	(.0220)	(.0162)
w^{FX}	−.0125	−.0013	−.1342***	.0424***
	(.0125)	(.0088)	(.0152)	(.0108)
$Size$	.0736***	.0566***	.0604***	.0625***
	(.0102)	(.0075)	(.0098)	(.0093)
$Corp$	−.0757***	−.0454***	.0218	−.0535***
	(.0217)	(.0143)	(.0194)	(.0173)
$Prof$	.0184	.0068	−.0234	.0053
	(.0438)	(.0288)	(.0380)	(.0341)
Rfr	−.0006	.0045	.0192	.0608***
	(.0190)	(.0133)	(.0277)	(.0180)
Fr	−.0686**	−.0562***	−.0723**	−.1418**
	(.0275)	(.0192)	(.0304)	(.0245)
Time FE	Y	Y	Y	Y
N	3,401	3,401	3,433	3,400
Left-censored	877	890	n/a	606
Uncensored	2,524	2,511	n/a	2,794

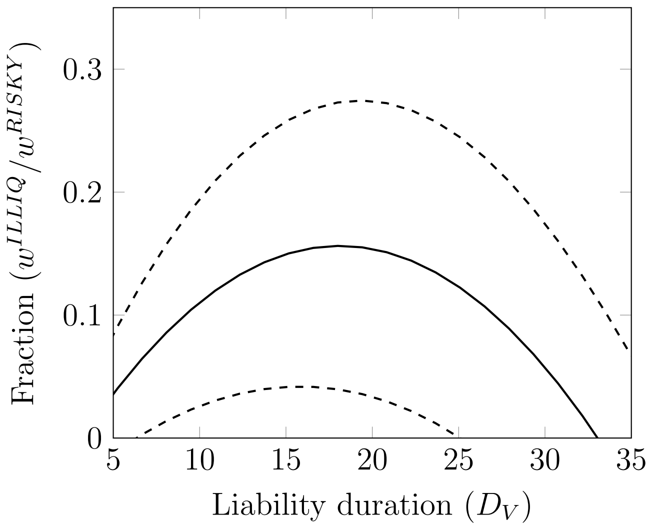

Figure 4.2. **The effect of the liability duration on the fraction of risky assets allocated to illiquid assets**
The calculations are based on assuming an industry-wide pension fund that has average foreign exchange risk hedging activities, average size, and average lag funding ratio (other variables are set equal to zero as they are not statistically significant). The dashed line represents the 95% confidence interval.

reports similar findings for Finnish pension funds. However, Figure 4.3 also highlights on the left-hand side that mature pension funds invest more in risky assets compared to pension funds with an average liability duration. A possible explanation is that mature pension funds can more easily hedge their liabilities with bonds instead of swaps and can consequently use their capital for risk-taking.

In Column (4) of Table 4.6 we use actual rather than strategic asset allocations. We observe the following. First, the liability duration has a again hump-shaped impact on the fraction of risky assets allocated to illiquid assets. The reflection point is now at a liability duration of 15.0 years. Second, hedging of interest rate risk and currency risk does not affect the fraction of risky assets allocated to illiquid assets. Third, foreign investments has a significant and positive impact. Although these results seem to better support or theoretical predictions, using actual instead of strategic asset allocations might cause effects that are (partly) driven by the performance of the different asset classes or imperfect rebalancing by pension funds.

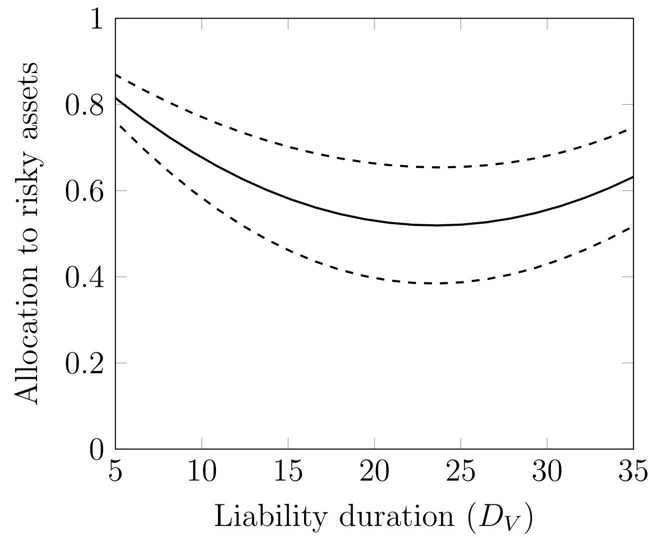

Figure 4.3. **The effect of the liability duration on the risky assets allocation**
The calculations are based on assuming an industry-wide pension fund that has average foreign exchange risk hedging activities, average bond hedging activities, average foreign investments, average size, and average lag funding ratio (other variables are set equal to zero as they are not statistically significant).The dashed line represents the 95% confidence interval.

B - Collateral requirements

Table 4.6 shows that the collateral requirements on interest rate swaps (CRr) do not have an effect on the allocation to illiquid assets. This is in line with the theoretical predictions of our model: the liquidity and capital requirement cancel out against each other. However, we do find a significant and positive impact of collateral requirements on currency forwards. At first glance, this result seems to conflict the predictions of our model. However, in practice collateral requirements for currency forwards are less strict than for interest rate swaps and in some cases even non-existent. In our theoretical framework, this implies the that the increase in liquidity requirements for currency risk hedging is smaller than the decrease in the capital requirement. This creates opportunities to invest in illiquid assets. A one standard deviation increase in the collateral requirements (an increase of 0.04 $CRfx$) implies an increase in the fraction of risky assets allocated to illiquid assets of approximately 0.71 percentage points. The average fraction of risky assets allocated to illiquid assets of the pension funds that have a positive allocation to illiquid assets equals 18 percent. This implies a relative increase in the fraction of risky assets allocated to illiquid assets of approximately 4.0 percent.

The impact of collateral requirements on the allocation to risky assets is also shown in Table 4.6, Column (3). The findings are comparable to the effects of the fraction of risky assets invested in illiquid assets. Notice that we control for the total fraction invested in foreign currencies such that the results we obtain are not mechanical. A one standard deviation increase in the collateral requirement (an increase of 0.04 $CRfx$) implies an increase in the risky assets allocation of approximately 1.64 percentage points. This implies a relative increase in the risky asset allocation of 2.6 percent. Taken together, a larger foreign exchange hedge ratio increases the allocation to risky assets which in turn increases the fraction of risky assets that is allocated to illiquid assets.

C - Bond hedge ratio and foreign investments

We do not find a statistically significant effect of the bond hedge ratio on the fraction allocated to illiquid assets, although the sign of the coefficient is in line with our theoretical framework. The bond hedge ratio negatively affects the allocation to illiquid assets and to risky assets. The latter however is a mechanical effect because hedging interest rate risk with bonds by construction lowers the allocation to risky assets.

We also do not find an effect of foreign investments on the fraction invested in illiquid assets, although the sign of the coefficient is again in line with our model. The same is true for the impact on the illiquid assets allocation. The fraction invested in foreign assets has a significant negative impact on the risky assets allocation. Investing more in foreign currencies, while keeping hedging fixed, increases the capital requirement and therefore limits opportunities to invest in risky assets. A 10 percentage points increase in the fraction invested in foreign assets decreases the risky assets allocation with 1.35 percentage points.

D - Control variables

We now turn to the control variables. Table 4.6 shows that size has a positive and significant impact on the allocation to illiquid assets. A pension fund that is ten times larger in terms of total assets under management allocates a 7.4 percentage points higher fraction of risky assets allocated to illiquid assets. Illiquid assets are generally complex investment products and therefore the pension fund needs to have sufficient knowledge to manage these products. The larger a pension fund, the better it can afford to pay the costs involved in managing complex investment products. Our finding is consistent with Andonov (2014) and Dyck and Pomorski (2016), who show that the increase in the allocation to illiquid assets is more pronounced for large institutional investors. Moreover, Stoughton and Zechner (2011) argue that economies of scale in alternative assets exist because only large investors can afford to pay high fixed search costs to identify profitable projects or select skilled external managers. On top of that, large institutional investors have more power to negotiate better fees (Broeders et al., 2016). Table 4.6 also shows that large pension funds invest more in risky assets in general, although the economic impact is somewhat smaller. A pension fund that is ten times larger invests 6.0 percentage points more in risky assets.

We also find that corporate pension funds allocate significantly less to illiquid assets as a fraction of risky assets compared to industry-wide pension funds. We believe that this difference is due to the fact that a corporation is required to report on its pension fund in the annual accounts and is therefore less willing to take risks. Indeed, the riskiness of a corporate pension plan impacts the risk profile of the corporation (Jin et al., 2006). An additional explanation is that corporate pension funds are more exposed to sponsor default risk compared to compulsory and professional group pension funds. Therefore, they are less willing to take risk (Broeders, 2010).

