Commercial Real Estate Investments
and the Term Structure of Risk and Return

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List of Abbreviations

AR	Autoregressive
CL	Constant liquidity
e.g.	for example (exempli gratia)
excl.	excluding
GDP	Gross domestic product
i.e.	that is (id est)
IID	Independently and identically distributed
IIDN	Independently and identically normal distributed
incl.	including
IPD	Investment Property Databank
MIT	Massachusetts Institute of Technology
MPRP	Marketing period risk premium
NCREIF	National Council of Real Estate Investment Fiduciaries
NPI	NCREIF Property Index
OLS	Ordinary least squares
p.a.	per annum
RE	Real estate
REIT	Real estate investment trust
St.dv.	Standard deviation
TBI	Transaction-Based Index
VAR	Vector autoregression
VL	Variable liquidity

UK	United Kingdom
US	United States

List of Symbols

a	Smoothing parameter
$\boldsymbol{c}$	Vector of transaction costs
$\boldsymbol{C}(j)$	j-th order autocovariance of the vector $\mathbf{z}_{t+1}$
$Corr(\cdot)$	Correlation operator
$Cov(\cdot)$	Covariance operator
$Cov_t(\cdot)$	Conditional covariance operator
CR_t	Cap rate at time t
CRU_t	Simple nominal capital return (unsmoothed) in period t
CV_t	Capital value index at time t
$diag(\cdot)$	Diagonal of
$\overline{d-p}$	Mean log cash-payout-yield
$\exp(\cdot)$	Exponential operator
$\mathbf{e1}$	Vector where the first element is one and the other elements are zero
$\mathbf{e2}$	Vector where the second element is one and the other elements are zero
$E(\cdot)$	Expectation operator
$E_t(\cdot)$	Conditional expectation operator
f	Mathematical function
g_t	True continuously compounded real capital return on real estate in period t
g_t^*	Appraisal-based continuously compounded real capital return on real estate in period t
I_{t+1}	Inflation rate in period $t+1$
i_{t+1}	Continuously compounded inflation rate in period $t+1$
$i_{t+k}^{(k)}$	Continuously compounded k-period inflation rate
$\bar{i}$	Sample average of continuously compounded inflation rates
$\mathbf{I}$	Identity matrix
Inc_t	Real estate income in period t
IR_t	Income return on real estate in period t
IRU_t	Income return on real estate with regard to unsmoothed capital value index in period t

j	Index variable
k	Investment horizon
k^*	Period after which the marketing activities begin
$\ln(\cdot)$	Natural logarithm operator
m	Marketing period
$\mathbf{M}_n$	A selector matrix
$\mathbf{M}_r$	A selector matrix
$\boldsymbol{n}_{t+1}$	Vector of continuously compounded nominal returns in period $t+1$
$\boldsymbol{n}_{t+k}^{(k)}$	Vector of continuously compounded *k*-period nominal returns
$n_{0,t+1}$	Continuously compounded nominal return on the benchmark asset in period $t+1$
$n_{0,t+k}^{(k)}$	Continuously compounded *k*-period nominal return on the benchmark asset
$n_{p,t+k}^{(k)}$	Continuously compounded *k*-period nominal portfolio return
$\overline{n}_0$	Sample average of continuously compounded nominal returns on the benchmark asset
p	Order of vector autoregressive process
P	Persistence measure
r_{t+1+j}	Continuously compounded real return in period $t+1+j$
$\boldsymbol{r}_{t+1}$	Vector of continuously compounded real returns in period $t+1$
$\boldsymbol{r}_{t+k}^{(k)}$	Vector of continuously compounded *k*-period real returns
$r_{0,t+1}$	Continuously compounded real return on the benchmark asset in period $t+1$
$r_{0,t+k}^{(k)}$	Continuously compounded *k*-period real return on the benchmark asset
$r_{RE,t+k}$	Continuously compounded *k*-period real return on real estate, per period
$r_{p,t+k}^{(k)}$	Continuously compounded *k*-period real portfolio return
$\overline{r}_0$	Sample average of continuously compounded cash returns
R_{t+1}	Nominal return in period $t+1$
R^2	Goodness of fit
RER_t	Total return on real estate in period t
s	Slope of the term structure of the periodic expected real return on real estate
$\boldsymbol{s}_{t+1}$	Vector of state variables at time $t+1$

UCV_t	Unsmoothed capital value index at time t
$\boldsymbol{v}_{t+1}$	Vector of regression residuals at time $t+1$
$\boldsymbol{V}(k)$	k-period matrix of total covariances of the vector $\boldsymbol{z}_{t+1}$
$Var(\cdot)$	Variance operator
$Var_t(\cdot)$	Conditional variance operator
$Vec(\cdot)$	Vec operator
$\boldsymbol{W}(k)$	Conditional k-period covariance matrix of the vector $\boldsymbol{z}_{\mathrm{t}}$
$\boldsymbol{x}_{t+1}$	Vector of continuously compounded excess returns in period $t+1$
$\boldsymbol{x}_{t+k}^{(k)}$	Vector of continuously compounded k-period excess returns
$\overline{\boldsymbol{x}}$	Vector of sample averages of continuously compounded excess returns
$\boldsymbol{z}_{t+1}$	Vector of VAR-variables at time $t+1$
$\boldsymbol{\alpha}(k)$	Vector of asset weights with regard to a k-period investment horizon
β	Regression slope coefficient
ε_{t+1}	Residual of regression at time $t+1$
$\varphi_{t+1}(k)$	Cumulative (k-period) price adjustment
γ	Coefficient of relative risk aversion
η_{t+1}	Unexpected return in period $t+1$
η_{t+1+j}	Innovations to future (period $t+1+j$) expected returns
$\eta_{d,t+1}$	Cash-flow news in period $t+1$
$\eta_{r,t+1}$	Discount rate news in period $t+1$
$\boldsymbol{\iota}$	Vector of ones
μ_p	Continuously compounded expected real portfolio return, per period
ρ	Parameter of linearization
$\sigma(\cdot)$	Standard deviation operator
$\sigma_0^2(k)$	Variance of shocks to the k-period return on the benchmark asset
$\sigma_i^2(k)$	Variance of shocks to the k-period inflation rate
$\boldsymbol{\sigma}_x^2(k)$	Diagonal vector of □$_{\mathrm{xx}}$ with regard to horizon k
$\sigma_{0i}(k)$	Covariance of shocks to the k-period return on the benchmark asset with k-period inflation shocks

$\boldsymbol{\sigma}_{0s}$	Vector of covariances between shocks to the return on the benchmark asset and shocks to the state variables
$\boldsymbol{\sigma}_{0x}(k)$	Vector of covariances between shocks to the *k*-period return on the basis asset and shocks to the *k*-period excess returns on the other assets
$\boldsymbol{\sigma}_{in}(k)$	Vector of covariances between *k*-period inflation shocks and shocks to *k*-period nominal returns
$\boldsymbol{\sigma}_{is}$	Vector of covariances between inflation shocks and shocks to the state variables
$\boldsymbol{\sigma}_{ix}(k)$	Vector of covariances between shocks to *k*-period excess returns and *k*-period inflation shocks
Δd_{t+1+j}	Cash-flow growth in period $t+1+j$
$\boldsymbol{\Sigma}_{ss}$	Conditional covariance matrix of the state variables
$\boldsymbol{\Sigma}_{sx}$	Conditional covariance matrix of excess returns and state variables
$\boldsymbol{\Sigma}_{v}$	Covariance-matrix of regression residuals
$\boldsymbol{\Sigma}_{xx}(k)$	Conditional covariance-matrix of *k*-period excess returns
$\boldsymbol{\Phi}$	Matrix of regression slope coefficients
$\boldsymbol{\Phi}_0$	Vector of regression intercepts
$\boldsymbol{\Phi}_1$	Matrix of regression slope coefficients
$\boldsymbol{\Omega}$	Covariance matrix of VAR coefficients

1 Introduction

Although commercial real estate makes up for a large proportion of the world's wealth, the analysis of real estate investments lags behind that of classic financial asset classes. According to Clayton et al. (2009, p. 10), the lag of the application of insights from the finance literature to the investment analysis of commercial real estate can be seen as "[…] one of the distinguishing features of the asset class." They state:

> "Many of the basic tools of portfolio management have now been applied to commercial real estate, but only in the last 10 to 15 years. The concepts may be 30, 40, or 50 years old, but institutional real estate investors have only just begun to use (and sometimes misuse) the standard techniques of the broader investment markets […]."

This thesis is devoted to the analysis of commercial real estate investments. The overall goal is to gain a better understanding of the financial characteristics of this asset class. With an average holding period of about ten years, direct commercial real estate investments are typically long-term investments (Collet et al. 2003, Fisher and Young 2000). Motivated by this fact, the calculation of long-term risk and return statistics is at the heart of this thesis.

Following the tradition in real estate research, approaches originally applied to the traditional asset classes are applied to commercial real estate investments. A common characteristic of the models used in this thesis is to acknowledge that asset returns are predictable. Up to the 1980s, the common view was that stock and bond returns are (close to) unpredictable (Cochrane 2005, Chapter 20). Fama and Schwert (1977) were among the first to challenge the view of constant expected returns, emphasizing that expected stock returns vary with inflation. Since then, many other studies have shown that bond and stock returns are in fact predictable (e.g., Campbell 1987, Campbell and Shiller 1988, Fama 1984, and Fama and French 1988a, 1989). Research by Case and Shiller (1989, 1991), Gyourko and Keim (1992), Barkham and Geltner (1995) and Fu and Ng (2001), among others, shows that residential and commercial real estate returns are predictable, too.

When returns are predictable, there are horizon effects in periodic variances and covariances of multi-period returns – there is a „term structure of risk“. Consider a two-period example. Let r_{t+1} denote the log (continuously compounded) return in period $t+1$, and r_{t+2} the log return in period $t+2$. Assuming that returns are identically distributed,

$$Var_t(r_{t+1}) + Var_t(r_{t+2}) = 2Var_t(r_{t+1}) + 2Cov_t(r_{t+1}, r_{t+2}) \tag{1.1}$$

is the variance of the two-period return. When returns are unpredictable, the variance increases in proportion to the investment horizons. When returns are predictable, however, the periodic (dividing by two) variance of the two-period return is greater (mean aversion) or less (mean reversion) than the single-period return variance, depending on the covariance (Cov_t) of returns. Thus, mean aversion reflects a positive correlation between single-period returns, and mean reversion reflects negative autocorrelation. There is an important difference between unconditional and conditional variances of multi-period returns. Early studies on the long-term risk of stocks (Fama and French 1988b, Poterba and Summers 1988) examine horizon effects focusing on unconditional variances by analyzing the behavior of multi-period realized returns directly. In this thesis, conditional (indicated by the subscript *t*) variances of multi-period returns are analyzed throughout by using a multivariate time-series model – a vector-autoregression (VAR) – that captures time-variation in expected returns and yields implied estimates of variances of multi-period returns. Campbell (1991) emphasizes that ex post returns can be serially uncorrelated, although there are horizon effects in the conditional periodic variance of returns. Similar to horizon effects in (conditional) return variances, return predictability induces horizon effects in (conditional) multi-period covariances of the returns on different assets (see Campbell and Viceira 2004).

Predictability of returns also induces horizon effects in expected returns.[1] For example, the simple return, per period, decreases with the investment horizon when returns are mean-reverting. Assume that an asset, currently valued at 100, either increases or decreases by 10% with a probability of 50%. After two periods, the asset will be worth 121 with a probability of 25%, 99 with a probability of 50%, or 81 with a

[1] See also Jurek and Viceira (2010) for a discussion.

probability of 25%, and the expected simple return is 0%. When returns are mean-reverting, the middle case will become more likely and the other cases will become less likely. In the extreme, there would be a 100% probability that the stock is worth 99, corresponding to a simple return of -1%, after two periods. Transaction costs induce additional horizon effects in expected returns. This has a large effect for the term structure of (periodic) expected returns on direct real estate, since transaction costs are very large compared to stock and bond investments.

With periodic variances, covariances and expected returns being horizon-dependent, the optimal asset allocation is horizon-dependent, too (Campbell and Viceira 2002, Chapter 2). This thesis focuses on the dependence of risk and return on the investment horizon. It rules out time-variation in risk. Chacko and Viceira (2005) analyze the importance of time-variation in stock market risk for the portfolio allocation of long-term investors. They conclude that changing risk does not induce large changes in the optimal allocation to stocks, because changes in risk are not very persistent.

Since the influential paper by Sims (1980), VARs have become a popular approach to analyze the dynamics of a set of variables in macroeconomics and finance, because "VARs are powerful tools for describing data and for generating reliable multivariate benchmark forecasts." (Stock and Watson 2001, p. 113). It should be noted that the VAR coefficients might be biased. Stambaugh (1999) has shown that persistency of forecasting variables leads to biased estimates in univariate forecasting regressions in small samples, when innovations to returns and innovations to the forecasting variable are correlated. For example, the coefficient obtained from a regression of stock returns on the lagged dividend yield has an upward bias, because stock return and dividend yield residuals are highly negatively correlated. However, Ang and Bekaert (2007) find that in a bivariate regression the bias can be negative instead of positive. Hence, coefficients in multivariate regressions (which form a VAR model) might not be biased. In line with the bulk of the literature (e.g., Campbell and Viceira 2002, 2005, Campbell et al. 2003, Fugazza et al. 2007, Hoevenaars et al. 2008) no adjustments are made.