Finally the required funding ratio does not affect asset allocations, while the lag of the actual funding ratio affects all allocations in Table 4.6 negatively. This implies that pension funds with a lower last period funding ratio invest a larger fraction of their risky assets in illiquid assets. This result supports the theoretical finding by Basak and Shapiro (2001) that pension funds for which a VaR requirement is binding take additional investment risks. This finding is also consistent with the empirical study of Peng and Wang (2019), who study alternative investments decisions of US public pension plans, and find that pension plans with lower funding ratios allocate more to alternative assets. A one standard deviation decrease in the previous period funding ratio increases the fraction of risky assets allocated to illiquid assets by 0.89 percentage points. Pension funds also increase the total risky assets allocation when previous period funding ratio decreased. In other words, a lower funding ratio implies a higher total risky assets allocation and a larger fraction of the risky assets allocation is invested in illiquid assets.

4.4.1 Empirical results separate illiquid asset classes

So far, we treated illiquid asset classes as a homogeneous group. However, the degree of immediacy differs across separate illiquid asset classes. For instance, the typical time between transactions for residential housing is 4-5 years, although it can vary from months to decades (Hansen, 1998) and (Miller et al., 2011). The average time between transactions is relatively high in case of private equity. Private equity investments generally run for 10 years and trading before a contract expires is unusual (Metrick and Yasuda, 2010).

To reflect these difference in immediacy, Table 4.7 presents the results for the following illiquid asset classes separately: real estate, mortgages, private equity and hedge funds. The hump-shaped effect of the liability duration on the fraction of risky assets allocated to illiquid assets is present in all four asset classes. The cut-off point where the marginal benefits (lower liquidity requirement) and the marginal costs (higher capital requirement) of a higher liability duration are equal, is close to the aggregate cut-off point of 18 for the overall fraction of risky assets allocated to illiquid assets.

The results of swap hedge ratios are however mixed across the different asset classes. Consistent with the aggregated results, the swap hedge ratio does not affect the allocation to real estate and mortgages. In case of private equity, the swap hedge ratio positively affects the real estate allocation. Notice that the economic magnitude is however small. A one standard deviation increase in collateral requirement leads to an increase of the fraction of risky assets allocated to private equity of 0.23 percentage points. On the other hand, the swap hedge ratio negatively affects the allocation to hedge funds. The results for hedge funds should however be interpreted with care for mainly two reasons. First, the number of uncensored observations is relatively small compared to the total number of observations. Second, events outside our model may have impacted hedge fund allocation. Some hedge funds received negative publicity during the financial crisis, because investors who tried to withdraw their money to meet liquidity needs where unable to do so. This may play a role in the allocation to hedge funds.

The results for foreign exchange hedge ratio are also mixed across the different asset classes. The foreign exchange hedge ratio does not affect the allocation to hedge funds and negatively affects the allocation to private equity. A one standard deviation increase in collateral requirement leads to an increase in the fraction of risky assets allocated to private equity of 0.80 percentage points.

The required funding ratio also has different effects. Pension funds with a higher required funding ratio invest more in private equity and less in mortgages. This reveals that pension funds with higher tolerance for risk might prefer certain illiquid assets over others.

These differences in findings indicate that strategic decisions made at the top level do not have to be implemented at each individual asset class level. What matters is that the overall investment policy, risk exposures, and liquidity profile are in accordance with the policy set by pension fund.

Table 4.7. **Main results - separate illiquid assets classes**

In this table, we show the random effects estimators based on the regression (4.15) *for separate illiquid asset classes*. The dependent variable in the first column is the fraction of risky assets allocated to real estate (w^{RE}/w^{RISKY}), in the second column the fraction of risky assets allocated to mortgages (w^{MG}/w^{RISKY}), in the third column the fraction of risky assets allocated to private equity (w^{PE}/w^{RISKY}), and in the fourth column the fraction of risky assets allocated to hedge funds (w^{HF}/w^{RISKY}). The independent variables include the liability duration (D_V), the liability duration squared (D_V^2), the collateral requirements on interest rate derivatives (CRr), the collateral requirements on currency derivatives ($CRfx$), bond hedge ratio (ϕ^B), fraction of foreign investments (w^{FX}), the log of total AUM ($Size$), $Corp$ indicates a corporate pension fund, $Prof$ indicates a professional pension fund, Rfr is the required funding ratio, and Fr the one period lag of the actual funding ratio. Standard errors are between parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
Dependent variable	w^{RE}/w^{RISKY}	w^{MG}/w^{RISKY}	w^{PE}/w^{RISKY}	w^{HF}/w^{RISKY}
D_V	.0138***	.0178**	.0076**	.0753***
	(.0045)	(.0070)	(.0036)	(.0088)
D_V^2	−.0004***	−.0004**	−.0002***	−.0022
	(.0001)	(.0002)	(.0001)	(.0002)
CRr	.0409	−.0453	.0585*	−.1474*
	(.0427)	(.0947)	(.0325)	(.0835)
$CRfx$	.1085***	.2535***	−.2068***	−.0216
	(.0316)	(.0420)	(.0435)	(.0653)
ϕ^B	.0187	.0151	−.0209**	−.0855***
	(.0143)	(.0281)	(.0102)	(.0243)
w^{FX}	.0767***	−.0454***	.0041	.0290*
	(.0101)	(.0172)	(.0069)	(.0164)
$Size$	.0541***	.0510***	.0608***	.0156
	(.0088)	(.0120)	(.0065)	(.0102)
$Corp$	−.0544***	−.0846***	−.0218**	.0068
	(.0175)	(.0223)	(.0091)	(.0178)
$Prof$	−.0004	−.0620	.0300*	.0937***
	(.0377)	(.0444)	(.0161)	(.0330)
Rfr	−.0001	−.2514***	.1340***	.0172
	(.0134)	(.0705)	(.0309)	(.0138)
Fr	−.1206***	.1164***	.0725***	−.1167
	(.0220)	(.0357)	(.0158)	(.0360)
Time FE	Y	Y	Y	Y
N	3,432	3,432	3,432	3,432
Left-censored	1,359	2,186	2,200	2,851
Uncensored	2,073	1,246	1,232	581

4.5 Robustness check

From the previous sections, it follows that the impact of liability duration on the illiquid assets allocation is strong. As a robustness check we take an alternative measure of liability duration in this section. Liability duration measures the maturity of a pension fund and this is directly related to demographics. Although we have no data on demographics, we do know the pension payments and the value of the liabilities per year. The ratio of pension payments to the value of the liabilities is an alternative measure for maturity (De Haan, 2018). If this ratio is high, a large part of the participants consists of retirees.

In the robustness check we replace the liability duration by the ratio of pension payments to liabilities ($Benefits$).[18] Table 4.8 shows that using this alternative measure also results in a hump-shaped impact on the fraction of risky assets allocated to illiquid assets. Up to a ratio of 4.8 percent, the fraction of risky assets allocated to illiquid assets is positively affected.[19] After this point, the effect is reversed. Column (3) of Table 4.8 shows that the hump-shaped effect is absent for the allocation to risky assets.

In our theoretical framework we saw that the ratio of pension payments to the value of liabilities is given by $\frac{1}{D_V}$ (see Eq. (4.4) in Section 4.2). Figure 4.4 provides evidence that the fitted curve for the observed ratios of pension payments to pension liabilities is indeed a convex and decreasing function of liability duration, in line with the theoretical framework. This confirms that the inverse of the liability duration is a good proxy for the liquidity requirement from pension payments.

4.6 Illiquid assets allocation other regulatory frameworks

Compared to banks and insurance companies, pension fund regulation is much more diverse across countries. Here, we focus on the difference in capital requirements for pension funds in the US and Canada to show our model implications outside the Netherlands. The US and Canada have fixed capital requirements, whereas the Netherlands has risk-based capital requirements.

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[18] We only include observations at the end of each year as the pension payments are only available on an annual basis. The sample period is 2012-2016, as the pension payments for the year 2017 are not available yet.

[19] $\frac{\partial w^{ILLIQ}/w^{RISKY}}{\partial Benefits} = \beta_1 + 2\beta_2 Benefits = 0 \rightarrow Benefits = -\frac{\beta_1}{2\beta_2}$.

Table 4.8. **Robustness - alternative measure of liability duration**

In this table, we show the random effects estimators based on (4.15) *using an alternative measure for the liability duration.* The dependent variable in the first column is the fraction of risky assets allocated to illiquid assets (w^{ILLIQ}/w^{RISKY}), the dependent variable in the second column is the allocation to illiquid assets (w^{ILLIQ}) and the third column uses the risky assets allocation as dependent variable (w^{RISKY}). The independent variables include the ratio of pension payments to liabilities ($Benefits$), the ratio of pension payments to liabilities squared ($Benefits^2$), the collateral requirements on interest rate derivatives (CRr), the collateral requirements on currency derivatives ($CRfx$), bond hedge ratio (ϕ^B), fraction of foreign investments (w^{FX}), the log of total AUM ($Size$), $Corp$ indicates a corporate pension fund, $Prof$ indicates a professional pension fund, Rfr is the required funding ratio, and Fr the one period lag of the actual funding ratio. Standard errors are between parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)
Dependent variable	w^{ILLIQ}/w^{RISKY}	w^{ILLIQ}	w^{RISKY}
$Benefits$	6.9264***	4.3555***	2.8844*
	(1.5747)	(1.0672)	(1.7548)
$Benefits^2$	−71.5539***	−38.0856**	12.4495
	(22.1661)	(15.0461)	(24.3063)
CRr	.0894	.0708	−.0512
	(.1408)	(.0964)	(.1830)
$CRfx$	.1016	.0875	.3857***
	(.0806)	(.0553)	(.1100)
ϕ^B	−.0767*	−.1045***	−.4227***
	(.0382)	(.0264)	(.0469)
w^{FX}	.0342	.0090	−.1412***
	(.0271)	(.0186)	(.0345)
$Size$	.0774***	.0543***	.0368***
	(.0125)	(.0083)	(.0131)
$Corp$	−.0760***	−.0466	.0069
	(.0216)	(.0142)	(.0227)
$Prof$	−.0026	−.0099	−.0485
	(.0415)	(.0272)	(.0431)
Rfr	.2196**	.2517***	.6764***
	(.1153)	(.0788)	(.1479)
Fr	−.0128	−.0406	−.1867***
	(.0513)	(.0349)	(.0576)
Time FE	Y	Y	Y
N	700	700	707
Left-censored	182	182	n/a
Uncensored	518	518	n/a

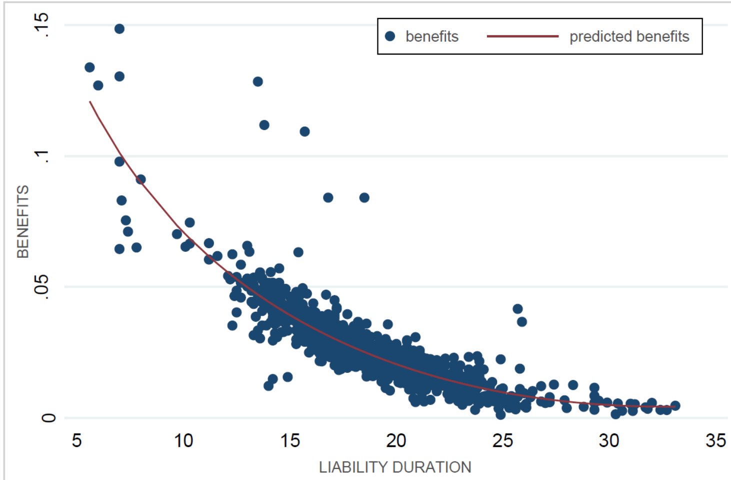

Figure 4.4. **Benefits as a function of the liability duration**
The dots in this figure show the observed ratios of pension payments to pension liabilities ($Benefits$) and the fitted curve for the observed ratios of pension payments to pension liabilities (red line), both as a function of the liability duration.

Boon et al. (2018) study public, corporate, and industry wide pension funds in the US, Canada, and the Netherlands and find that the regulatory framework matters for the asset allocation decisions. They show that risk-based capital requirements and mark-to-market valuation are associated with a 7 percentage points lower allocation to risky assets, regardless of market conditions. Given this evidence and the setup of our model we conjecture the following implications for the illiquid assets allocations in the US and in Canada. A higher interest rate risk exposure does not increase the capital requirements for pension funds in the US and Canada. Under this condition the impact of the liability duration on the illiquid assets allocation is likely to be increasing. In other words, the higher the liability duration, the higher we expect the illiquid assets allocation to be. Therefore, we expect higher illiquid asset allocations in the US and Canada. This is indeed what we observe empirically. The Willis Towers Watson Global Pension Assets Study (2018) shows that the value weighted average illiquid assets allocation in the US equals 28 percent and Canada equals 31 percent, whereas in the Netherlands it is only 17 percent.[20]

The predictions of our model are likely to be amplified when considering life insurers. Life insurers have high liability durations and are subject to Solvency II regulation in Europe.

[20]https://www.willistowerswatson.com/-/.../Global-Pension-Asset-Study-2018-Japan.pdf

Under this solvency regime the capital requirement is calibrated on a 0.5% one year default probability. This implies that the capital requirement is more profound for European life insurers than for Dutch pension funds, for which the capital requirement is calibrated on a 2.5% probability. We therefore predict the turning point of the hump-shaped effect of the liability duration on the illiquid assets allocation to be at a lower liability duration for insurance companies. In other words, the negative effect of having a higher liability duration (higher capital requirements) will outweigh the benefits (lower liquidity requirements) at a faster rate.

4.7 Conclusion

In this paper, we empirically study the impact of liquidity and capital requirements on a pension fund's illiquid assets allocation. Liquidity requirements result from short-term pension payments and collateral requirements on derivatives used for hedging purposes. In addition, the pension funds in our sample are capital constrained. Liquidity and capital requirements interact. By hedging interest rate risk and currency risk, a pension fund is less exposed to these two risk factors and can take additional investment risks. However, hedging strategies using derivatives involve margining. This hampers a pension fund to invest in illiquid assets as they impose a liquidity requirement.

The key conclusions of our empirical analysis are as follows. First, we find a hump-shaped impact of liability duration on the fraction of risky assets allocated to illiquid assets. Up to 18 years, the liability duration positively affects this allocation. However, beyond this point, the effect is reversed and the allocation to illiquid assets decreases. Second, we do not find evidence that swap hedge ratios impact the illiquid assets allocation: the liquidity and capital requirements cancel each other out. In the case of currency risk, however, hedging does impact the illiquid assets allocation positively. Finally, pension fund size, pension fund type and funding ratio also impact the illiquid assets allocation.

These findings offer important policy implications. Based on our model and empirical findings it does not appear obvious for long-term investors to always invest more in illiquid assets. The capital requirement for defined benefit pension funds becomes a binding constraint if the liability duration is substantially high. Although relaxing capital requirements for interest rate risk might seem a reasonable solution to mitigate the impact of this constraint, this is not what we recommend. The interest rate risk is inherent to the nature of the pension liabilities in a defined benefit pension contract. If a pension fund guarantees benefits, interest rate risk becomes the key risk factors to manage. An alternative approach would be to redefine pension liabilities such that they no longer embed long-term interest rate guarantees. This, however, means that the interest rate risk shifts to the beneficiaries. Beneficiaries are less knowledgeable to understand and less equipped to manage interest rate risk.

A more important policy implication concerns adequate liquidity and collateral management for pension funds. Pension funds increasingly use derivatives to hedge risks. Derivatives involve greater liquidity needs. These liquidity needs can increase exponentially in times of market turbulence. Collateral management is therefore key and becomes even greater once pension funds are integrated in the central clearing of derivatives. Pension funds should prepare adequate contingency planning to be able to manage collateral through periods of market turbulence. More emphasis could, therefore, be placed on liquidity and collateral management in pension regulations.

Chapter 5

A Survey of Institutional Investors' Investment and Management Decisions on Illiquid Assets[1]

5.1 Introduction

Investment and management decisions regarding illiquid assets (e.g. real estate, private equity, and infrastructure) are of particular relevance to pension funds since they are important investors in these asset classes. The recent Willis Towers Watson Global Pension Assets Study 2018 shows that the seven largest pension markets in the world,[2] with total pension assets of USD 37,770 billion at the end of 2017, increased their average illiquid asset allocation from 4% in 1997 to 25% in 2017. While there is a large literature on the benefits and challenges of investing in illiquid assets, to the best of our knowledge the self-reported attitudes and policies of institutional investors with respect to illiquid assets have not been documented extensively before.

In this survey we provide insight into the self-reported attitudes and policies with respect to illiquid assets and present the results of a survey of nine Dutch and five Canadian pension funds and fiduciary managers. We have interviewed these survey participants regarding the role of illiquid assets in the strategic asset allocation, the valuation of illiquid assets, and

[1]This chapter is based on joint work with Patrick Tuijp and forthcoming in the Journal of Portfolio Management. We thank the survey participants for their willingness to participate and for their valuable input, and Ortec Finance and Theo Nijman for arranging the interviews. We thank Mark Anson, Martin Bakker, Marie Brière, Dirk Broeders, Chantal de Groot, Bert Kramer, Loranne van Lieshout, Rients Miedema, Theo Nijman, Bas Werker, Pieter Wijnhoven, and the Netspar Editorial Board for their helpful suggestions and comments. Kristy Jansen gratefully acknowledges the financial support from Netspar.

[2]Australia, Canada, Japan, the Netherlands, Switzerland, the UK, and the US.

liquidity management. We formulate four best practices based on the results of the survey.