The specific characteristics of real estate asset markets make it necessary to be careful when models developed for classic financial assets are applied to the real estate market. Throughout the thesis, variables specific to the real estate market are incorporated in the VAR models to capture the dynamics of real estate returns adequately. As indicated above, transaction costs are considered for estimating the term structure of expected returns. In Chapter 3, an aspect of the lack of liquidity of direct real estate investments – marketing period risk – is accounted for. A result of the specific microstructure of direct real estate asset markets is the lack of return indexes, which are comparable to stock and bond indexes. The available history of commercial real estate indexes is usually relatively short, and the indexes are subject to a range of biases. When analyzing direct real estate, appraisal-based returns are used (as it is common in real estate research). Appraisal-based returns are unsmoothed using the method proposed by Geltner (1993), which avoids the a priori assumption of uncorrelated true market returns, and robustness checks are conducted by recalculating main results with different parameter values used to unsmooth appraisal-based returns.[2] One of the implications of the use of indexes for direct real estate is that the results are more relevant for investors with a well-diversified portfolio than for investors holding only a few properties.[3] It should be emphasized that the thesis focuses on commercial real estate. Some of the results may also apply to residential real estate, though, given the similarities between the dynamics of housing markets and commercial real estate markets (Gyourko 2009).

The remainder of this thesis consists of three self-contained chapters. In Chapter 2, the term structures of return volatility for UK and US direct and securitized commercial real estate are compared. The implications of the term structures of return volatility for the dependence of the degree of return predictability (R^2 statistics) on the investment horizon are examined. In order to get deeper insights into the term structures of return volatility, the variance of unexpected returns is decomposed into the variance of news about future cash flows, news about future returns and their covariance. A discussion of the informational efficiency of the asset markets is also part of this Chapter. Chapter 3 analyzes the role of the investment horizon for the allocation to UK direct commercial real estate in a mixed asset portfolio accounting for transactions costs, marketing period risk and return predictability. Furthermore, the chapter examines the relative importance of return predictability, transaction costs and marketing period risk for the optimal allocation to real estate. Chapter 4 analyzes how the inflation hedging abilities of UK cash, bond, stock and direct commercial real estate investments change with the investment horizon. The implications of the differing inflation hedge properties of the assets for the difference between the return volatility of

[2] See Geltner et al. (2007, Chapter 25) for a textbook discussion of the data issues.
[3] For a diversification analysis based on individual properties see Kallberg et al. (1996).

real returns versus the return volatility of nominal returns, and for portfolio choice are explored.

2 Dynamics of Commercial Real Estate Asset Markets, Return Volatility, and the Investment Horizon

This chapter is joint work with Steffen Sebastian.

Abstract

The term structure of return volatility is estimated for UK and US direct and securitized commercial real estate using vector autoregressions. To capture the dynamics of the real estate asset markets it is important to account for a valuation ratio specific to the asset market analyzed. In the UK, direct real estate and property shares exhibit mean reversion. US REIT returns are mean reverting, too. In contrast, US direct real estate shows a considerable mean aversion effect over short investment horizons. This can be explained by the positive correlation between cash-flow and discount rate news, which can be interpreted as underreaction to cash-flow news. In all of the asset markets analyzed, unexpected returns are primarily driven by news about discount rates. In the UK, direct real estate returns remain more predictable than property share returns in the medium and long term, whereas US REIT returns appear to be equally predictable to US direct real estate returns at a ten-year investment horizon.

2.1 Introduction

A lot of research in real estate focuses on the problem of how to correct ("unsmooth") appraisal-based returns in order to obtain returns, which are closer to true market returns (e.g., Blundell and Ward 1987, Geltner 1993, Fisher et al. 1994). The unsmoothed returns are used to assess the volatility of real estate markets. The studies use quarterly or annual return data, however. Typically, real estate investors have longer investment horizons than a quarter or a year. With an average holding period of about ten years, direct commercial real estate investments are typically long-term investments (Collet et al. 2003, Fisher and Young 2000). The relationship between the short-term and the long-term return volatility is straightforward when returns are independently and identically distributed (IID) over time: The variance of (log) returns increases in proportion to the investment horizon. When returns are predictable, however, there may be substantial horizon effects in the periodic (divided by the square root of the investment horizon) volatility of returns. For example, there is a lot of evidence suggesting that stock returns are mean reverting, i.e., that the periodic long-term volatility of stock returns is lower than the short-term volatility.[4]

The widespread view is that commercial real estate returns are predictable. Securitized real estate investments are often seen to exhibit similar dynamics as the general stock market. Conventional wisdom and empirical evidence (Clayton 1996, Geltner and Mei 1995, Scott and Judge 2000) suggest that direct real estate asset markets exhibit cyclicality. A series of high returns tends to be followed by a series of low returns, and vice versa. Hence, cyclicality implies that real estate returns are mean reverting over long investment horizons, making real estate relatively less risky in the long run. Cyclicality also implies that direct real estate exhibits return persistence over short investment horizons, so that we see mean aversion in the short run. The return persistence is typically attributed to the specific microstructure of the direct real estate asset market characterized by high transaction costs, low transaction frequency and heterogeneous goods, causing slow information diffusion (e.g., Geltner et al. 2007, Chapter 1). Thus, horizon effects in the volatility of returns are likely to be linked to the informational efficiency of an asset market.

[4] Early references include Campbell (1991), Fama and French (1988a, 1988b), Kandel and Stambaugh (1987) and Porterba and Summers (1988).

The goal of this chapter is to analyze how important mean aversion and mean reversion effects are in UK and US direct and securitized commercial real estate markets. Using vector autoregressions (VARs), the term structure of the annualized return volatility is estimated for direct and securitized real estate in these two countries. We explore the implications of the term structure of return volatility for the dependence of the degree of return predictability (R^2 statistics) on the investment horizon. In order to get deeper insights into the term structure of the return volatility of an asset, the variance of unexpected returns is decomposed into the variance of news about future cash flows, news about future returns, and their covariance.

We find that in the UK the results for direct real estate and property shares are similar to the results for the general stock market. Both UK direct and securitized real estate exhibit strong mean reversion. US REIT returns are strongly mean reverting, too. In contrast, US direct real estate returns are considerably mean averting over short investment horizons, after which the term structure of the annualized volatility is slightly decreasing. To estimate the long-term return volatility of the assets adequately, it is important to include a valuation ratio specific to the asset market analyzed in the VAR models. The low short-term standard deviation and the mean aversion of US direct real estate returns can be explained by the positive correlation between cash-flow and discount rate news, which can be interpreted as underreaction to cash-flow news. In all of the asset markets analyzed, unexpected returns are primarily driven by news about discount rates. The choice of the parameter used to unsmooth appraisal-based returns has a large effect on the short-term, but not on the long-term volatility of direct real estate returns. In the UK, direct real estate returns remain more predictable than property share returns in the medium and long term, whereas US REIT returns appear to be equally predictable to US direct real estate returns at a ten-year investment horizon.

The remainder of the chapter is organized as follows: The next section contains a review of the literature and some background discussion. We proceed with a description of the VAR model and the data and present the VAR estimates. The next section contains the discussion of the term structure of return volatilities and the multi-period R^2 statistics implied by the VARs. The variance decompositions are presented in the subsequent section. A discussion and further analysis with regard to the informational efficiency of the real estate asset markets follows. The final section concludes the chapter.

2.2 Background and literature review

How does return predictability induce horizon effects in the periodic volatility of returns? To address this issue, most recent studies use VAR models. In this framework, risk is based on the unpredictable component of returns, i.e., the return variance is computed relative to the conditional return expectation. The conditional periodic volatility of multi-period returns can be calculated from the VAR results and may increase or decrease with the investment horizon. The standard example of horizon effects in the return volatility is the mean reversion effect in stock returns induced by the dividend yield. The dividend yield has been found to positively predict stock returns (Campbell and Shiller 1988, Fama and French 1988a). In combination with the large negative correlation between shocks to the dividend yield – whose process is usually well described by an AR(1) process – and shocks to the stock return, mean reversion in stock returns emerges: A low realized stock return tends to be accompanied by a positive shock to the dividend yield, and a high dividend yield predicts high stock returns for the future, and vice versa. Campbell and Viceira (2005) show that this effect cuts the periodic long-term standard deviation of US stock returns to approximately 50% of the short-term standard deviation. In general (see Campbell and Viceira 2004), returns exhibit mean reversion if the sign of the parameter obtained from a regression of an asset's return on a lagged predictor variable has the opposite sign as the correlation between the contemporaneous shocks to the asset return and the predictor variable; mean aversion is induced if the regression parameter and the correlation of the residuals are of the same sign. The higher the persistence of the forecasting variable, the more important is this predictor for the long-term asset risk.[5]

There are a lot of studies suggesting that commercial real estate returns are not IID. Direct real estate returns appear to be positively related to lagged stock returns (Quan and Titman 1999) and more specifically to the lagged returns on property shares (e.g., Gyourko and Keim 1992, Barkham and Geltner 1995). Furthermore, direct real estate returns appear to be positively autocorrelated over short horizons (Geltner 1993, Fu and Ng 2001). Fu and Ng (2001), Ghysels et al. (2007) and Plazzi et al. (2010) show that the cap rate predicts commercial real estate returns positively. (The cap rate of the

[5] There is an additional effect, which always leads to an increase in the periodic conditional return variance. If the forecasting variable is very persistent, this effect – reflecting the variance of expected returns – may lead to a notable increase of the long-term return volatility, a point emphasized by Schotman et al. (2008).

real estate market is like the dividend yield of the stock market – the ratio of the income to the price of an asset.) Variables that have been used to predict REIT returns include the dividend yield of the general stock market, the cap rate of the direct real estate market and interest rate variables (e.g., Bharati and Gupta 1992, Liu and Mei 1992, 1994).

A few articles have looked at the implications of the predictability of commercial real estate returns for the term structure of return volatility. Geltner et al. (1995) calculate five-year risk statistics based on regressions of real estate returns on contemporaneous and lagged asset returns. These authors find that the variance of US private real estate returns at a five-year horizon is higher than five times the annual variance – reflecting mean-aversion. Using a VAR model, Porras Prado and Verbeek (2008) also find that US direct real estate exhibits mean aversion. Hence, the existing evidence points towards mean-aversion in direct US real estate returns.[6] With regard to securitized real estate, the results are mixed. Fugazza et al. (2007) find that the standard deviation (per period) of European property shares is increasing with the investment horizon. Porras Prado and Verbeek (2008) find that returns of US property shares are mean averting. In contrast, Liu and Mei (1994) and Hoevenaars et al. (2008) find that US REIT returns exhibit mean-reversion, which is, however, weaker than the mean-reversion effect in the general stock market.

The VAR results can also be used to calculate the implied R^2 statistics of multi-period returns. Judging from regressions with quarterly or annual returns, direct real estate returns are more predictable than real estate share returns, but this may change with the investment horizon, because when expected returns are persistent, R^2 statistics can be much larger for longer horizons (Fama and French 1988a). Technically, persistence in expected returns makes the variance of expected multi-period returns increase faster than the total variance of multi-period returns. Chun et al. (2004) document rising R^2 statistics for US REITs over investment horizons of up to five years.

[6] An exception is the article by MacKinnon and Al Zaman (2009), who find strong mean reversion in US direct real estate returns. The long-term (25-year) return volatility of real returns on direct real estate is estimated to be slightly below 2.0% per annum, identical to the estimated long-term stock return volatility. All of the asset classes analyzed by MacKinnon and Al Zaman – including US REITs – exhibit very strong mean reversion, though. For example, MacKinnon and Al Zaman find that the annualized 25-year volatility of US real cash returns is only 0.3%, compared to estimates of about 3% by Campbell and Viceira (2005), Hoevenaars et al. (2008) and Porras Prado and Verbeek (2008). Therefore, the results can be regarded as unusual.

Plazzi et al. (2010) find rising R^2 statistics over short investment horizons for US direct commercial real estate investments. More distant returns become less predictable, of course, so the R^2 statistics eventually decrease. Hence, we see a hump-shaped pattern of implied R^2 statistics in the general stock market (Kandel and Stambaugh 1987, Campbell 1991).

The variance of unexpected returns can be decomposed into the variance of news about future cash-flows, the variance of news about future returns (discount rates), and their covariance (Campbell 1991). This yields insights with regard to the return volatility. Discount rate news justify large changes in asset prices when expected returns are persistent. This mechanism induces mean reversion in returns: When discount rates increase, the price of the asset decreases, but expected returns are higher than before. In contrast, there is no such mechanism with regard to cash-flow news. Liu and Mei (1994) analyze US REITs and find that the variance of cash-flow news is larger than the variance of discount rate news, which results in a relatively weak mean-reversion effect, compared to the general stock market. Liu and Mei also find a positive correlation between cash-flow news and discount rate news, which attenuates the short-term return volatility. The reason is that positive cash-flow news increase prices, but positive discount rate news decrease prices. Though not employing Campbell's (1991) variance decompositions, Geltner and Mei (1995) show that returns of US direct real estate investments are primarily driven by changing expected returns. In-sample forecasts of commercial real estate values track the market values closely when time-variation in discount rates is allowed for, whereas the forecasts are virtually constant over time and far removed from the actual market values when discount rates are held constant and only cash-flow forecasts are allowed to vary. Clayton (1996) analyzes the Canadian direct commercial real estate market and confirms the conclusion of Geltner and Mei that most of the volatility of direct real estate returns is caused by time-variation in discount rates.

In this chapter, we compare the UK and US direct and securitized real estate markets with regard to their term structure of return volatility. The comparison of the UK and the US market is particularly interesting with regard to the direct real estate market, because there is evidence that in the UK direct real estate market new information is timelier incorporated into prices than in the US. Specifically, annual appraisal-based US direct commercial real estate returns, unsmoothed with the Geltner (1993) method, still exhibit high autocorrelation, but in the case of the UK market, returns are virtually uncorrelated after unsmoothing (Barkham and Geltner 1994). Barkham and Geltner (1995) and Eichholtz and Hartzell (1996) find that in the UK direct real estate returns respond rather quickly to changes in securitized real estate returns, compared to the US. Thus, lag effects are more important in the US, whereas in the UK the contemporaneous relation between direct real estate and securitized real estate is stronger than in the US. For example, Barkham and Geltner (1995) find that the correlation between annual (unsmoothed) direct real estate returns and real estate stock returns is 61% in the UK, but only 19% in the US. These differences in the dynamics of the direct real estate markets should affect the term structure of the return volatility.