The six Dutch pension funds in our survey represent assets under management (AUM) of EUR 342 billion, and the four Canadian pension funds represent AUM of CAD 203 billion.[3] We exclude the AUM of the three Dutch fiduciary managers and the one Canadian fiduciary manager from the reported numbers since they also manage assets for investors other than pension funds. The Dutch pension funds in our sample on average invest 15% of their portfolio in illiquid assets, while for Canadian pension funds this is 34%.

The interviews with the survey participants were arranged by Ortec Finance and Theo Nijman and took place during the period from December 2017 to January 2019. While we do not have a random sample, we do cover approximately 26% of total pension assets in the Netherlands and approximately 9% for Canada.[4] These percentages do not include the fiduciary managers for the same reason why we do not include them in the AUM figures. We specifically asked the fiduciary managers to give answers from the perspective of their pension fund clients. We therefore jointly analyze the answers given by pension funds and fiduciary managers. The participating pension funds focus mainly on defined benefit plans. The interview questions and the list of survey participants are listed in the Appendix. The survey participants were allowed to give more than one answer to each survey question.

In our survey, we define the following asset classes as illiquid: private equity, private debt, direct real estate, infrastructure, hedge funds, and mortgages. We base this classification on the criterion that pension funds might not be able to trade the asset for a substantial period of time. While the classification for particular asset classes may sometimes differ, the survey participants generally indicated that our definition of illiquid asset classes aligns with theirs.

5.2 Investing in illiquid assets

The academic literature shows that illiquid assets may offer benefits to pension funds and other investors in terms of liquidity premiums (Driessen and De Jong, 2015; Vayanos

[3]Total AUM reflects the situation at year-end 2017 and is based on the annual reports of the participating pension funds.

[4]Willis Towers Watson (2019) reports total Dutch pension assets at year-end of 2017 of about EUR 1,331 billion and total Canadian pension assets at year-end of 2017 of about CAD 2,225 billion. Exchange rate conversion has been applied from USD to local currency against year-end 2017 foreign exchange rates obtained from Exchange Data International.

and Wang, 2013),[5] liability hedging (e.g. Sharpe and Tint, 1990b; Lucas and Zeldes, 2009), and portfolio diversification (e.g. Kallberg et al., 1996; Hoesli et al., 2004; Bianchi et al., 2014). In addition to these benefits, the long investment horizon of pension funds makes them well-suited for investing in illiquid assets classes (Attig et al., 2012). The search for yield in a low interest rate environment may provide additional incentives to consider riskier and less liquid investments (e.g. Rajan, 2006; Yellen, 2011).

Investing in illiquid assets also involves challenges. Infrequent trading of illiquid assets may lead to large losses in case of forced selling (Diamond and Rajan, 2011), for instance due to sudden and unpredictable margin requirements on derivative positions. In addition, whether real estate investments are managed internally or externally matters for investment costs (Andonov et al., 2015). Finally, the valuation smoothing that results from appraisal effects may present a challenge when assessing illiquid investments. Using an appraisal-based index could lead to lower volatility and higher autocorrelation estimates relative to a transaction-based index for similar assets (Fisher et al., 1994; Hoesli et al., 2004). Anson (2016) demonstrates how to un-smooth illiquid asset returns for asset allocation, risk management, and performance evaluation purposes.

In addition to these benefits and challenges, the literature has investigated portfolio choice with illiquid assets. Ang et al. (2014) show that an investor should reduce the allocation to illiquid assets in order to avoid situations where it would not be possible to meet, e.g., pension payments.[6] Given a certain allocation to illiquid assets, investors may still adopt different strategies in response to immediate liquidity needs. For instance, they may sell liquid assets first to minimize transactions costs, as opposed to selling illiquid assets, and keeping a cushion of liquid assets (Duffie and Ziegler, 2003; Scholes, 2000). Empirical evidence indicates that institutional investors tend to follow the former strategy (Ben-David et al., 2012; Manconi et al., 2012; Driessen and Xing, 2017).

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[5]However, the literature shows mixed evidence of liquidity premiums in different asset classes. For instance in the case of direct real estate, Qian and Liu (2012) report a positive effect of illiquidity on expected returns, although the effect is relatively small. Benveniste et al. (2001) show that REITs increase the value of underlying real estate assets by 12-22%, which suggests that a direct real estate liquidity premium may indeed exist. Ang et al. (2013b), on the other hand, show comparable performance of REITs and direct real estate, which indicates the absence of a direct real estate liquidity premium.

[6]Beber et al. (2020) go a step further and show that short-term investors may choose not to invest in the least liquid assets at all because the expected transaction costs may be prohibitively high relative to the return over a short horizon.

5.3 Pension fund regulations

Pension fund regulations are highly relevant to understand how pension funds invest. For instance, Andonov et al. (2017) show that U.S. public pension funds have incentives to invest in risky assets as their liability discount rate is linked to the expected return on assets. In addition, Boon et al. (2018) study U.S., Canadian, and Dutch pension funds and show that risk-based capital requirements and mark-to-market valuation of assets and liabilities are associated with a 7 percentage points lower risky asset exposure.

In this section we provide an overview of relevant aspects of the Dutch and Canadian pension fund regulations. First, we summarize the retirement systems for both countries. Second, we focus on the following four aspects of pension fund regulation: investment restrictions, asset and liability valuation methods, funding requirements, and recovery periods.

5.3.1 Regulations in the Netherlands

The Dutch pension system is built on three pillars. The first pillar is a pay-as-you-go (PAYG) system and consists of state pensions that provide a basic income, called AOW (Algemene Ouderdomswet). The second pillar consists of collective pension schemes which are administered by pension funds. The pension schemes are financed from mandatory contributions by employers and employees. The contribution rate amounts on average to 20-25% of total wages.[7] In most cases the employer contributes 2/3 and the employee 1/3.[8] The first pillar replaces broadly 30% of average wages and the second pillar 60-65% of average lifetime wages (Gerard, 2019). The third pillar consists of individual pension products, such as an annuity insurance. The pension funds participating in our survey are second pillar funds.

Dutch pension funds do not face any quantitative investment restrictions, but they are required to invest in accordance with the prudent-person rules outlined in the Pension Act.[9] This implies that pension funds should invest in the best interest of the fund participants. Pension funds use market valuation for both assets and liabilities. Market valuation of defined benefit liabilities implies that they are discounted using a yield curve that is based

[7]Pension funds differ in their contribution rates, to be found in the annual reports of pension funds.

[8]https://www.rijksoverheid.nl/onderwerpen/pensioen/opbouw-pensioenstelsel

[9]https://wetten.overheid.nl/BWBR0020809

on the euro swap curve as set by the Dutch Central Bank (DNB). The minimum funding requirement (Minimaal Vereist Eigen Vermogen, MVEV) is determined by a calculation method described in the Pensions Act. Importantly, the minimum funding ratio is based on nominal valuation of liabilities, and only accrued benefits are taken into account. For most pension funds, the minimum capital requirement corresponds to a funding ratio of about 104.2%.[10]

Besides the minimum capital requirement, Dutch pension funds also have risk-based capital requirements. In fact, the required capital is calculated such that the probability that the nominal funding ratio falls below 100% on a one-year horizon equals 2.5%. For a stylized pension fund with equal investment in equity and bonds, the capital requirement (Vereist Eigen Vermogen, VEV) amounts to a funding ratio of approximately 120%. If the funding ratio falls below the required capital threshold, the pension fund enters a ten-year recovery period to meet the capital requirement. If the funding ratio remains below the minimum requirement for five years, a pension benefit cut may be necessary if recovery of the fund is not possible otherwise.[11]

Since the valuation of the liabilities is nominal and market-based, the most important risk factor for Dutch pension funds is interest rate risk. This is especially true for green pension funds, i.e. pension funds with relatively young participants and therefore long-term pension liabilities. Pension funds can substantially reduce their capital requirements by hedging interest rate risk.

The regulatory framework does not force pension funds to hold capital depending on their portfolio liquidity, although the prudent-person rule requires pension funds to carefully consider liquidity in their investment strategies. Moreover, the capital requirements for liquid and illiquid assets may vary. For instance, non-listed equities, such as private equity, require a larger amount of capital than listed equities. On the other hand, direct real estate investments have lower capital requirements than listed equities. The differences in risk-based capital requirements depend on the overall perceived risk profile of the asset class.

[10] http://www.toezicht.dnb.nl/2/50-202138.jsp

[11] http://www.toezicht.dnb.nl/2/50-232915.jsp

5.3.2 Regulations in Canada

The Canadian pension system also consists of three pillars. The first pillar is a PAYG system and consists of state pensions, called Old Age Security (OAS). Canadians whose income is below a certain threshold receive a Guaranteed Income Supplement (GIS) in addition to OAS. The second pillar is the Canadian Pension Plan (CPP), except for Quebec, which has its own Quebec Pension Plan (QPP). CPP and QPP provide contributors and their families with partial replacement of earnings in case of retirement. The contribution rate is set each year and equals 10.2% in 2019.[12] The intention is to replace up to 25% of full-time income upon retirement. The contribution is equally split between employer and employee. The third pillar consists of workplace pensions and private savings plans. The Canadian pension funds participating in the interviews focus on the third pillar.

Although prior to 2010 restrictions applied for investments in foreign assets, real estate, and Canadian resource property, no investment restrictions exist for Canadian pension funds today. Canadian pension funds are also subject to a prudent-person rule.[13] The valuations of assets and liabilities to determine the funding ratio are typically market-based. However, the Canadian Institute of Actuaries argues that valuation of assets producing a value different from market value may be suitable in some cases. For instance, smooth valuation of assets may be appropriate to moderate the volatility of contributions.[14] In accordance with the Pension Benefits Act (PBA) and the Income Tax Act (ITA), each pension fund must file an actuarial valuation at least every three years in order to estimate the fund's surplus or deficit and to determine the fund's minimum funding requirements.[15]

The reported liabilities and funding ratios are based on a going-concern assumption as well as on a solvency basis. The going-concern basis implies that all assumptions made in estimating total pension fund liabilities are based on the principle that the pension fund will continue to operate. The liabilities under the going-concern assumption depend on expected returns of investment portfolios, inflation expectations, and the future growth rate of employee wages. The solvency basis focuses on the ability of the plan to meet its liabilities

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[12]https://www.canada.ca/en/services/benefits/publicpensions/cpp/contributions.html

[13]For instance, such as set out in Section 22 of the Ontario Pension Benefits Act, R.S.O. 1990, c. P.8. https://www.ontario.ca/laws/statute/90p08

[14]https://www.cia-ica.ca/docs/default-source/2014/214100e.pdf

[15]For further details we refer to the certified general accountants association of Canada (Chartered Professional Accountants Canada): https://www.cpacanada.ca.

assuming that the plan is terminated on the date on which the report is filed. Liabilities are computed based on market interest rates, where in some provinces pension funds are allowed to average interest rates over the preceding five years.[16]

Unlike the minimum funding requirements in the Netherlands, the Canadian minimum funding requirements are not risk-based. The recovery period for pension funds that do not meet the minimum funding ratio differs across provinces. Federal plans and provincial plans in Alberta and Ontario have a maximum recovery period of ten years. Other provinces typically set this at five years (Boon et al., 2018).

5.4 Survey outcomes

In this section we provide the outcomes of our survey. We start by discussing the outcomes for The Netherlands and Canada separately, and we conclude this section with a comparison of the Dutch and Canadian outcomes.

5.4.1 Dutch fund outcomes

We start with the summary statistics of the Dutch pension funds in our sample (see Exhibit 5.1). The average AUM equals 57 billion euros, with a standard deviation of 73 billion euros. This shows that our sample contains both large and small funds. The average allocation to illiquid assets is 15%, close to the average 14% illiquid asset allocation reported in the Willis Towers Watson Global Pension Assets Study 2018 for the Netherlands. The ratio of active members to retirees is on average 1.2, indicating that the fraction of active members is only slightly higher than that of retirees. The average (nominal) funding ratio equals 115% with a standard deviation equal to 13%, revealing substantial variation in the funding status across pension funds. As noted in the introduction, the fiduciary managers are not included in the summary statistics as they manage assets for investors other than pension funds as well.

[16]For further details we refer to the certified general accountants association of Canada (Chartered Professional Accountants Canada): https://www.cpacanada.ca.

Table 5.1. **Summary Statistics Dutch Pension Funds**

This table provides summary statistics for six Dutch pension funds (fiduciary managers are excluded). AUM is in millions of euros. Source: annual reports (ultimo 2017) of participating pension funds.

	mean	**std.dev.**
AUM	57,030	72,510
Percentage illiquid assets	15%	5%
Actives to retirees ratio	1.2	0.9
Funding ratio	115%	13%

Strategic asset allocation to illiquid assets for Dutch funds

From the full set of interviews, including both Dutch and Canadian survey participants, five main reasons for investing in illiquid assets emerge: diversification benefits, liability hedging purposes, risk-return trade-off, smooth valuation of assets, and steady cash flows. Smooth valuation of assets results from the infrequent valuation of illiquid assets, and valuations may also lag relative to those of more frequently traded assets. From a balance sheet perspective these aspects may reduce the volatility of illiquid asset valuations. Several illiquid asset classes provide steady cash flows, such as rental income for real estate, which may help in ensuring that sufficient cash is available to meet cash requirements in the future.

The main reported reasons for the nine Dutch survey participants to invest in illiquid assets are summarized in Table 5.2. The risk-return trade-off is one of the main reasons for investing in illiquid assets, which fits with the search for yield phenomenon described by Rajan (2006) and Yellen (2011). Some survey participants specifically mentioned the natural comparative advantage that they have as long-term investors to capture liquidity premiums. As a second important reason for investing in illiquid assets, six out of nine also mentioned diversification. For the other three funds diversification is a positive side effect, but not the main reason to invest in illiquid assets. Only a few pension funds indicated liability hedging as a principal reason to invest in illiquid assets. The funds mentioning liability hedging as a main reason particularly see benefits for real estate and infrastructure but not so much for private equity. However, not all survey participants are convinced that real estate and infrastructure are good hedges against inflation risk. A fourth reason for investing in illiquid assets, given by one of the survey participants, is the ability to reduce balance sheet volatility through the smooth valuation of illiquid assets (see e.g. Hoesli et al., 2004, for a further discussion). Representatives of the Dutch pension funds did not mention steady cash flows as a principal reason for investing in illiquid assets.

Table 5.2. **Reasons for Investing in Illiquid Assets**

This table summarizes the number of Dutch survey participants who mentioned one of the following main reasons to invest in illiquid assets: steady cash flows, smooth valuation, risk-return trade-off, liability hedging, and diversification. The total number of survey participants is nine, and survey participants could mention more than one reason.

	number of participants
Smooth valuation	1
Steady cash flow	0
Risk-return trade-off	9
Liability hedging	2
Diversification	6

Table 5.3 summarizes how the survey participants determine their illiquid asset allocation. Six of the nine survey participants determine their illiquid asset allocation using an asset liability management (ALM) study. However, two survey participants mentioned that, if the optimal allocation resulting from the ALM study is too high, the pension fund board might decide to invest less in illiquid assets. Three of the nine survey participants stipulate a target return for illiquid assets. These pension funds invest only in illiquid assets that they expect to achieve at least the specified target return. Pension funds may therefore deviate from initial strategic allocations depending on the amount of assets available for investment that meet the specified target return.

The third question concerns whether pension funds apply an upper limit to the percentage of assets allocated to illiquid assets. Most pension funds do have a maximum illiquid asset allocation, of approximately 20-25%. The maximum allocations mentioned are relatively close to each other. The prudent-person rule described in the Pension Act is interpreted by many Dutch pension funds as a maximum of 25% in illiquid assets. Although some pension funds have not explicitly specified their maximum allocation to illiquid assets, some note that the maximum is implicitly set by the size of their portfolio components.

Dutch pension funds typically divide their total portfolio in a liability matching portfolio

Table 5.3. **Determination of Illiquid Asset Allocation**

This table summarizes the number of Dutch survey participants who mention one of the following ways to determine the allocation to illiquid assets: a target return, board decision, and/or ALM study. The total number of survey participants is nine, and survey participants could mention more than one approach.

	number of participants
Target return	3
Board	2
ALM study	6

and a return portfolio. As mentioned in our discussion of the regulatory framework, the liabilities of Dutch pension funds are computed using a market-based yield curve. For this reason, Dutch pension funds invest part of their portfolio in liquid fixed income assets to reduce the interest rate exposure mismatch between their assets and liabilities. These fixed income assets used for liability hedging purposes reside in the matching portfolio. With potential exceptions such as mortgages, illiquid assets typically reside in the return portfolio. If the liability matching portfolio is relatively large (say 60% of total assets), then even with a relatively modest allocation the illiquid assets (say 10% of total assets) forms a sizable fraction (in the example 25%) of the return portfolio. This may limit the allocation to illiquid assets as a fraction of the total portfolio, since these would otherwise crowd out return portfolio investments in more liquid assets such as listed equities.

Lastly, we asked pension funds which other aspects are taken into account when investing in illiquid assets. We mention a few of these aspects here. Pension funds also take into account the sustainability aspect of illiquid investments such as wind parks. The cost aspects of illiquid assets also play a major role for Dutch pension funds. They mentioned that the costs to invest in illiquid assets are generally much higher than the costs for liquid assets. Finally, pension funds set strategic asset allocation bounds on the target weights for all asset classes that they invest in. Since illiquid assets do not trade frequently, remaining within asset class bounds is more challenging for illiquid assets than for liquid assets.