The high negative correlation between dividend yield and stock return residuals is crucial to capture mean reversion in stock returns (Campbell and Viceira 2005). Therefore, we include common valuation ratios specific to real estate asset markets in the VAR models, whose residuals are highly negatively correlated with the return residuals. In particular, the cap rate of the direct real estate market is used to predict the return of the direct real estate market, and a valuation ratio specific to the market for securitized real estate is used as a return predictor for the securitized real estate market. This point has been neglected by previous research on the term structure of the return volatility of real estate assets. (Previous studies on securitized real estate accounted for the dividend yield of the general stock market, but not for the dividend yield of the market for real estate stocks, or a similar valuation ratio specific to the real estate stocks market). Therefore, previous studies may have overestimated the long-term volatility of these assets. We link the results for the term structure of return volatilities to the variance decomposition of Campbell (1991), and use the VAR results to calculate multi-period R^2 statistics for real estate investments. Finally, we use the results of the variance decompositions to analyze the informational efficiency of the real estate asset markets.

2.3 VAR model and data

2.3.1 VAR specification

The results are based on separate VARs for each country using annual data from 1972 to 2008 (37 observations) for the UK market and from 1979 to 2008 (30 observations) for the US market.[7] Let $\boldsymbol{z}_{t+1}$ be a (5x1) vector, whose first two elements are log

[7] The main results for the UK market remain qualitatively unchanged, if the shorter time span 1979 to 2008 is used (as for the US market).

(continuously compounded) real asset returns, $r_{t+1} = \ln(1+R_{t+1}) - \ln(1+I_{t+1})$, where R_{t+1} is the simple nominal return on an asset and I_{t+1} is the inflation rate. The first element of the vector $\boldsymbol{z}_{t+1}$ is the log real return on direct real estate; the second element is the log real return on securitized real estate. Asset returns are measured in real terms, since real rather than nominal returns are relevant for investors who are concerned about the purchasing power of their investments. Three additional state variables that predict the asset returns are included in $\boldsymbol{z}_{t+1}$. All variables are mean-adjusted. Assume that a VAR(1) model captures the dynamic relationships of the variables:[8]

$$\boldsymbol{z}_{t+1} = \boldsymbol{\Phi}\boldsymbol{z}_t + \boldsymbol{v}_{t+1}. \tag{2.1}$$

$\boldsymbol{\Phi}$ is a (5x5) coefficient-matrix. The shocks are stacked in the (5x1) vector $\boldsymbol{v}_{t+1}$ with time-invariant (5x5) covariance-matrix $\boldsymbol{\Sigma}_v$.

2.3.2 Data

To calculate the log real total return on securitized real estate, a property share index is used for the UK market and a REIT index is used for the US market. For the UK market the log of the dividend yield of the property share index is used as a state variable to predict the return on property shares. In analogy, we considered the dividend yield of the REIT market for the US VAR. However, this variable is not a significant predictor of REIT returns at any conventional levels. In contrast, another valuation ratio, the price to cash-flow ratio of the REIT market is a significant predictor of REIT returns. Hence, this variable is included as a state variable in the US VAR model in form of the log of the inverse of the variable, i.e., the log of the cash-flow yield. US REITs are restricted in their dividend policy since they have to pay out at least 90% (formerly 95%) of their taxable income as dividends. This restriction links the dividend payments of REITs to their earnings. Lamont (1998) shows with regard to the general stock market that in a univariate regression the earnings yield is not – in contrast to the dividend yield – a significant predictor of stock returns. This suggests that the dividend restriction of REITs might explain why the cash-flow to price ratio is a better valuation ratio to

[8] The VAR(1) framework is not restrictive since a VAR(p) model can be written as a VAR(1) model, see Campbell and Shiller (1988).

forecast REIT returns than the dividend yield.[9] We also include the yield spread as a state variable that has been shown to predict asset returns (e.g., Campbell 1987, Fama and French 1989). The variable is computed as the difference of the log yield on a long-term bond minus the log yield of three-month treasury bills. Details on the data can be found in the Appendix.

Appraisal-based capital and income returns are the basis for the calculation of the total return series and the cap rate series of direct real estate. The indexes used are the NCREIF property index (NPI) for the US market and the IPD long-term index for the UK market. The appraisal-based returns are unsmoothed using the approach introduced by Geltner (1993) for the US market and applied by Barkham and Geltner (1994) for the UK market. This unsmoothing approach does not presume that true real estate returns should be uncorrelated. Annual appraisal-based log real capital returns g_t^* are unsmoothed using the formula

$$g_t = \frac{g_t^* - (1-a)\cdot g_{t-1}^*}{a}, \tag{2.2}$$

where g_t is the true log real capital return (or growth) and a is the smoothing parameter. We use the value 0.40 (0.625) for unsmoothing annual US (UK) returns as favored by Geltner (1993) and Barkham and Geltner (1994), respectively. Total real estate returns and the cap rate series are constructed from the unsmoothed log real capital return and income return series as follows: The unsmoothed log real capital returns are converted to simple nominal capital returns (CRU_t). This series is used to construct an unsmoothed capital value index (UCV_t). The unsmoothed capital value index is calibrated such that the average of the capital values over time matches the corresponding average of the original index. A real estate income series (Inc_t) is obtained by multiplying the (original) income return (IR_t) with the (original) capital value index (CV_t): $Inc_t = IR_t \cdot CV_{t-1}$. New income returns are computed with regard to the unsmoothed capital value index: $IRU_t = Inc_t / UCV_{t-1}$. Total returns are obtained by adding the adjusted simple income and capital returns: $RER_t = CRU_t + IRU_t$. The cap rate series is

[9] Chun et al. (2004) show that, after controlling for payout and book-to-market ratios, the price-dividend ratio is a significant predictor of excess US REIT returns.

calculated as $CR_t = Inc_t / UCV_t$. The variables included in the VAR are the log real total return, and the log of the cap rate.

As a robustness check for the UK market, we estimate additional VARs based on direct real estate return and cap rate series that result from using the smoothing parameters 0.50 and 0.75, which Barkham and Geltner (1994) consider as reasonable lower and upper bounds. In analogy, US results are recalculated for the alternative smoothing parameters 0.33 and 0.50 following Geltner (1993). To save space, we provide only the results concerning direct real estate from these additional VAR estimates, since the results for securitized real estate and the three state variables are not much affected by using the different real estate return and cap rate series resulting from the alternative smoothing parameters in the VARs.

Table 2.1 lists the standard deviations and first-order autocorrelations of the variables included in the benchmark UK VAR (*a* = 0.625) and the benchmark US VAR (*a* = 0.40). Direct real estate returns are much more volatile in the UK than in the US, and the UK returns exhibit less autocorrelation than the US returns. The returns of securitized real estate investments are also more volatile in the UK compared to the US. The additional three state variables all show notable positive autocorrelation.

Table 2.1 Sample statistics

This table shows statistics for the variables included in the VAR models, which are based on annual data. The sample period is 1972 to 2008 for the UK. The US sample period is 1979 to 2008. Direct real estate return and cap rate statistics are based on the smoothing parameter (*a*) 0.625 for the UK and 0.40 for the US. St.dv.: Standard deviation. Autocorrelation refers to the first-order autocorrelation.

	UK ($a = 0.625$)		US ($a = 0.40$)	
	St.dv.	Auto-correlation	St.dv.	Auto-correlation
Log real return on direct real estate	17.22%	15.49%	10.39%	38.82%
Log real return on securitized real estate	31.18%	-2.22%	23.30%	-3.31%
Log of cap rate	0.2636	60.91%	0.1938	81.07%
Log of yield of securitized real estate	0.3176	40.03%	0.3433	69.27%
Log yield spread	1.81%	45.28%	1.40%	40.26%

Since the Center for Real Estate at MIT provides the Transaction-Based Index (TBI) for the US commercial real estate market, one might object the use of (unsmoothed) appraisal-based returns. The TBI is based on property transactions in the pool of properties that are used to construct the appraisal-based NPI (for details on the construction of the TBI see Fisher et al. 2007). It should be emphasized, however, that, while transaction-based indexes have the advantage to be based on transaction prices (instead of appraisal), they are not generally preferable to (unsmoothed) appraisal-based indexes, because they might be subject to other problems such as noise due to the relatively small amount of property transactions (in contrast to appraisals).[10] The NPI index has the advantage that it goes back further in time than the TBI. Nevertheless, to see how the unsmoothed NPI returns used in this chapter compare to TBI returns, Table 2.2 provides some statistics of unsmoothed NPI and TBI returns for the period of overlap 1985 to 2008. TBI returns are reported for both the variable and the constant liquidity version of the TBI. (We compare appreciation returns instead of total returns, since the constant liquidity version is available as an appreciation return index only.) The construction of a constant liquidity transaction-based index is motivated by the fact that liquidity is time-varying and pro-cyclical in real estate markets (see Fisher et al. 2003 and Goetzmann and Peng 2006). While the variable liquidity TBI tracks the development of transaction prices in the commercial real estate markets, it reflects variable market liquidity. The constant liquidity TBI is an index that tracks the development of transaction prices under the assumption of constant liquidity.

Table 2.2 Statistics of US direct real estate returns

This table shows statistics of mean-adjusted log real capital returns, based on annual data from 1985 to 2008. Unsmoothed NPI return statistics are reported for three smoothing parameters a. TBI return statistics are reported for the variable liquidity (VL) and the constant liquidity (CL) version. St.dv.: Standard deviation. Autocorrelation refers to the first-order autocorrelation.

	St.dv.	Auto-correlation	Correlation with VL	Correlation with CL
NPI				
$a = 0.33$	14.04%	37.70%	77.34%	83.38%
$a = 0.40$	11.70%	40.94%	78.87%	83.05%
$a = 0.50$	9.64%	46.31%	79.89%	81.45%
TBI				
Variable liquidity (VL)	9.00%	47.62%	100.00%	92.98%
Constant liquidity (CL)	11.19%	37.71%	92.98%	100.00%

[10] See Geltner et al. (2007, Chapter 25) for a discussion of appraisal-based and transaction-based commercial real estate indexes.

As can be seen in Table 2.2, the constant liquidity returns show a higher volatility and lower autocorrelation than the variable liquidity returns. Unsmoothed NPI returns have correlations with TBI returns of about 80%, and the correlations are generally higher with regard to the constant liquidity version of the TBI than with the variable liquidity version. This is consistent with the view of Fisher et al. (1994, 2003) that unsmoothing procedures can be seen as an attempt to control for pro-cyclical variable liquidity. Constant liquidity returns are better comparable to stock returns, since well-developed stock markets offer (approximately) constant liquidity. Judging from the return standard deviations, the smoothing parameter $a = 0.40$ favored by Geltner (1993) indeed appears to be more reasonable than the values 0.33 and 0.50. Annual TBI returns show a similar autocorrelation as unsmoothed appraisal-based returns. Hence, the notable autocorrelation in annual returns of about 40% indeed seems to be a feature of the direct US real estate market.

2.3.3 VAR estimates

The results of the VARs, estimated by OLS, are given in Tables 2.3 (UK) and 2.4 (US). Panels A contain the coefficients. In square brackets are *t*-values. The rightmost column contains R^2 statistics and the *p*-value of the *F*-test of joint significance (in parentheses).

With R^2 values of about 29 and 35% the degree of predictability of annual securitized real estate returns is similar in the two countries. With an R^2 value of 60%, US direct real estate returns are much more predictable than US REIT returns and UK direct and securitized real estate returns. Direct real estate has a higher R^2 value than securitized real estate in the UK as well. The *p*-values of the test of joint significance are below or close to 5% and thus indicate that real returns of direct and securitized real estate are indeed predictable in both countries.

Table 2.3 UK VAR results

The results are based on mean-adjusted annual data from 1972 to 2008. Full VAR results are reported for the smoothing parameter *a* = 0.625, and VAR results concerning only direct real estate are reported for *a* = 0.50 and *a* = 0.75. Panel A shows the VAR coefficients. The *t*-statistics are in square brackets; values corresponding to *p*-values of 10% or below are highlighted. The rightmost column contains the R^2 values and the *p*-value of the *F*-test of joint significance in parentheses. Panel B shows results regarding the covariance matrix of residuals, where standard deviations are on the diagonal and correlations are on the off-diagonals.

Panel A: VAR coefficients

	Coefficients on lagged variables					
Variable	1	2	3	4	5	R^2 (*p*)
a = 0.625						
1 Log real return on direct real estate	0.199	0.162	0.323	0.016	2.180	42.82%
	[0.858]	[1.177]	**[2.414]**	[0.122]	[1.590]	(0.28%)
2 Log real return on property shares	0.105	0.161	0.344	0.336	2.109	29.24%
	[0.219]	[0.569]	[1.251]	[1.240]	[0.748]	(4.72%)
3 Log of cap rate	-0.087	-0.224	0.600	0.024	-4.594	57.06%
	[-0.295]	[-1.280]	**[3.520]**	[0.140]	**[-2.632]**	(0.00%)
4 Log of dividend yield	-0.065	-0.027	-0.334	0.622	-4.054	26.81%
	[-0.134]	[-0.095]	[-1.204]	**[2.271]**	[-1.426]	(7.04%)
5 Log yield spread	0.012	-0.032	0.004	0.001	0.460	42.66%
	[0.461]	**[-2.182]**	[0.243]	[0.086]	**[3.118]**	(0.29%)
a = 0.50						
1 Log real return on direct real estate	0.133	0.212	0.387	0.024	2.736	43.65%
	[0.564]	[1.196]	**[2.452]**	[0.147]	[1.612]	(0.23%)
a = 0.75						
1 Log real return on direct real estate	0.285	0.132	0.278	0.014	1.835	43.79%
	[1.269]	[1.199]	**[2.419]**	[0.124]	[1.585]	(0.22%)

Panel B: Standard deviations and correlations of VAR residuals

	1	2	3	4	5
a = 0.625					
1 Log real return on direct real estate	13.73%	76.92%	-96.90%	-73.36%	-39.13%
2 Log real return on property shares	76.92%	28.21%	-76.44%	-94.23%	-30.86%
3 Log of cap rate	-96.90%	-76.44%	17.47%	78.46%	36.92%
4 Log of dividend yield	-73.36%	-94.23%	78.46%	28.46%	33.05%
5 Log yield spread	-39.13%	-30.86%	36.92%	33.05%	1.48%
a = 0.50					
1 Log real return on direct real estate	17.14%	76.69%	-97.65%	-73.09%	-39.14%
a = 0.75					
1 Log real return on direct real estate	11.44%	76.91%	-96.04%	-73.37%	-38.88%

Table 2.4 US VAR results

The results are based on mean-adjusted annual data from 1979 to 2008. Full VAR results are reported for the smoothing parameter $a = 0.40$, and VAR results concerning only direct real estate also reported for $a = 0.33$ and $a = 0.50$. Panel A shows the VAR coefficients. The *t*-statistics are in square brackets; values corresponding to *p*-values of 10% or below are highlighted. The rightmost column contains the R^2 values and the *p*-value of the *F*-test of joint significance in parentheses. Panel B shows results regarding the covariance matrix of residuals, where standard deviations are on the diagonal and correlations are on the off-diagonals.

Panel A: VAR coefficients

	Coefficients on lagged variables					
Variable	1	2	3	4	5	R^2 (*p*)
a = 0.40						
1 Log real return on direct real estate	0.710	0.186	0.242	0.011	1.013	60.10%
	[3.570]	**[2.791]**	**[2.878]**	[0.238]	[0.972]	(0.03%)
2 Log real return on REITs	0.376	-0.015	0.266	0.309	4.520	34.79%
	[0.667]	[-0.077]	[1.117]	**[2.369]**	[1.530]	(5.35%)
3 Log of cap rate	-0.604	-0.237	0.795	-0.004	-1.182	80.04%
	[-2.304]	**[-2.699]**	**[7.187]**	[-0.074]	[-0.861]	(0.00%)
4 Log of cash-flow yield	-0.127	-0.011	-0.154	0.621	-2.934	50.32%
	[-0.194]	[-0.050]	[-0.556]	**[4.096]**	[-0.853]	(0.30%)
5 Log yield spread	-0.033	0.008	-0.003	0.003	0.356	21.85%
	[-0.957]	[0.663]	[-0.207]	[0.438]	**[1.979]**	(26.56%)
a = 0.33						
1 Log real return on direct real estate	0.652	0.228	0.256	0.014	1.199	58.32%
	[3.146]	**[2.784]**	**[2.757]**	[0.243]	[0.936]	(0.05%)
a = 0.50						
1 Log real return on direct real estate	0.780	0.148	0.222	0.008	0.865	63.34%
	[4.246]	**[2.839]**	**[3.059]**	[0.227]	[1.053]	(0.01%)

Panel B: Standard deviations and correlations of VAR residuals

	1	2	3	4	5
a = 0.40					
1 Log real return on direct real estate	7.17%	51.30%	-90.31%	-38.23%	-49.89%
2 Log real return on REITs	51.30%	20.34%	-36.69%	-87.12%	-27.10%
3 Log of cap rate	-90.31%	-36.69%	9.45%	32.15%	44.55%
4 Log of cash-flow yield	-38.23%	-87.12%	32.15%	23.67%	18.36%
5 Log yield spread	-49.89%	-27.10%	44.55%	18.36%	1.24%
a = 0.33					
1 Log real return on direct real estate	8.80%	51.60%	-93.11%	-38.12%	-50.29%
a = 0.50					
1 Log real return on direct real estate	5.65%	51.21%	-86.03%	-38.70%	-49.30%

The dynamics of real estate returns in the UK and in the US are qualitatively similar. But there are notable differences with regard to the magnitude and significance of some coefficients. In particular, direct real estate returns in the US strongly depend positively and significantly on its own lag, which is not the case for direct real estate in the UK. The return on securitized real estate has a positive influence on direct real estate returns in both countries, but the influence is not significant in the UK. Direct real estate returns are significantly affected by the lagged cap rate in both countries. The lagged cap rate also has a positive (though not significant) influence on securitized real estate returns. The lagged dividend/cash-flow yield of the securitized real estate markets has a positive influence on securitized real estate returns. The coefficient is not significant in the UK, but in a regression of property share returns on the lagged dividend yield alone this is the case (t-value of 2.75). Finally, the lagged yield spread is positively related to direct and securitized real estate returns. The coefficients are never significantly different from zero at the 10% level, though. All three additional state variables show persistent behavior with coefficients on their own lags of between 0.356 and 0.795. Since these state variables predict asset returns, the persistency of the state variables carries over to expected asset returns, making expected returns positively autocorrelated. A shock to the expected return persists for some periods ahead, but eventually dies out. The dynamics of some of the state variables are more complex, however. In the UK, the lagged yield spread is also a significant predictor of the cap rate. In the US, lagged direct real estate returns and REIT returns have a significantly negative influence on the cap rate. Due to the positive autocorrelation in direct real estate returns, a price increase of direct real estate in period $t-1$ tends to be associated with a price increase in t, which lowers the cap rate in t. Similarly, the dependence of the cap rate on the lagged REIT return can be explained by the dependence of direct real estate returns on lagged REIT returns. The dynamics are very similar, when the results are based on the alternative smoothing parameter assumptions.

Panels B of Tables 2.3 and 2.4 contain the standard deviations (diagonal) and correlations (off-diagonals) of the VAR residuals. We see that the standard deviation of direct real estate return residuals is much lower in the US than in the UK. There are two reasons for this result. First, the total return variance is lower in the US, as seen in Table 2.1. Second, annual direct real estate returns are more predictable in the US, which means that the unexpected part of the total variance is smaller. The choice of the smoothing parameter has a notable influence on the residual standard deviation of UK direct real estate returns. When appraisal-based returns are assumed to exhibit relatively little smoothing ($a = 0.75$) the volatility is 11.4%, compared to 17.1% when it is assumed that there is a lot of smoothing ($a = 0.50$). Qualitatively, we see the same result in the US estimates. As with the total standard deviation, the residual standard deviation of US REIT returns is lower than the residual standard deviation of UK property shares. The correlation between direct and securitized real estate return residuals is positive and particularly strong in the UK (77%). US direct real estate and REIT residuals have a correlation of about 51%. The residual correlation between direct and securitized real estate is similar to the correlation between the real log return series itself in the UK, but in the US the residual correlation is higher. In the US, the correlation of the return variables is 33.6% $(a = 0.40)$ compared to the 51.3% residual correlation. This effect is similar to the result of Giliberto (1990), who finds that the residuals obtained from regressions of US direct real estate and REIT returns on other (contemporaneous) asset returns are significantly correlated, although the return series itself are not. The residual correlations between direct real estate returns and cap rates and between securitized real estate returns and dividend/cash-flow yields are highly negative. In the UK, the correlations are about -95% and in the US they are about -90%.

2.4 Multi-period volatility and R^2 statistics

2.4.1 Methodology

The term structure of an asset's conditional (i.e., taking predictability into account) standard deviation of real returns can be extracted from the conditional multi-period covariance matrix of the vector $\boldsymbol{z}_{t+1}$, scaled by the investment horizon k (see, e.g., Campbell and Viceira 2004):

$$
\begin{aligned}
\frac{1}{k} Var_t(\boldsymbol{z}_{t+1} + \ldots + \boldsymbol{z}_{t+k}) = \frac{1}{k}\boldsymbol{W}(k) \\
&= \frac{1}{k}(\boldsymbol{\Sigma}_v + (\mathbf{I}+\boldsymbol{\Phi})\boldsymbol{\Sigma}_v(\mathbf{I}+\boldsymbol{\Phi})' \\
&\quad + (\mathbf{I}+\boldsymbol{\Phi}+\boldsymbol{\Phi}^2)\boldsymbol{\Sigma}_v(\mathbf{I}+\boldsymbol{\Phi}+\boldsymbol{\Phi}^2)' + \ldots \\
&\quad + (\mathbf{I}+\boldsymbol{\Phi}+\ldots+\boldsymbol{\Phi}^{k\text{-}1})\boldsymbol{\Sigma}_v(\mathbf{I}+\boldsymbol{\Phi}+\ldots+\boldsymbol{\Phi}^{k\text{-}1})'),
\end{aligned} \tag{2.3}
$$

where $\mathbf{I}$ is the identity matrix.

Define **e1** (**e2**) as a (5x1) vector where the first (second) element is one and the other elements are zero. Then $\boldsymbol{e1}'\frac{1}{k}\boldsymbol{W}(k)\boldsymbol{e1}$ picks out the annualized conditional variance of real direct real estate returns, and $\boldsymbol{e2}'\frac{1}{k}\boldsymbol{W}(k)\boldsymbol{e2}$ picks out the annualized conditional variance of real securitized real estate returns, at horizon k.

The VAR results can also be used to calculate implied R^2 statistics for multi-period asset returns (see Hodrick 1992). The R^2 statistic can be expressed as one minus the ratio of the unexplained variance to the total variance of multi-period returns. $\boldsymbol{W}(k)$ contains the unexplained variance of k-period returns. To calculate the k-period total variance we need to calculate the unconditional variance of the vector $\boldsymbol{z}_{t+1}$, which is:[11]

$$\boldsymbol{C}(0) = \sum_{j=0}^{\infty} \boldsymbol{\Phi}^j \boldsymbol{\Sigma}_v \boldsymbol{\Phi}^{j}{}'. \tag{2.4}$$

The k-period matrix of total covariances is:

$$\boldsymbol{V}(k) = k\boldsymbol{C}(0) + \sum_{j=1}^{k-1} (k-j)(\boldsymbol{C}(j) + \boldsymbol{C}(j)'), \tag{2.5}$$

where $\boldsymbol{C}(j) = \boldsymbol{\Phi}^j \boldsymbol{C}(0)$ is the j-th order autocovariance of the vector $\boldsymbol{z}_{t+1}$. Hence, the k-period R^2 statistic of direct real estate returns, implied by the VAR estimates, is:

$$R^2(k) = 1 - \frac{\boldsymbol{e1}'\boldsymbol{W}(k)\boldsymbol{e1}}{\boldsymbol{e1}'\boldsymbol{V}(k)\boldsymbol{e1}}. \tag{2.6}$$

The k-period R^2 statistic of securitized real estate returns can be calculated in the same way using the vector **e2** instead of **e1**.

2.4.2 Results

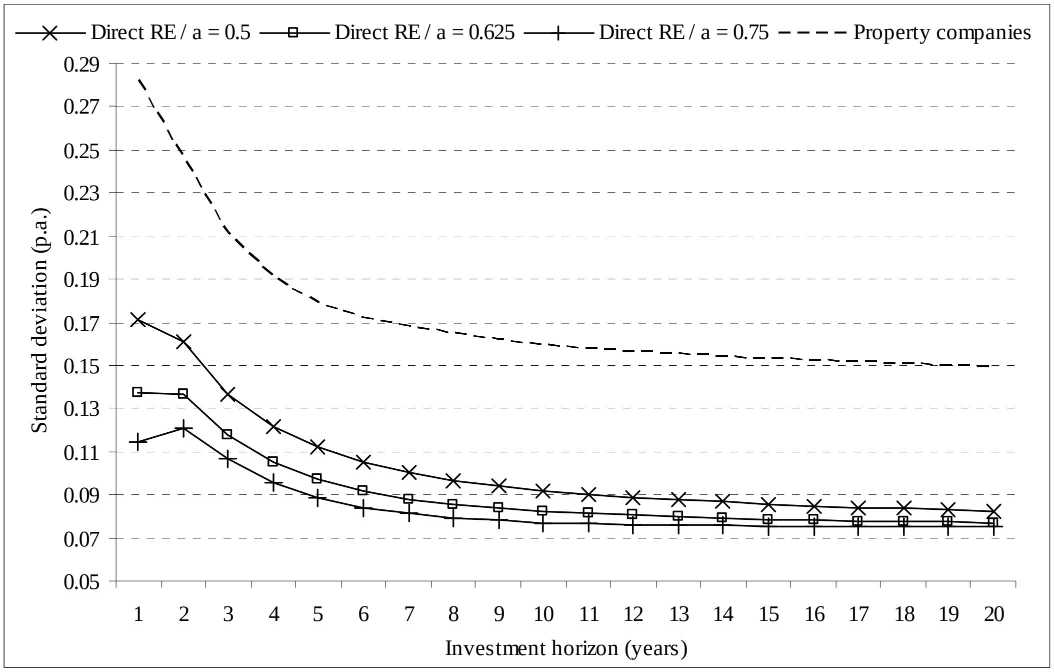
Figure 2.1 shows the estimates of the term structure of the conditional standard deviation for real direct and securitized real estate returns. Panel A shows the results for the UK, and Panel B shows the results for the US. The panels contain the term structures for direct real estate for the three alternative smoothing parameters. The term

[11] The infinite sum is truncated at j = 1000 in the calculations.