Asset valuation for Dutch funds

The second set of questions focuses on the asset valuation of illiquid assets. We first asked how pension funds value their illiquid assets. The Dutch pension funds that we interviewed only invest in illiquid assets via fiduciary managers. Most pension funds rely on the valuations of their external fiduciary managers. A large fraction of pension funds analyzes past performance of illiquid assets to evaluate their performance. Some pension funds monitor whether the valuation method used by fiduciary managers is compliant with standards such as the ILPA Private Equity Principles. The fiduciary managers usually use discounted cash flow (DCF) methods for real estate and infrastructure, whereas for private equity the EBITDA multiple and the public market equivalent (PME) approach are more commonly used valuation methods.

Second, we asked how expected returns on illiquid assets are characterized, and in particular whether pension funds make assumptions for liquidity premiums. Most pension funds use a benchmark-plus-spread approach to determine expected returns. The benchmark is generally used as a public market equivalent, such as the S&P500 for private equity and REIT returns for real estate. On top of the benchmark, pension funds assign a spread, which they report varies between 100 to 300 basis points depending on the asset class and the beliefs of the pension funds about the asset classes. The survey participants report that this spread represents different aspects such as skill of the investment manager and compensation for illiquidity. This spread is relatively conservative compared to the respective liquidity premium estimates of 300 bps and 370 bps found by Franzoni et al. (2012) and Anson (2017) for private equity investments.[17] The difference could be driven by differences in beliefs, the asset class, or both. Three of the nine pension funds aim to make explicit various components of the spread and thus have an explicit number for the liquidity premium of illiquid asset classes, at least where possible. Only one participant mentioned direct valuation of illiquid assets as a way to determine expected returns.

The final question was about the certainty of contract periods for illiquid assets. For private equity, all pension funds are aware that the scenario of an extension of the contract period beyond ten years is quite likely. Pension funds indicated that the announcement of contract extensions is more towards the end of the contract, and usually equals a two or three year period. As pension funds already take into account the possibility of a contract extension when entering the contract, pension funds do not consider contract extensions as a potential risk.

[17] Franzoni et al. (2012) use the Pastor and Stambaugh (2003) liquidity risk measure, whereas Anson (2017) considers the liquidity level.

Table 5.4. **Assumption of Expected Returns on Illiquid Assets**

This figure summarizes the number of Dutch survey participants who mention one of the following ways to determine expected returns of illiquid assets: direct valuation or benchmark plus a spread. We also asked whether survey participants specifically assume a liquidity premium for illiquid assets. The total number of survey participants is nine, and survey participants could mention more than one approach.

	number of participants
Separate liquidity premium	3
Direct valuation	1
Benchmark + spread	7

Liquidity management and stress scenarios for Dutch funds

Many of the survey participants indicated that they have put either implicit or explicit policies in place to ensure that sufficient resources are available to fulfill immediate obligations. For instance, a cash buffer of about 0% to 7.5% of AUM may be maintained to cover immediate liquidity needs. For the survey participants the cash buffer mainly exists to cover margin payments for derivatives positions. This need may grow as central clearing becomes the standard in the near future (EMIR regulation). Some survey participants have outsourced liquidity management to their fiduciary manager.

The survey participants indicated that they perform stress tests (for instance, a negative shock of a certain magnitude to financial markets) to analyze whether they have sufficient liquid instruments to cover immediate obligations. This may be done through an analysis that indicates after how many days they need to liquidate existing positions to free up cash.

In case of a stress event, the repo market may provide initial liquidity for some survey participants. A few survey participants reported that they may consider securities lending. Others indicated that they would sell positions in their most liquid instruments first (e.g. equities and highly rated government bonds). This may be done either in the order of liquidity, or according to the respective portfolio weights. In some cases the assets which are most above strategic portfolio weights are sold first.

Although all survey participants indicated that there is an implicit policy, not all of them have formally and explicitly formulated policies regarding which assets would be sold first and in what quantities in case of a stress event. In spite of these policies being in place, many survey participants mentioned that they do not expect to have to sell securities to free up liquidity. According to their stress analyses, the cash buffer should cover immediate liquidity needs.

5.4.2 Canadian fund outcomes

For the Canadian pension funds in our sample, we also start with the summary statistics (Exhibit 5.5). Average AUM of Canadian funds is 53 billion euros, with a standard deviation equal to 37 million euros. Also for Canadian pension funds, our sample represents a mix of relatively large and small funds. The ratio of active members relative to retirees is on average 1.8, showing that the average group of active members is larger than the group of retirees. As for the Dutch funds, the standard deviation of the ratio of active members to retirees reveals substantial variation across Canadian funds. Canadian funds invest on average 34% in illiquid assets, in line with findings of the Willis Towers Watson Global Pension Asset Study 2018.[18] The average funding ratio (on a going-concern assumption) equals 109% and the standard deviation 14%, which again shows that pension funds substantially differ in their funding status. As noted in the introduction, the fiduciary managers are not included in the summary statistics as they manage assets for investors other than pension funds as well.

Table 5.5. **Summary Statistics Canadian Pension Funds**

This table provides summary statistics for four Canadian pension funds (fiduciary managers are excluded). AUM is in millions of Canadian dollars. Source: annual reports (year-end 2017) of participating pension funds.

	mean	**std.dev.**
AUM	50,748	41,977
Illiquid assets percentage	34%	12%
Actives to retirees ratio	1.8	0.5
Funding ratio	109%	14%

[18]The average illiquid asset allocation in Canada equaled 31% in 2017.

Strategic asset allocation to illiquid assets for Canadian funds

The main reported reasons for the five Canadian survey participants to invest in illiquid assets are summarized in Table 5.6. For all survey participants the risk-return trade-off and diversification benefits are the most important reasons for investing in illiquid assets, again fitting with the search for yield phenomenon described by Rajan (2006) and Yellen (2011). Some survey participants specifically mentioned their comparative advantage as long-term investors to capture liquidity premiums. Four out of five also mentioned liability hedging as an important determinant to invest in illiquid assets. Liability hedging is a relevant reason mainly for real estate and infrastructure, and less so for private equity. Three out of five survey participants also mentioned a fourth reason to invest in illiquid assets: cash flow matching of liabilities. Canadian survey participants consider real estate and infrastructure most suitable to obtain steady cash flow streams. Smooth valuation of illiquid assets was not mentioned by Canadian survey participants as a principal reason for investing in illiquid assets.

Table 5.6. **Reasons for Investing in Illiquid Assets**

This table summarizes the number of Canadian survey participants who mentioned one of the following main reasons to invest in illiquid assets: steady cash flows, smooth valuation, risk-return trade-off, liability hedging, and diversification. The total number of survey participants is five, and survey participants could mention more than one reason.

	number of participants
Smooth valuation	0
Steady cash flow	3
Risk-return trade-off	5
Liability hedging	4
Diversification	5

One participant mentioned that they see an important advantage of investing in illiquid assets in the degree of control that pension funds have when investing in these asset classes. Canadian pension funds manage a substantial fraction of their illiquid assets internally. This implies that they invest directly in, for instance, real estate investments and unlisted equity. The participant noted that this gives pension funds a high degree of active ownership, incentive alignment, and superior information compared to listed asset classes.

Table 5.7 summarizes the responses to our second question, which concerns the most important ways to determine the allocation to illiquid assets. The answers vary, and pension funds may take more than just one factor into account. Three out of five funds may deviate from target allocations, which could be arrived at via e.g. an ALM study, depending on a specified target return for illiquid assets. For instance, one survey participant stressed that the fund would like to implement a (much) larger allocation to illiquid assets, but insufficient investment opportunities that meet the target return were available at the time. Other funds mainly arrive at their illiquid asset allocation based on an ALM study. Two out of five funds mention the importance of the pension board in explicitly setting targets for the allocation to illiquid assets.

Table 5.7. **Determination of Illiquid Asset Allocation**

This table summarizes the number of Canadian survey participants who mention one of the following ways to determine the allocation to illiquid assets: a target return, board decision, and/or ALM study. The total number of survey participants is five, and survey participants could mention more than one approach.

	number of participants
Target return	3
Board	2
ALM study	2

Third, we asked whether funds have an upper limit for how much they invest in illiquid assets. In general, Canadian survey participants do have an upper limit for their illiquid asset allocation. For those who do have such an upper limit, it varies significantly across survey participants, from 15% to 80%. In most cases the board decides on the upper limit.

Finally, we asked if there are any other aspects that are considered when investing in illiquid assets. The survey participants indicated that there might be limits on how much the pension fund can invest in domestic versus foreign investments, that there may be limits for the amount invested in individual investments, and that there may be limits for the amount of embedded leverage that illiquid assets create for the portfolio.

Asset valuation for Canadian funds

The second set of questions addresses the valuation of illiquid assets. The valuation method for illiquid assets varies mainly across asset classes. For real estate and infrastructure the valuation is often done by an external appraiser using the DCF method. For private equity a mix of valuation methods is used by pension funds: DCF, EBITDA multiples, and PME multiples are often applied.