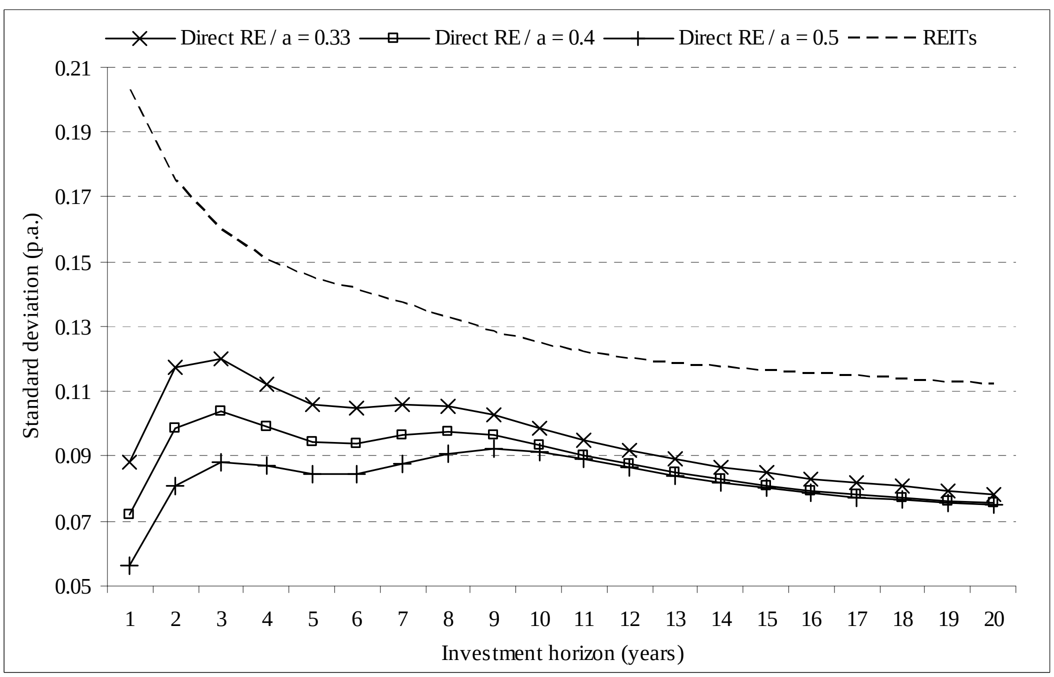
structures for securitized real estate are obtained from the VARs with the benchmark smoothing parameter assumption.

In the UK, property share returns show strong mean reversion, which cuts the annualized standard deviation from 28.2% at the one-year horizon to 15.0% at the twenty-year horizon. Similarly, Campbell and Viceira (2005) report that the annualized volatility of US general stock market returns falls by about 50%. The level of the return volatility of the US general stock market is lower, though. The mean reversion of UK property share returns can be traced back to the positive dependence of the return on the lagged dividend yield of the property shares market, since return and dividend yield residuals are highly negatively correlated.

Direct UK real estate returns show a similar pattern as securitized real estate. For the $a = 0.625$ case, the annualized long-term standard deviation is only 56% of the one-year volatility. Over the short-term, however, the pattern is different from property shares. Depending on the assumed smoothing parameter, the term structure is slightly increasing ($a = 0.75$), flat ($a = 0.625$), or slightly decreasing ($a = 0.50$). The counteracting mean-aversion effect is due to the positive dependence of direct real estate returns on lagged securitized real estate returns in combination with the high positive correlation of direct and securitized real estate return residuals. When there is a positive shock to the property share return, the return on direct real estate tends to be high as well, and a high return on property shares predicts a high return on direct real estate, and vice versa. As noted above, the choice of the smoothing parameter has a strong effect on the one-year return volatility. In contrast, the choice of the smoothing parameter has little influence on the long-term volatility. Depending on the smoothing parameter, the annualized twenty-year volatility is between 7.5% and 8.25%. Thus, for long-term direct real estate investment decisions the choice of the smoothing parameter is of minor importance. The cap rate is crucial to capture the long-term mean-reversion effect in direct UK real estate returns. When the cap rate is excluded from the five-variable VAR model, the returns still exhibit (slight) mean reversion, but the estimated annualized 20-year return volatility is much higher with values between 11.2% ($a = 0.75$) and 14.6% ($a = 0.50$). Thus, the cap rate captures mean reversion of direct real estate returns, just like the dividend yield of the property share market captures mean reversion in the securitized real estate market.



Panel A: UK



Panel B: US

Figure 2.1 The term structure of return volatilities

The figure shows conditional annualized standard deviations of real returns depending on the investment horizon. RE: Real estate. *a* is the smoothing parameter.

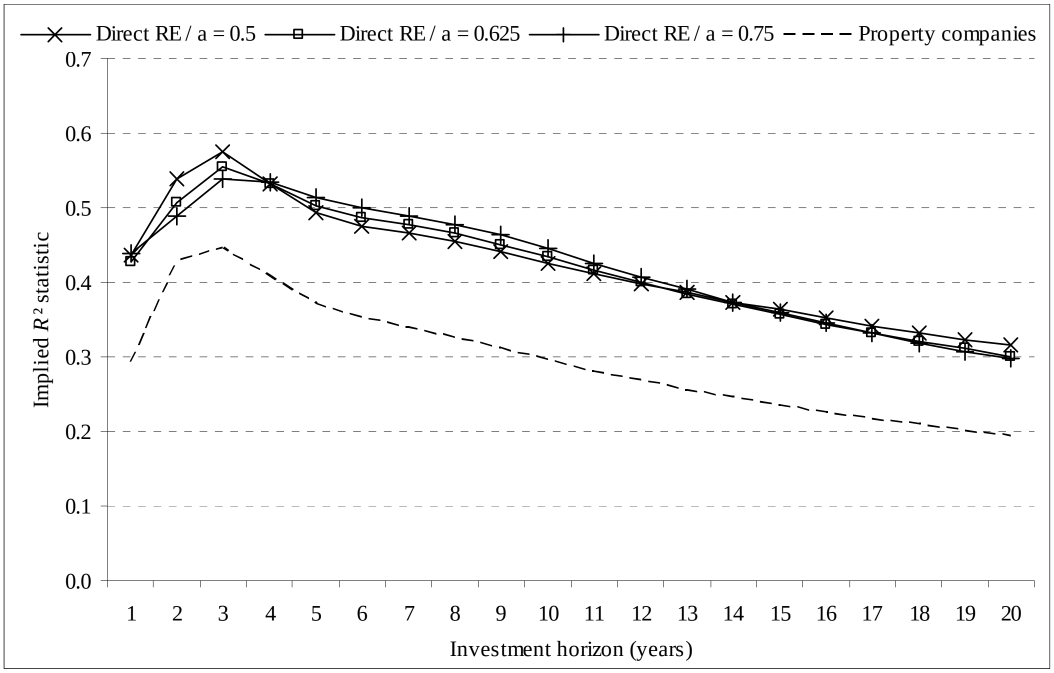
Looking at the estimates for US securitized real estate, we see a pattern similar to the UK results. The periodic long-term volatility of REIT returns is only about 55% of the one-year volatility. Thus, when a valuation ratio specific to the securitized real estate market is included in the VAR model, the mean reversion effect appears to be very similar to the general stock market.

Turning to US direct real estate, we see a strong mean aversion effect over short investment horizons. The annualized three-year return standard deviation is more than three percentage points higher than the one-year standard deviation (this is true for all three smoothing parameters). Thus, the short-term mean aversion effect is much stronger in the US than in the UK direct real estate market. As in the UK, the mean aversion effect can be attributed to the relationship with securitized real estate returns. Direct real estate returns are positively related to lagged REIT returns and the correlation of the residuals is also positive. In addition to that, direct real estate returns are positively autocorrelated in the US, which also induces a mean-aversion effect. The term structure is downward sloping or relatively flat over medium investment horizons of up to ten years, depending on the assumption regarding the smoothing parameter. For every smoothing parameter we see a mean-reversion effect, however, such that the annualized twenty-year return volatility is lower than the volatility at medium investment horizons. The twenty-year volatility is 7.5 to 7.8%, very similar to the UK estimates. Hence, one important conclusion from Figure 2.1 is that in the long run, US direct real estate returns do not appear to be less volatile than UK direct real estate returns, which contrasts sharply with short-term statistics. Again, the choice of the smoothing parameter has little influence on the return volatility at medium and long horizons. Only the return volatility for short investment horizons (not relevant for most investors in the direct real estate market) is strongly affected by the choice of the smoothing parameter. Even more than in the UK, it is important to include the cap rate in the VARs to capture mean reversion in direct real estate returns. Specifically, when the cap rate is excluded from the five-variable VAR, the twenty-year volatility (per period) is between 15.6 and 17.9% (depending on the unsmoothing parameter), more than twice the estimates from the VARs that include the cap rate.

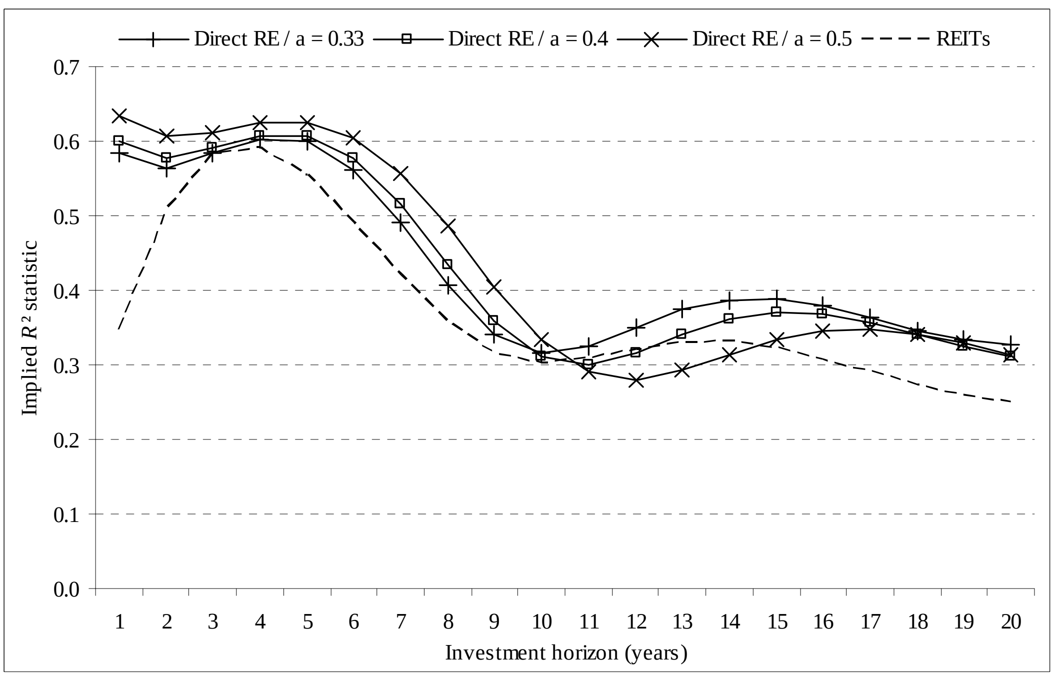
In both countries, the volatility of securitized real estate returns is notably higher than the volatility of direct real estate returns over all investment horizons. One explanation for this is leverage (see, e.g., Barkham and Geltner 1995 and Pagliari et al. 2005). It is well known that leverage increases the volatility of equity returns. As the indexes used for the direct real estate markets measure the performance of unlevered investments, while the indexes used for the securitized real estate markets measure the performance of levered real estate firms, leverage is a straightforward explanation for the return volatility differences. Due to the short-term mean aversion effects in the direct real estate markets, in contrast to the mean reversion of securitized real estate returns, the ratio of the volatility of direct real estate returns to the volatility of securitized real estate returns is particularly low at the one-year horizon in the UK and at the one- and two-year horizons in the US. This is similar to the finding of Geltner et al. (1995) that unlevered US REIT returns and direct real estate returns have a similar volatility at a five-year horizon, whereas the one-year volatility of unlevered REIT returns is notably higher.

The R^2 statistics for the one-year horizon calculated from (2.6) match the actual R^2 statistics reported in Tables 2.3 and 2.4 quite good for the UK market. This is also true for the R^2 statistic of US REITs. The one-year R^2 statistics calculated from (2.6) are notably higher than the actual R^2 statistics for US direct real estate. Therefore, we generally rescaled the k-year R^2 statistics obtained from (2.6) such that the one-year R^2 statistics are equal to the actual R^2 statistics reported in Tables 2.3 and 2.4. These rescaled implied R^2 statistics are shown in Figure 2.2.

In the UK market, the general pattern is quite similar for the three direct real estate estimates and the estimate for property shares. The R^2 statistics increase over short investment horizons, reaching its maximum at the three-year horizon with 45% for property shares and about 55% for direct real estate ($a = 0.625$), respectively. For investment horizons longer than three years, however, the implied R^2 statistics decrease with the investment horizon. The implied R^2 statistic decreases to 20% at the twenty-year horizon for property shares and to 30% for direct real estate. Thus, direct real estate remains to be more predictable than securitized real estate at longer horizons. For comparison, Campbell (1991) reports that the R^2 statistic of US stock returns implied by a VAR estimate for the 1952 to 1988 period rises to about 45% at a horizon of nine years and only slightly decreases over longer horizons. Over the longer 1927 to 1988 period, the implied R^2 statistics are generally lower, the peak is earlier at about four years and the R^2 statistic is decreasing faster with the investment horizon.



Panel A: UK



Panel B: US

Figure 2.2 Implied R^2 statistics

The figure shows R^2 statistics, implied by the VAR estimates, depending on the investment horizon. The k-year R^2 statistics obtained from (2.6) are rescaled such that the one-year R^2 statistics are equal to the actual R^2 statistics reported in Tables 2.3 and 2.4. RE: Real estate. a is the smoothing parameter.

The results for the US market are more complex than the UK results. The implied R^2 statistics for direct real estate are quite flat at horizons between one and five years. As in the UK market, the variance of expected returns increases more than in proportion to the investment horizon. However, recall from Table 2.1 that realized returns are highly positively autocorrelated in the US (in contrast to the UK), so that the variance of realized returns increases more than in proportion to the investment horizon, too. Therefore, we see the flat line in the US and the increasing R^2 statistics in the UK over short horizons. As in the UK, the implied R^2 statistic is strongly increasing for securitized real estate returns over short horizons. The implied R^2 statistic of REITs is almost 60% at the three-year horizon, much more than the 45% estimated for property shares in the UK. The implied R^2 statistics decrease strongly over medium investment horizons for both direct real estate and REIT returns. At the ten-year horizon all estimates are very similar with implied R^2 statistics of about 30 to 35%. Thus, while US direct real estate returns are more predictable than REIT returns when judged from regressions with annual returns, they appear to be equally predictable over an investment horizon, which is typical for investors in direct real estate. With about 32%, the twenty-year R^2 statistic for direct real estate is again higher than the 24% R^2 statistic for REIT returns.

2.5 Variance decompositions

2.5.1 Methodology

Building on Campbell and Shiller's (1988) log-linear present-value model with time-varying discount rates, Campbell (1991) shows that for investor's expectations to be internally consistent, high unexpected returns $r_{t+1} - E_t(r_{t+1})$ must be associated with revisions in expectations about future cash-flow growth or future returns (discount rates), or both:[12]

$$r_{t+1} - E_t(r_{t+1}) = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j}\ , \tag{2.7}$$

where r_{t+1+j} is the log real return and Δd_{t+1+j} is the growth in cash-flow in period $t+1+j$. E_t is the conditional expectation operator such that $(E_{t+1} - E_t)$ denotes the

[12] Rational bubbles need to be ruled out in the derivation.

revision in expectations due to the arrival of news in period $t+1$. ρ is a parameter of linearization defined as $\rho = 1/[1+\exp(\overline{d-p})]$, where $\overline{d-p}$ is the mean log cash-payout-yield, i.e., the dividend yield of the securitized real estate market and the cap rate of the direct real estate market, respectively.[13] Revisions in expectations have a greater effect on unexpected returns the more persistent the revisions are, since discounted individual news terms are summed up. Equation (2.7) can be expressed in more compact form as

$$r_{t+1} - E_t(r_{t+1}) = \eta_{t+1} = \eta_{d,t+1} - \eta_{r,t+1}. \tag{2.8}$$

We refer to $\eta_{d,t+1}$ as cash-flow news and to $\eta_{r,t+1}$ as discount rate news, for short. In the remainder, we provide formulas for direct real estate, using the vector $\boldsymbol{e1}$. The same formulas apply to securitized real estate, if $\boldsymbol{e1}$ is exchanged by $\boldsymbol{e2}$. Campbell shows that discount rate news can be calculated as:

$$\eta_{r,t+1} = \boldsymbol{\lambda}'\boldsymbol{v}_{t+1}, \tag{2.9}$$

where $\boldsymbol{\lambda}' = \boldsymbol{e1}'\rho\boldsymbol{\Phi}(\mathbf{I} - \rho\boldsymbol{\Phi})^{-1}$. It is easy to calculate $r_{t+1} - E_t(r_{t+1}) = \eta_{t+1} = \mathbf{e1}'\boldsymbol{v}_{t+1}$, so that cash-flow news can be obtained as a residual from equation (2.8):

$$\eta_{d,t+1} = \eta_{t+1} - \eta_{r,t+1} = (\boldsymbol{e1}' + \boldsymbol{\lambda}')\boldsymbol{v}_{t+1}. \tag{2.10}$$

The variances and the covariance of the news terms can be calculated as:

$$\begin{aligned}
&Var(\eta_{r,t+1}) = \boldsymbol{\lambda}'\boldsymbol{\Sigma}_v\boldsymbol{\lambda}, \\
&Var(\eta_{d,t+1}) = (\boldsymbol{e1}' + \boldsymbol{\lambda}')\boldsymbol{\Sigma}_v(\mathbf{e1} + \boldsymbol{\lambda}), \\
&Cov(\eta_{d,t+1}, \eta_{r,t+1}) = \boldsymbol{\lambda}'\boldsymbol{\Sigma}_v(\boldsymbol{e1} + \boldsymbol{\lambda}).
\end{aligned} \tag{2.11}$$

[13] The mean log dividend yield of US REITs is -3.33 and thus ρ = 0.9654. For the US direct real estate market ρ is 0.9296 (for a = 0.40). For the UK market we obtain ρ = 0.9658 for the property shares market and ρ = 0.9437 for the direct real estate market (a = 0.625). Small changes due to unsmoothing direct real estate returns with different smoothing parameters are ignored.

Campbell defines persistence as the ratio of the standard deviation of the news about discount rates to the standard deviation of the innovation in the one-period ahead expected return:

$$P = \frac{\sigma(\boldsymbol{\lambda}'\boldsymbol{v}_{t+1})}{\sigma(\boldsymbol{e1}'\boldsymbol{\Phi}\boldsymbol{v}_{t+1})}. \tag{2.12}$$

This measure says that a typical 1% negative innovation in the expected return causes a *P*% capital gain. When expected returns are highly persistent, asset prices are very sensitive to movements in expected returns.

The statistics (2.11) and (2.12) are functions $f(vec(\boldsymbol{\Phi}))$ of the coefficients in the VAR matrix $\boldsymbol{\Phi}$.[14] Using the Delta-method, we calculate standard errors for any statistic as $\sqrt{\partial f / \partial Vec(\boldsymbol{\Phi}) \boldsymbol{\Omega} \partial f / \partial Vec(\boldsymbol{\Phi})'}$. Here, $\partial f / \partial Vec(\boldsymbol{\Phi})$ denotes the (1x25) vector of partial derivatives, evaluated at the estimate of the VAR coefficient matrix $\boldsymbol{\Phi}$, and $\boldsymbol{\Omega}$ is the (25x25) covariance matrix of the VAR coefficients.

2.5.2 Results

Table 2.5 shows the variance decomposition results. The terms $Var(\eta_{d,t+1})$, $Var(\eta_{r,t+1})$ and $-2Cov(\eta_{d,t+1}, \eta_{r,t+1})$ are reported both in absolute terms and in relative terms, i.e., as a fraction of the variance of unexpected returns, such that the three terms sum to one.

In the UK, about three quarters of the variance of unexpected returns is attributed to discount rate news for both direct real estate and property shares. About 20% is attributed to cash-flow news. In absolute terms, the variances of cash-flow and discount rate news are much higher for property shares than for direct real estate. The covariance terms and hence the correlations between cash-flow and discount rate news are small. These variance decomposition results (in relative terms) are similar to the results for the US general stock market in the 1952 to 1988 period (Campbell 1991).

[14] They are also a function of the residual covariance matrix $\boldsymbol{\Sigma}$, but we treat this as fixed (as in Campbell and Shiller 1988).

Table 2.5 Variance decompositions

This table reports how much of the variance of unexpected returns is attributed to the variance of cash-flow news, $Var(\eta_{d,t+1})$, to the variance of discount rates news, $Var(\eta_{r,t+1})$, and minus two times the covariance, $-2Cov(\eta_{d,t+1},\eta_{r,t+1})$. The three terms are reported in absolute terms, and as a fraction of the variance of unexpected returns, such that the three terms sum to one. $Corr(\eta_{d,t+1},\eta_{r,t+1})$ is the correlation between cash-flow and discount rate news. Persistence refers to the persistence measure for expected returns defined in (2.12). β is the regression coefficient of the one-period unexpected return on the two-period cumulative price adjustment. Standard errors are in parentheses. a is the smoothing parameter.

	$Var(\eta_{d,t+1})$		$Var(\eta_{r,t+1})$		$-2Cov(\eta_{d,t+1},\eta_{r,t+1})$		$Corr(\eta_{d,t+1},\eta_{r,t+1})$	Persistence	β
	Relative	Absolute	Relative	Absolute	Relative	Absolute			
UK									
Direct real estate ($a = 0.50$)	13.83%	0.0041	75.83%	0.0223	10.33%	0.0030	-0.160	2.453	1.081
	(7.04%)	(0.0021)	(13.84%)	(0.0041)	(15.43%)	(0.0045)	(0.271)	(0.936)	(0.063)
Direct real estate ($a = 0.625$)	20.53%	0.0039	73.54%	0.0139	5.93%	0.0011	-0.076	2.824	0.974
	(10.35%)	(0.0020)	(18.26%)	(0.0034)	(21.60%)	(0.0041)	(0.297)	(1.219)	(0.049)
Direct real estate ($a = 0.75$)	29.28%	0.0038	74.28%	0.0097	-3.55%	-0.0005	0.038	2.838	0.881
	(14.82%)	(0.0019)	(23.77%)	(0.0031)	(30.36%)	(0.0040)	(0.314)	(1.282)	(0.039)
Property companies	22.61%	0.0180	69.26%	0.0551	8.14%	0.0065	-0.103	2.131	1.309
	(9.06%)	(0.0072)	(21.77%)	(0.0173)	(24.68%)	(0.0196)	(0.337)	(0.835)	(0.070)
US									
Direct real estate ($a = 0.33$)	20.17%	0.0016	119.68%	0.0093	-39.85%	-0.0031	0.406	1.522	0.614
	(2.85%)	(0.0002)	(25.81%)	(0.0020)	(27.49%)	(0.0021)	(0.219)	(0.412)	(0.035)
Direct real estate ($a = 0.40$)	33.34%	0.0017	139.35%	0.0072	-72.69%	-0.0037	0.533	1.525	0.592
	(6.49%)	(0.0003)	(34.61%)	(0.0018)	(39.47%)	(0.0020)	(0.185)	(0.393)	(0.034)
Direct real estate ($a = 0.50$)	61.32%	0.0020	179.48%	0.0057	-140.80%	-0.0045	0.671	1.571	0.564
	(15.83%)	(0.0005)	(51.33%)	(0.0016)	(64.84%)	(0.0021)	(0.140)	(0.386)	(0.032)
REITs	21.40%	0.0089	105.03%	0.0435	-26.43%	-0.0109	0.279	2.087	1.287
	(6.43%)	(0.0027)	(28.91%)	(0.0120)	(33.83%)	(0.0140)	(0.286)	(0.832)	(0.116)

Qualitatively, the estimates for the UK and the US have in common that discount rate news are much more important than cash-flow news. The variance of discount rate news accounts for more than 100% of the variance of unexpected returns for both US direct real estate and REIT returns. From an absolute perspective it makes sense that discount rates are relatively more important in the US than in the UK, because the conditional return volatilities are on a lower level, so that the absolute contributions of discount rate news are more similar across the countries. Despite the larger relative amounts in the US, the absolute amounts of the variance of discount rate news are still lower than in the UK, especially in the direct real estate market. This is reflected in the lower estimates of the persistence measure for expected returns in the US, which are about 1.5. Recall that this estimate says that a 1% positive shock to the expected return tends to be associated with a 1.5% capital loss. This compares to persistence measures of 2.5 to 2.8 for UK direct real estate. In the securitized real estate markets, the absolute contributions of the variance of discount rate news to the variance of unexpected returns are relatively similar in the UK and the US, and so are the estimated persistence measures.

The variance of cash-flow news of US direct real estate ($a = 0.40$) accounts for one third of the variance of unexpected returns, compared to 21% for the benchmark case ($a = 0.625$) in the UK. In absolute terms, however, the variance of cash-flow news is lower in the US. Thus, relative to the variance of unexpected returns, the variance of cash-flow news as well as the variance of discount rate news are more important in the US than in the UK direct real estate market. This implies that the covariance term is substantially negative and hence the correlation between cash-flow news and discount rate news is substantially positive in the US. When there is good news about future cash-flows, expected future returns tend to rise. The correlation estimate is 53% when $a = 0.40$ is used. This estimate is almost three standard errors above zero. Closest to the UK results is the estimate for US REITs; the correlation between cash-flow and discount rate news is relatively mildly positive (28%, with a standard error of 29%).

The variance decompositions help to interpret the differences between the volatility term structures shown in Figure 2.1. In the UK, most of the variability of unexpected returns for both direct and securitized real estate can be explained by discount rate news, and the correlation between cash-flow and discount rate news is about zero. The term structures reflect strong mean reversion (except for direct real estate at very short horizons), because positive discount rate news decrease prices but increase expected future returns. In the US direct real estate market, the correlation between cash-flow and discount rate news is positive, i.e., positive discount rate news tend to be accompanied by positive cash-flow news. Hence, a positive shock to expected returns (the discount rate effect) may not decrease prices. On the other hand, the persistence in expected returns carries over to realized return, generating mean aversion. The positive correlation between cash-flow and discount rate news also explains the low short-term volatility of US direct real estate returns, since cash-flow and discount rate news of the same sign influence prices in opposite directions. The correlation between cash-flow and discount rate news of US REITs is positive, but relatively small, such that the discount rate effect generates mean reversion.[15]

2.6 Market efficiency

Time-variation in expected returns can be due to irrational behavior or rational changing risk aversion of investors. There is an ongoing debate which explanation is more relevant for stock return predictability (see, e.g., Fama 1991 and Shiller 2003). Fama and French (1989) show that the dividend yield and the yield spread track business cycle movements, being low in good times and high in bad times. The variables forecast both stock and bond returns positively, meaning that future returns are expected to be higher (lower) in bad (good) economic conditions. Because the same is likely to be true for investor's risk aversion, time-variation in expected stock and bond returns may be rational rather than reflect market inefficiency. Plazzi et al. (2010) analyze the role of the cap rate as a predictor of direct real estate returns in detail and find that the cap rate captures the dynamics of direct real estate returns in a similar fashion as the dividend yield captures the dynamics of stock returns. Hence, the predictive power of the yield spread, the cap rate and the yield of the securitized real estate market for direct and securitized real estate returns may also reflect rational time-variation in expected returns.