Table 5.8 summarizes the responses regarding the return assumptions on illiquid assets. As for Dutch survey participants, most Canadian survey participants formulate expected returns on illiquid assets through a benchmark-plus-spread approach, where the spread consists of different components including skill of the manager and liquidity. Two funds also aim to quantify the liquidity premium explicitly. As for Dutch survey participants, only one mentioned direct valuation of illiquid assets as a way to determine expected returns.

Table 5.8. **Assumption of Expected Returns on Illiquid Assets**

This figure summarizes the number of Canadian survey participants who mention one of the following ways to determine expected returns of illiquid assets: direct valuation or benchmark plus a spread. We also asked whether survey participants specifically assume a liquidity premium for illiquid assets. The total number of survey participants is five, and survey participants could mention more than one approach.

	number of participants
Separate liquidity premium	2
Direct valuation	1
Benchmark + spread	4

The final survey question asked how certain the contract periods of illiquid assets are. The answers are comparable to those given by Dutch survey participants. For private equity, all pension funds are aware that the scenario of an extension of the contract period beyond ten years is quite likely. Most survey participants indicated that a two to three year extension of the contract period is expected and taken into consideration when entering the contract.

Liquidity management and stress scenarios for Canadian funds

Similar to the Dutch survey participants, their Canadian counterparts also have put either implicit or explicit policies in place for liquidity management. Cash is held mainly to cover the liquidity needs of derivatives rather than to account for illiquid assets, although in certain cases it is necessary to plan for large capital calls generated by illiquid investments. The repo market was mentioned by one participant as a serious avenue for managing liquidity needs. One participant remarked that the attitude towards liquidity may depend on the ratio of payouts to contributions. For funds with higher payout amounts, liquidity may be more important since cash needs are larger.

Survey participants have projections for their cash inflows and outflows, so they explicitly plan sufficient liquidity to meet immediate obligations, also under adverse market conditions. When such obligations arise, many survey participants report the preference to first use cash, then the repo market, then selling liquid public securities, and as a last resort selling illiquid private assets.

We found that, when making their investment decision, some survey participants take into account the possibility to liquidate the investment in order to free up cash for immediate obligations. They tailor the investment type of the illiquid assets that they choose to invest in (e.g. open-end vs. closed-end real estate funds) such that they do not have their full position in a relatively illiquid type.

5.4.3 Comparison of Dutch and Canadian outcomes

In this section we describe the main differences in survey results between the Dutch and the Canadian survey participants and we provide a comprehensive summary of these differences in Exhibit 5.9. From the summary statistics we immediately note the biggest difference: the Canadian pension funds invest substantially more in illiquid assets, on average 34% of AUM, than the Dutch pension funds, for which the average is 15% of AUM. The variation in the fraction allocated to illiquid assets across pension funds is also substantially larger in Canada compared to the Netherlands. These differences are also reflected in the maximum allocations to illiquid assets reported by the survey participants. Dutch survey participants often indicated a maximum allocation to illiquid assets of approximately 20-25%, whereas this upper limit varies from 15 to 80% across Canadian survey participants.

The Willis Towers Watson Global Pension Assets Study 2018 shows that the difference in average allocations to illiquid assets between Dutch and Canadian pension funds was relatively small in 2007 and has increased strongly since then. The average allocation of Canadian pension funds to assets other than equities, bonds, and cash has increased from 14% in 2007 to 22% in 2017. For the eight largest Canadian pension funds, Bédard-Pagé et al. (2016) report that the allocation to less-liquid alternative assets has even increased from 21% in 2007 to 29% in 2015, in line with the finding of Broeders et al. (2020) that large pension funds invest more in illiquid assets than small pension funds. In contrast, for Dutch pension funds the allocation to assets other than equities, bonds, and cash has remained

Table 5.9. **Comparison Dutch and Canadian outcomes**

This table summarizes the main differences in the survey results between the Dutch and they Canadian survey participants. The statistics refer to six Dutch and four Canadian pension funds (fiduciary managers are excluded).

	Netherlands	**Canada**
Average AUM in millions of EUR	57,030	33,608
Average allocation illiquid assets	15%	34%
Cross-sectional variation allocation illiquid assets	5%	12%
Maximum allocation illiquid assets	20-25%	15-80%
Management illiquid assets	external	internal
Regulatory framework	nominal	real

stable going from 18% in 2007 to 17% in 2017.

Interestingly, the average AUM of the Canadian pension funds is slightly more than half the average AUM of the Dutch pension funds in the sample and yet they have a much larger allocation to illiquid assets on average. Consequently, pension fund size does not seem to be the driver of the stark difference in allocations. We put forward three other reasons to explain the allocation gap between the two countries.

First, the cost aspect of illiquid assets plays a major role for Dutch pension funds. One of the underlying reasons is that Dutch pension funds have to mandatorily report their investment costs to the supervisor (DNB), who subsequently publishes the investment costs for each individual pension fund on their website.[19] The supervisor holds the position that pension funds should be able to justify the investment costs to the public, which creates the potential for public scrutiny and reputational risk. During the interviews, Dutch survey participants mentioned that the costs to invest in illiquid assets are generally much higher than the costs for liquid assets and that this plays an important role in their asset allocation decision. On the other hand, competitive pays are the standard in Canada. Commonwealth Partners (2017) reports that Canadian pension funds pay competitively such that they can build internal investment teams.[20] Canadian compensation costs are therefore generally

[19]The pension fund specific investment costs are available at https://statistiek.dnb.nl/downloads/.

[20]See also PwC (2016), page 17, which reports on insourcing portfolio management that "In order to retain high-level talent, pension funds must pay competitive salaries to people who might otherwise choose to work in the commercial fund management sector."

higher than those of pension funds in some other countries. However, competitive pays also give pension funds the ability to bring investment management and other functions internally, which they believe tend to result in lower costs and better net performance, in line with the findings of Andonov et al. (2015).

The second explanation relates to both the supervisory framework as well as the difference in how illiquid assets are managed. The Dutch supervisor imposes stricter requirements on pension funds when they invest in alternative investments and other non-listed assets, and also when assets are managed internally.[21] The Dutch supervisor may examine whether it finds that a pension fund sufficiently understands its investments and knows the associated risks.[22] When pension funds do not manage illiquid assets directly, which is typically the case for Dutch pension funds, understanding illiquid assets is a much harder task. On the other hand, Canadian survey participants manage a large fraction of their illiquid assets internally. As mentioned by one of the Canadian survey participants, in-house management of illiquid assets has the advantage that there is a high degree of control. This participant finds that this gives a high degree of active ownership, incentive alignment, and superior information compared to listed asset classes.

Third, there is a division of Dutch pension fund assets into a liability matching portfolio and a return portfolio, where illiquid assets typically reside in the return portfolio. If the liability matching portfolio, which contains mainly fixed income assets, is relatively large (say 60% of total assets), then even with a relatively modest allocation the illiquid assets (say 10% of total assets) forms a sizable fraction of the return portfolio (in the example 25%). This may limit the allocation to illiquid assets as a fraction of the total portfolio, since these would otherwise crowd out return portfolio investments in more liquid assets such as listed equities. One of the Dutch survey participants indicated explicitly that the division in a matching and return portfolio limits their allocation towards illiquid assets.

Regarding the allocation decision, Dutch survey participants tend to arrive at their

[21] See e.g. the DNB policy rule regarding risk management for alternative investments, https://www.toezicht.dnb.nl/binaries/50-211807.pdf, and the DNB letter dated 3 July 2019 on their investment review findings, https://www.toezicht.dnb.nl/binaries/50-237819.pdf.

[22] That the supervisory pressure is restrictive for Dutch funds is supported by the IPE article dated 20 June 2016 “APG: Dutch pension funds should follow Canadian schemes’ example”, https://www.ipe.com/apg-dutch-pension-funds-should-follow-canadian-schemes-example/10013847.article. In this article, the CIO of the Dutch pension fund APG is quoted saying “Pension funds over here are apprehensive because of regulatory pressure” regarding investments in infrastructure, private equity, and real estate in a specific comparison of the Netherlands and Canada.

illiquid asset allocation via an ALM study. Canadian survey participants indicate that they may deviate from target allocations, which could be arrived at via e.g. an ALM study, depending on how many investment opportunities are available that meet a specified required target return on illiquid assets.

In terms of liquidity management, the main difference is that Dutch survey participants are more concerned about larger future cash needs due to the central clearing of derivatives, while we see a large similarity between Dutch and Canadian survey participants in the approaches to liquidity stress testing and which assets to sell first to free up cash when necessary. The preference to sell liquid assets first to cover their liquidity needs is in line with Ben-David et al. (2012), Manconi et al. (2012), and Driessen and Xing (2017).

5.5 Best practices

We have formulated four best practices based on the results of our survey of nine Dutch and five Canadian pension funds and fiduciary managers on their investment and management decisions regarding illiquid assets. These best practices focus mainly on the actions and processes of the fiduciary managers and investors.