Recall, however, that direct real estate returns also depend positively on the lagged return on securitized real estate investments and they are also positively autocorrelated, particularly strongly in the US. The finding that price discovery occurs first in the more liquid securitized real estate market and then in the direct real estate market has been documented in many studies (for a review see Geltner et al. 2003). Barkham and Geltner (1995) argue that the securitized market leading the direct real

[15] See Campbell et al. (1997, Chapter 7) for a textbook discussion of these effects.

estate market is hard to reconcile with a rational explanation and conclude that this finding reflects informational inefficiency of the direct real estate market. Positive autocorrelation in real estate returns is seen to be evidence of an inefficient market, too (e.g., Case and Shiller 1989, Fu and Ng 2001). As noted above, autocorrelation and the positive relationship of direct real estate returns on lagged securitized real estate returns (in combination with the positive correlation of the return residuals) induce mean aversion in direct real estate returns. Since the UK direct real estate market shows less mean aversion than the US market, the UK market appears to be relatively more informational efficient. An explanation for this might be that the UK market is more homogeneous (Barkham and Geltner 1995).

The variance decompositions shed some more light on the issue of market efficiency. In contrast to the aggregate stock market, where the correlation between cash-flow news and discount rate news is estimated to be negative or close to zero (Campbell 1991, Campbell and Vuolteenaho 2004a), Vuolteenaho (2002) finds that the correlation with regard to firm-level stock returns is notably positive. The correlation is largest for small firms (often viewed to be most likely subject to behavioral mispricing), whereas the correlation is almost zero for the largest firms. Vuolteenaho points out that the positive correlation could be due to an underreaction to cash-flow news. When good cash-flow news arrives, the price increase does not reflect the good news fully. In turn, expected returns must increase. Campbell et al. (2009) suggest that this explanation may be relevant for the US housing market. The results reported here suggest that the underreaction explanation may also apply to the US direct commercial real estate market.

To address the question of informational efficiency of a market, Fu and Ng (2001) suggest regressing the one-period unexpected return η_{t+1} on a cumulative price adjustment $\varphi_{t+1}(k) = \eta_{t+1} + \rho\eta_{t+2} + ... + \rho^{k-1}\eta_{t+k}$, where $\eta_{t+1+j} = \mathbf{e1'\Phi}^j \boldsymbol{v}_{t+1}$, $j > 0$, are the innovations to future expected returns. (Again, the formula is for direct real estate; if ***e*1** is exchanged by ***e*2** it applies to securitized real estate.) Consider the example of a two-period cumulative price adjustment. A regression coefficient of larger than one means that η_{t+1} and η_{t+2} are negatively correlated, which can be explained by the discount rate effect: When the contemporaneous unexpected return is negative, this is caused by an upward revision of the future expected return. A coefficient of below one is consistent with the underreaction to cash-flow news hypotheses. Suppose that news about cash-flows justifies a positive contemporaneous unexpected return, but due to underreaction the price adjustment is not complete. Therefore, the full adjustment must take place through a future price appreciation, so that η_{t+1} and η_{t+2} are positively correlated. More generally, a positive correlation between η_{t+1} and η_{t+2} can also be due to an underreaction with regard to news about future expected returns.

We follow the approach of Fu and Ng, and report the coefficient β estimated from a regression of the one-period unexpected return on the two-period cumulative price adjustment $\varphi_{t+1}(2) = \eta_{t+1} + \rho\eta_{t+2}$ in the rightmost column of Table 2.5:

$$\eta_{t+1} = \beta\varphi_{t+1}(2) + \varepsilon_{t+1}. \qquad (2.13)$$

In line with the underreaction to cash-flow news explanation, we see that the annual unexpected return in the US direct real market captures only about 60% of the two-year cumulative price adjustment. In the securitized real estate markets, we see no evidence of underreaction. The coefficients are larger than one, consistent with the discount rate effect. These results are in line with the results reported by Fu and Ng. They find a regression coefficient of 60% for the (direct) Hong Kong office real estate market and coefficients of about 110 to 120% for the stock market. However, Fu and Ng regress quarterly unexpected returns on the five-quarter cumulative price adjustment, whereas the dependent variable in our regression is the annual unexpected return. Hence, the underreaction appears to be more severe in the US compared to Hong Kong, since there is a notable underreaction even at an annual frequency in the US. The regression coefficients for the direct real estate market in the UK are about one. This result suggests that the discount rate effect tends to be compensated by an underreaction to news effect. Since the correlation between discount rate news and cash-flow news of about zero does not support an underreaction to cash-flow news story, the underreaction appears to be related to discount rate news.

The regression results correspond to the term structure of return volatilities shown in Figure 2.1. In the UK direct real estate market, the term structures are relatively flat between the one- and two-year horizons. This corresponds to the regression coefficients of about one. The increase in the periodic return volatility of the US direct real estate market can be explained by an underreaction to cash-flow news. It takes some time until prices have fully adjusted to new information, and this slow response leads to the pronounced mean aversion effect over short investment horizons. The regression coefficients of above one in the securitized real estate markets reflect a full adjustment of prices to new information, so that the term structure of the return volatility is decreasing due to the discount rate effect.

2.7 Conclusion

Using vector autoregressions, we find – in line with conventional wisdom – that US and UK direct real estate returns exhibit short-term mean aversion and long-term mean reversion. But comparing the two markets, we find huge differences with regard to the importance of these effects. The UK direct real estate market is characterized by a strong mean reversion effect. Over short investment horizons, there is a mean aversion effect in both the UK and the US direct real estate market, but the mean aversion effect is much more pronounced in the US. In the long-term, however, the estimated annualized return volatilities of UK and US direct real estate returns are quite similar. The choice of the parameter used to unsmooth appraisal-based returns has a large effect on the short-term, but not on the long-term volatility of direct real estate returns. UK property shares and US REITs exhibit strong mean reversion, very much like the general stock market. UK direct real estate returns remain more predictable than property share returns in the medium and long term, whereas US REIT returns appear to be equally predictable to direct real estate returns in the medium term.

News about discount rates is more important than cash-flow news in the analyzed real estate markets. The low short-term standard deviation and the mean aversion of US direct real estate returns can be explained by the positive correlation between cash-flow and discount rate news, which can be interpreted as underreaction to cash-flow news.

Of course, the results in this chapter have implications for portfolio choice. The volatility results would seem to justify larger allocations to securitized real estate and to direct UK real estate for long-term investors. This is not true for direct US real estate. But of course, horizon effects in return volatilities, return correlations and expected returns of several asset classes have to be considered jointly.

2.8 Appendix: Data

Table 2.A1 provides information on the data used to construct the VAR variables. Information on the direct real estate data can be found in section 2.3.2.

Table 2.A1: Data information

Panel A: UK

	Description	Source
Index of securitized real estate	UK DS real estate total return index	Datastream
Yield of securitized real estate	Dividend yield of UK DS real estate index	Datastream
Cash yield	UK three-month treasury bills rate	Datastream
Long-term bond yield	Yield of Barclays gilt index	Barclays Equity Guilt Study 2009
Inflation rate	Change (%) of UK cost of living index	Barclays Equity Guilt Study 2009

Panel B: US

	Description	Source
Index of securitized real estate	US DS REITs index (rebased)	Datastream
Valuation ratio of securitized real estate	Price/Cash-flow ratio of US DS REITs index	Datastream
Cash yield	US three-month treasury bills rate	Datastream
Long-term bond yield	Yield of US treasury constant maturities 10 years	Datastream
Inflation rate	Change (%) of Consumer Price Index - All Urban Consumers	Bureau of Labor Statistics

3 Real Estate in a Mixed Asset Portfolio: The Role of the Investment Horizon

A slightly shorter version of this chapter is forthcoming in *Real Estate Economics*.

Abstract

In this chapter, three oft-mentioned special characteristics of the real estate asset market – high transaction costs, marketing period risk and return predictability – are addressed in analyzing the role of UK commercial real estate investments in a mixed asset portfolio. Due to favorable horizon effects in risk and return, the allocation to real estate in a portfolio with stocks, bonds and cash increases strongly with the investment horizon. Examining the relative importance of return predictability, transaction costs and marketing period risk for the optimal allocation to real estate, the chapter finds that the consideration of return predictability is very important, except for short-term horizons. Accounting for transaction costs is crucial for short- and medium-term investors. Marketing period risk appears to be negligible. Traditional mean-variance analysis – i.e., ignoring return predictability, transaction costs and marketing period risk – can be very misleading.

3.1 Introduction

Real estate is an important asset class. In the US, for example, the market capitalization of private commercial real estate is estimated to be $8 trillion, compared to a value of $17 trillion for stocks, as of the early 2000s (Geltner et al. 2007, Chapter 7). Furthermore, typical studies suggest that the allocation to real estate in a mixed asset portfolio should be about 15 to 20% (Hoesli and MacGregor 2000, Chapter 10). Hoesli et al. (2004) analyze the asset allocation problem from the perspective of investors from seven countries and find that the optimal share allocated to direct real estate is 15 to 25% in portfolios representing high to medium risk aversion. This result is remarkably similar across the countries. In contrast, in most countries the share of real estate in portfolios of institutional investors is much smaller: Estimates are 7.3% for the US and 8.5% for the UK (Clayton 2007, JPMorgan 2007). The difference between relative market capitalization and suggested allocation on the one hand and the low actual allocations to real estate in portfolios of institutional investors on the other hand is considered to be a puzzle in real estate research (Chun et al. 2004).

Most of the evidence on the optimal share of real estate in a mixed asset portfolio is based on the traditional Markowitz (1952) approach, with quarterly or annual returns used to estimate expected returns, standard deviations and correlations. The common procedure contrasts with the fact that most investors have longer investment horizons. Nevertheless, the traditional approach is justifiable if the assets are traded in frictionless markets, the investor has power utility, and asset returns are independently and identically distributed (IID) over time. In such a world, the solution to the long-term asset allocation problem with rebalancing does not differ from a short-term, one-period optimization. In other words, short- and long-term investors should choose the same asset allocation (Samuelson 1969, Merton 1969).[16] For real estate, the assumptions underlying the classic result of Samuelson and Merton are likely to be violated. Transaction costs and lack of liquidity are obvious market frictions, and it is widely assumed that returns of direct (i.e., unsecuritized) real estate are not IID. In this chapter, these three oft-mentioned special characteristics of the real estate asset market – high transaction costs, lack of liquidity (in the form of marketing period risk) and return predictability – are addressed in analyzing the role of real estate in a mixed asset

[16] Even if returns are IID, markets are frictionless, and the investor has power utility, there are horizon effects when rebalancing is not permitted, but they appear to be negligible; see Barberis (2000).

portfolio. All of these aspects induce horizon effects, pointing towards the problem of the common procedure to conduct a traditional portfolio optimization.

The long-term asset allocation approach introduced by Campbell and Viceira (2005) is used to estimate the “term structure of risk” for stocks, bonds, cash and direct commercial real estate. This approach is based on the estimation of a vector autoregressive (VAR) model. By accounting for transaction costs and a (horizon-dependent) premium for real estate's marketing period risk I try to make a fair comparison to financial assets when conducting horizon-dependent portfolio optimizations. Empirically, I look at the UK market and find that the conditional (i.e., taking return predictability into account) standard deviation of commercial real estate returns changes with the investment horizon in a similar fashion as it is estimated for stocks. The annualized long-term (20-year) standard deviation of real returns of both asset classes amounts to approximately 60% of the short-term (one-year) risk. A horizon-dependent marketing period risk premium has only a small effect on the volatility of real estate returns. Due to high transaction costs, expected real estate returns, per period, are much higher in the long run than in the short run. In portfolio optimizations, the allocation to real estate strongly increases with the investment horizon.

I compare portfolio choice results for alternative asset allocation approaches, analyzing the relative importance of return predictability, marketing period risk and transaction costs for the allocation to real estate. Accounting for return predictability is crucial for portfolio optimization, except for very short investment horizons. Transaction costs are important for the weight assigned to real estate in the short to medium term. Incorporating the marketing period risk premium is of least importance. Traditional mean–variance analysis – i.e., ignoring return predictability, transaction costs and marketing period risk – can be very misleading.

In the next section, I review the related literature. Then I discuss the VAR model, the data and the VAR results. The impact of return predictability and transaction costs on the term structure of risk and return is examined in the following section. Then, the impact of marketing period risk on the volatility of real estate returns is analyzed. The asset allocation results are explained in the next section. A discussion of robustness checks follows. Finally, the main findings are summarized.

3.2 Literature review

3.2.1 Return predictability and mixed asset allocation

With IID log (continuously compounded) returns, *k*-period expected returns, variances and covariances are *k* times the one-period statistics. This is the reason why under the IID assumption the investment horizon is irrelevant for asset allocation decisions. However, the classic assumption of IID returns has been called into question.[17] Campbell and Viceira (2005) show that return predictability induces major horizon effects in annualized standard deviations and correlations of real stock, bond and cash returns. Thus, the optimal asset allocation depends on the investment horizon. Using a VAR approach to estimate the term structure of risk, return predictability is taken into account so that risk is based on the unexpected component of returns; in other words, variances and covariances of returns are computed relative to the conditional return expectations. Campbell and Viceira analyze the US market and find that stock returns are mean reverting, i.e., the long-term volatility of stock returns, per period, is lower than the short-term return volatility. In contrast, they find mean aversion in cash returns; due to return persistence, the periodic long-term return volatility is higher than the short-term volatility. Bond returns exhibit slight mean reversion.