Rationale for investing in illiquid assets

Investors should have a clear rationale for investing in illiquid assets. Based on this rationale, informed decisions can be made regarding the role of specific illiquid assets in the investment portfolio. For instance, inclusion of illiquid assets to ensure an attractive risk-return tradeoff may lead to different decisions than inclusion for liability hedging purposes (this is illustrated by the framework of Sharpe and Tint, 1990b).

Awareness of valuation method used for illiquid assets

Investors should be aware of the valuation methods used for the illiquid assets they invest in. For example, the valuation method has important consequences for the extent to which the risk and return statistics reflect transaction-based prices. Appraisal-based valuations may lead to a lower volatility assessment than transaction-based valuations (Fisher et al., 1994; Hoesli et al., 2004). Depending on the intended method, inadvertently using a different method could lead to volatility measures which understate the actual risk. Investors should therefore understand how valuation methods affect their overall portfolio value, their risk measures, and in particular their solvency position. Anson (2016), for instance, demonstrates how to un-smooth illiquid asset returns for asset allocation and risk management purposes.

Analysis of liquidity needs and liquidity stress testing

Investors should regularly analyze their current and future liquidity needs. The available cash and liquid instruments should be sufficient to cover the net cash outflows arising from the various inflows and outflows (see, for instance, the framework of Ang et al., 2014). Cash inflows could, for example, originate from pension contributions and from distributions obtained from investments. Cash outflows could occur due to margin payments on derivatives, payouts to retirees, and capital calls related to investments.

Stress tests are needed to analyze the impact of an adverse shock to market conditions on the ability to satisfy immediate cash requirements since the latter may be substantial (Brunnermeier, 2009). Such stress tests should take into account that the size of the cash requirements themselves may also depend on these market conditions.

Liquidity stress testing is particularly relevant for investors in illiquid assets. Even when sufficient cash and liquid instruments are available to cover immediate cash requirements, the impact of an adverse shock as well as the sale of liquid instruments may lead to deviations from target asset allocations. Rebalancing towards the desired allocation may then involve the forced sale of illiquid assets, potentially with large losses (e.g. Diamond and Rajan, 2011), even though it was initially possible to satisfy the cash requirements without such forced sale.

Policy for liquidation of assets during stress events

Investors in illiquid assets should have an explicit policy regarding the methods to free up cash for immediate liquidity needs (see the considerations in Duffie and Ziegler, 2003). Such policy should stipulate the preferred order in which these methods should be used, as well as which assets to sell, and in which sequence and amount, should other sources to fulfill immediate obligations prove insufficient.

By establishing explicit policies to free up cash for immediate liquidity needs, it will be possible to investigate the impact of different policy choices under adverse shocks to market conditions. Such analyses are highly relevant to investors in illiquid assets for the same reasons as outlined in the best practice regarding the analysis of liquidity needs and liquidity stress testing.

5.6 Conclusions

In this paper we report the results of a survey of nine Dutch and five Canadian pension funds and fiduciary managers on their investment and management decisions towards illiquid assets. This is of particular relevance in a low interest rate environment where a search for yield may arise (e.g. Rajan, 2006; Yellen, 2011). The Dutch pension funds in our sample invest 15% of their portfolio in illiquid assets, while for the Canadian pension funds this fraction is 34%.

We put forward three reasons to explain the allocation difference between the two countries. First, the cost aspect of illiquid assets plays a major role for Dutch pension funds. During the interviews, Dutch survey participants mentioned that the costs to invest in illiquid assets are generally much higher than the costs for liquid assets and that this plays an important role in their asset allocation decision. The supervisor holds the position that pension funds should be able to justify the investment costs to the public, which creates the potential for public scrutiny and reputational risk. The second explanation relates to both the supervisory framework as well as the difference in how illiquid assets are managed. The Dutch supervisor imposes stricter requirements on pension funds when they invest in alternative investments and other non-listed assets, and also when assets are managed internally. Third, there is a division of Dutch pension fund assets into a liability matching portfolio and a return portfolio, where illiquid assets typically reside in the return portfolio. Even with a relatively modest allocation to illiquid assets, these potentially crowd out other more liquid investments from the return portfolio such as listed equities.

Both Dutch and Canadian survey participants most often indicated the risk-return trade-off as their main reason to invest in illiquid assets, with diversification benefits as the second most often provided reason. The Canadian survey participants indicated steady cash flow and liability hedging as main reason more often than Dutch survey participants. In terms of the implementation, Canadian survey participants manage a large fraction of their illiquid assets internally, whereas Dutch survey participants typically manage illiquid assets externally.

Dutch survey participants often mentioned ALM studies as their main basis for determining how much to invest in illiquid assets, while Canadian survey participants often mentioned that they may deviate from target allocations, which could be arrived at via e.g. an ALM study, depending on how many investment opportunities are available that meet a specified target return on illiquid assets. One Canadian survey participant indicated that the fund would like to achieve a (much) larger allocation to illiquid assets, but that insufficient investment opportunities that meet the fund's target return were available at the time.

Regarding the valuation methods for illiquid assets, we found that most survey participants use discounted cash flow methods for real estate and infrastructure, and EBITDA multiples or the public market equivalent for private equity. Survey participants indicated that they determine expected returns on illiquid assets through a benchmark-plus-spread approach. The spread may include components such as liquidity and asset manager skill, although these components are not necessarily made explicit.

Most participants in the survey have either explicit or implicit liquidity policies in place, such as maintaining a cash buffer, making use of the repo market or securities lending, and an implicit or explicit sequence in which to liquidate positions to free up cash if necessary. Many of the survey participants perform liquidity stress tests under a given adverse market shock. They find that their cash buffer should be sufficient in most cases, and they do not expect to have to sell assets to free up cash under adverse market conditions.

The survey participants reported that the main cause of immediate cash requirements is margin payments on derivatives. They expect that this cause may become even more relevant in the near future as central clearing becomes the standard. The survey participants indicated that they either apply cash flow planning or specifically set cash aside for other immediate cash requirements, such as capital calls by private equity funds and payments to retirees.

We close with four best practices based on the results of the survey. First, investors should have a clear motivation for investing in illiquid assets, as this may depend on the role that illiquid assets play in the overall portfolio. Second, investors should be aware of the valuation methods used for illiquid assets that they invest in, so as to correctly interpret their portfolio value, risk measures, and solvency position. Third, to assess the adequacy of liquid resources in the portfolio, investors should regularly analyze their current and future liquidity needs. Fourth, investors should have an explicit policy regarding which methods to use and in which sequence to free up cash when immediate liquidity needs arise.

5.7 Appendix

A Survey questions illiquid assets

This appendix provides the list of questions answered by the survey participants.

Role in the organization

1. What is your role in your organization and how does it relate to the investment process?

Strategic asset allocation to illiquid assets

1. What are the main reasons to invest in illiquid assets (e.g. private equity, private debt, direct real estate, infrastructure, hedge funds)?
2. What determines the amount of total assets invested in illiquid assets? In other words, how is the optimal allocation to illiquid assets defined?
3. Is there an upper limit to the percentage of total assets invested in illiquid investments? If so, what is this upper limit based on?
4. Which aspects are taken into account in the decision to invest in illiquid assets?

Valuation illiquid assets

1. How is the value of an illiquid asset determined? Can you provide an example, i.e. how does it work in the case of private equity?
2. How are the expected returns of these assets characterized? In particular, what is the assumption about the liquidity premium for these assets?
3. How certain is the contract period of illiquid assets? For instance, private equity contracts generally last for ten years, but sometimes the contract is extended by one or two years. Is this known well in advance or does it remain uncertain for a long time?

Liquidity and fund management

1. What are the policies put in place to ensure that sufficient resources are available to fulfill immediate obligations at any point in time? For instance, does the fund hold a cash buffer to specifically compensate for the illiquidity of the portfolio?

2. Suppose a stress scenario occurs and market liquidity dries up. Is there a particular strategy to deal with this? Are there certain securities that would be sold first if the cash at hand is not sufficient to fulfill immediate obligations?

Other

1. Do you have any additional information that you think would be relevant in the context of the discussion?

B Survey participants

This appendix provides the list of survey participants.

Netherlands

- BlackRock
- Pensioenfonds ING
- Pensioenfonds Metaal en Techniek (PMT)
- Pensioenfonds Zorg en Welzijn (PFZW)
- PGB Pensioendiensten
- Philips Pensioenfonds
- SPF Beheer B.V.
- Stichting Pensioenfonds Vopak
- TKP Investments / Aegon Asset Management

Canada

- Healthcare Of Ontario Pension Plan (HOOPP)
- IMCO
- OPTrust
- UTAM
- One anonymous survey participant

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This dissertation is a collection of five independent chapters that aim to better understand the investment decisions of institutional investors. Summarizing, this dissertation has three main findings. First, regulation drives a large part of the investment decisions of institutional investors. Second, their investment decisions matter for asset prices. And third, their investment decisions have important welfare implications for the investors where we ultimately care about, namely, the households.

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