Many studies have shown that the IID-assumption is likely to be violated for direct real estate returns. In particular, real estate returns appear to be positively related to lagged stock returns (Quan and Titman 1999) and more specifically to the lagged returns on property shares (e.g., Gyourko and Keim 1992, Barkham and Geltner 1995). Fu and Ng (2001), Ghysels et al. (2007), and Plazzi et al. (2010) show that the cap rate predicts commercial real estate returns positively. The cap rate of the real estate market is like the dividend yield of the stock market – the ratio of the income to the price of an asset. In the stock market, the dividend yield is the natural predictor of stock returns, because Campbell and Shiller's (1988) log-linear present-value model with time-varying discount rates implies that the dividend yield should forecast either dividend growth or returns, or both. Thus, the cap rate is a natural candidate as a predictor of real estate returns.

Some papers address the role of the predictability of real estate returns in the context of a long-term mixed asset allocation problem. Fugazza et al. (2007) analyze

[17] Early references on the predictability of asset returns include Campbell (1987), Campbell and Shiller (1988), Fama (1984), Fama and French (1988a, 1989), and Fama and Schwert (1977).

European property shares within a portfolio of general stocks, bonds and cash investments. Contrary to general stocks, the standard deviation (per period) of property shares increases with the investment horizon. However, as the authors also find that the expected return (per period) of property shares strongly increases with the investment horizon, property shares are a very attractive long-term asset class. Hoevenaars et al. (2008) analyze the role of US REITs in a large asset menu. They find that the return dynamics of REITs are already well captured by stocks and bonds and that REIT returns exhibit slight mean reversion in the long run. REITs do not gain notable shares in the optimized portfolios; this result holds in an asset-only and in an asset-liability framework. It is important to note that these papers look at real estate shares traded on the stock exchange, where illiquidity and transaction costs are usually of minor concern, and the process of price determination may be remarkably different from the unsecuritized real estate market.

There are also a few studies that look at the direct commercial real estate market. Geltner et al. (1995) calculate five-year risk statistics based on regressions of real estate returns on contemporaneous and lagged asset returns. Although the variance of direct real estate returns at a five-year horizon is higher than five times the annual variance – reflecting mean aversion – and the correlation with stocks turns from negative (direct statistic based on annual data) to positive, they find that real estate is still an important asset class, especially at lower risk/return profiles. Two recent papers use the Campbell and Viceira (2005) approach to analyze the role of US direct and securitized real estate in a mixed asset portfolio. Porras Prado and Verbeek (2008) find that the annualized volatility of direct real estate returns increases from about 7.5% at a one-quarter horizon to 11% at a 25-year horizon. Property shares exhibit mean aversion, too. Direct real estate tends to become less important both in an asset-only and in an asset-liability framework the longer the investment horizon. MacKinnon and Al Zaman (2009) find that the estimated long-term return volatility of US direct real estate returns is virtually identical to the estimated long-term stock return volatility. The weight of direct real estate in a mixed asset portfolio increases with the investment horizon due to decreasing correlations with bonds and stocks over medium and long horizons.

3.2.2 Illiquidity and transaction costs

Liquidity is a multi-faceted concept and there are many measures of liquidity, but it is obvious that real estate markets are far more illiquid than well-developed stock or bond markets. While in many financial markets an asset can be sold quickly with almost no price impact, the sale of a property takes time and a quicker disposal is usually related to a price discount. Furthermore, liquidity is time-varying in real estate markets, with more liquidity in up markets and less liquidity in down markets. Motivated by this fact, Fisher et al. (2003) and Goetzmann and Peng (2006) develop transaction-based real estate indexes under the assumption of constant liquidity. The returns of these indexes exhibit higher volatility and less autocorrelation than the returns of common (variable liquidity) indexes.

Lin and Vandell (2007) argue that a constant liquidity index still does not allow a fair comparison to financial assets, because the uncertainty of the marketing period is not accounted for. They develop the concept of marketing period risk as a component of illiquidity risk, recognizing that it is the ex ante risk which is relevant for investment decisions. Price indexes are based on successful sales and hence measure only price (or ex post) risk. Lin and Vandell show that price risk underestimates the true ex ante risk, and that the effect of marketing period risk decreases with the investment horizon. Over short horizons the ex ante standard deviation of returns can be several times the usual ex post standard deviation. However, the risk adjustment is much smaller when appraisal-based returns have been unsmoothed (Bond et al. 2007). Lin and Vandell (2007) also define a second bias, which arises when an investor experiences a sudden liquidity shock, forcing the investor to sell a property quickly. They show that this liquidation bias affects both return and risk adversely. Cheng et al. (2010a) show that, under some simplifying assumptions, their formula for the ex-ante risk of a single property also holds for a real estate portfolio. Motivated by return persistence in US housing and (appraisal-based) commercial real estate returns, Cheng et al. (2010a) and Lin and Liu (2008) assume that the ex post variance of cumulative returns increases more than in proportion to the investment horizon. When returns are mean averting, there exists a tradeoff between price risk – making long-term investments very risky – and marketing period risk – favoring longer investment horizons.

Closely related to liquidity are transaction costs: Being much higher in most real estate markets than in well-developed financial markets, they lead to less frequent trading. Obviously, transaction costs induce horizon effects, since the expected return per period, net of transaction costs, increases with the investment horizon (see, for example, Collet et al. 2003). Illiquid assets with high transaction costs must offer an expected return premium (gross of transaction costs) to induce some investors to hold these assets. A clientele effect arises, where long-term investors prefer to hold assets with high transaction costs (Amihud and Mendelson 1986). Cheng et al. (2010b) account for marketing period risk, mean aversion in real estate returns and transaction costs, and find that there is an optimal holding period for properties, which is estimated to be about five years.

In this chapter, the asset allocation problem is analyzed accounting jointly for return predictability, marketing period risk and transaction costs. Previous research addressed these issues separately, or analyzed the single asset case only. By including the cap rate in the VAR model, mean reversion in real estate returns is captured, a point neglected by previous research.[18] The calculation of real estate's marketing period risk premium is based on this mean reversion pattern. Finally, I analyze the relative importance of return predictability, marketing period risk and transaction costs for the allocation to real estate.

3.3 VAR model and data

3.3.1 VAR specification

Campbell and Viceira (2005) assume a buy and hold investor, who is concerned about real returns. Let $\boldsymbol{z}_{t+1}$ be a vector that includes log asset returns and additional state variables that predict returns. Assume that a VAR(1) model captures the dynamic relationships between asset returns and the additional state variables:[19]

$$\boldsymbol{z}_{t+1} = \boldsymbol{\Phi}_0 + \boldsymbol{\Phi}_1 \boldsymbol{z}_t + \boldsymbol{v}_{t+1}. \tag{3.1}$$

In the specification of this study, the real return on cash ($r_{0,t+1}$), and the excess returns on real estate, stocks and long-term bonds (stacked in the (3x1) vector

[18] Liu and Mei (1994) estimate a VAR model, which includes the cap rate, and show that REIT returns exhibit mean reversion.

[19] The VAR(1) framework is not restrictive since a VAR(p) model can be written as a VAR(1) model; see Campbell and Shiller (1988).

$\boldsymbol{x}_{t+1} = \boldsymbol{r}_{t+1} - r_{0,t+1}\boldsymbol{\iota}$, where $\boldsymbol{\iota}$ is a vector of ones) are elements of $\boldsymbol{z}_{t+1}$. In addition, four state variables are included, stacked in the (4x1) vector $\boldsymbol{s}_{t+1}$. Thus,

$$\boldsymbol{z}_{t+1} = \begin{bmatrix} r_{0,t+1} \\ \boldsymbol{x}_{t+1} \\ \boldsymbol{s}_{t+1} \end{bmatrix} \tag{3.2}$$

is of order (8x1). $\boldsymbol{\Phi}_0$ is a (8x1) vector of constants and $\boldsymbol{\Phi}_1$ is a (8x8) coefficient-matrix. The shocks are stacked in the (8x1) vector $\boldsymbol{v}_{t+1}$, and are assumed to be IID normal with zero means and covariance-matrix $\boldsymbol{\Sigma}_v$, which is of order (8x8): $\boldsymbol{v}_{t+1} \sim IIDN(\boldsymbol{0}, \boldsymbol{\Sigma}_v)$.

3.3.2 Data

The results are based on an annual dataset from 1965 to 2008 (44 observations) for the UK market; Appendix A provides details on the data used. The inception of the sample period is determined by the availability of a performance index for property shares. As noted above, cash (T-bills), real estate, stocks and long-term bonds are the available assets to the investor. The bond index represents a security with constant maturity of 20 years. The implicit strategy assumed is to sell a bond at the end of each year and buy a new bond to keep the bond maturity constant, an assumption that is common for bond indexes. The (log of the) cap rate and the excess return on property shares are included in the VAR model as state variables to capture the dynamics of (direct) real estate returns. Property shares are not considered as an asset class since there is evidence that direct real estate and property shares are cointegrated (for evidence regarding the UK market see Wang et al. 1997). Because of this, the long-term linkage between these assets may be underestimated in a VAR without an error-correction term capturing the long-term relationship (Engle and Granger 1987).[20] As in Campbell and Viceira (2005), the log of the dividend yield of the stock market and the log yield spread, i.e., the

[20] In fact, the long-term correlation of direct real estate returns and property share returns estimated from the VAR results is even lower than the short-term correlation. We would expect that the correlation is increasing with the investment horizon. Hence, the VAR apparently cannot capture the long-term relationship between direct real estate and property shares. Therefore, it does not appear to be reasonable to include property shares as an asset class.

difference between the log yield of a long-term bond and the log yield of T-bills, are incorporated as state variables that have been shown to predict asset returns.[21]

Appraisal-based capital and income real estate returns used to calculate the annual real estate total return and the cap rate series have been obtained from two sources. The returns from 1971 to 2008 are based on IPD's long-term index. Initially, the index covered a portfolio of 651 properties, increasing to 11,328 properties by 1981 (Newell and Webb 1994). Returns from 1964 to 1970 are from Scott (1996).[22] These returns are based on valuations of properties in portfolios of two large financial institutions covering more than 1,000 properties throughout this period (Scott and Judge 2000).[23] Key et al. (1999) find that the Scott return series used here as well as the IPD 1971 to 1980 return series are fairly reliable in terms of coverage.

Real estate returns are unsmoothed using the approach of Barkham and Geltner (1994). This unsmoothing approach is based on modeling optimal behavior of property appraisers as introduced by Geltner (1993). Appraisal-based log real capital returns g_t^* are unsmoothed using the formula

$$g_t = \frac{g_t^* - (1-a)g_{t-1}^*}{a}, \tag{3.3}$$

where g_t is the true log real capital return (or growth), and a is the smoothing parameter. I use the value 0.625 for unsmoothing annual returns as favored by Barkham and Geltner (1994). While it is not explicitly accounted for variable market liquidity, unsmoothing procedures, such as the one employed in this chapter, may be seen as an attempt to control for the pro-cyclical variable liquidity (Fisher et al. 2003). Total real estate returns and the cap rates are constructed from the unsmoothed log real capital return and income return series; see Appendix A.

[21] Campbell and Viceira (2005) also include the nominal interest rate as a state variable, partly because this allows the inflation hedging abilities of the assets to be analyzed (an issue which is not addressed in this chapter). When added to the eight variables VAR, the nominal interest rate is not a significant predictor of any variable, except for the nominal interest rate itself. To avoid proliferation of the VAR parameters, the nominal interest rate is not included.
[22] Note that due to the unsmoothing procedure for real estate returns, one additional observation is needed.
[23] For comparison, the widely-used NCREIF Property Index (NPI) was based on 233 properties at the index inception; see "Frequently asked questions about NCREIF and the NCREIF Property Index (NPI)" on the NCREIF website (www.ncreif.org).

Table 3.1 provides an overview of the sample statistics of the variables used in the VAR model. Mean log returns of the assets are adjusted by one half of the variance to reflect log mean returns. Compared to the US data used in Campbell and Viceira (2005), the mean excess returns on stocks and bonds are similar, whereas the volatilities are higher. Real cash returns are more volatile, too. Real estate lies in between stocks and bonds with regard to volatility, mean return, and Sharpe ratio. The unsmoothed real estate returns do not show notable autocorrelation. The cap rate has a higher mean and a lower volatility than the dividend yield of the stock market.

Table 3.1 Sample statistics

This table shows statistics for the variables included in the VAR model for the annual dataset (1965 to 2008). Autocorrelation refers to the first-order autocorrelation.

	Mean	Standard deviation	Sharpe ratio	Auto-correlation
Real return on cash*	2.09%	3.70%	-	76.21%
Excess return on real estate*	3.17%	16.44%	0.1926	6.23%
Excess return on stocks*	6.25%	24.57%	0.2542	-16.78%
Excess return on bonds*	1.44%	11.61%	0.1241	-12.16%
Log excess return on property shares	2.50%	30.52%	-	-4.45%
Log of cap rate	-2.8380	0.2530	-	63.37%
Log of dividend yield	-3.1809	0.3287	-	71.13%
Log yield spread	0.66%	1.75%	-	46.41%

*Mean log returns are adjusted by one half of the return variance to reflect log mean returns.

Figure 3.1 shows the logarithm of the total real return index values of the four asset classes. In the 1970s, a period of high inflation, bonds performed poorly in real terms. It took until the early 1990s for bonds to have a higher index value than cash investments. Real estate and stock markets collapsed during the oil crisis of 1973-74. After that, the stock market was characterized by a long upswing until the turn of the century. The real estate market experienced a significant downturn in the early 1990s and again – like the stock market – in recent times. The cash index reflects the persistent behavior of cash returns.

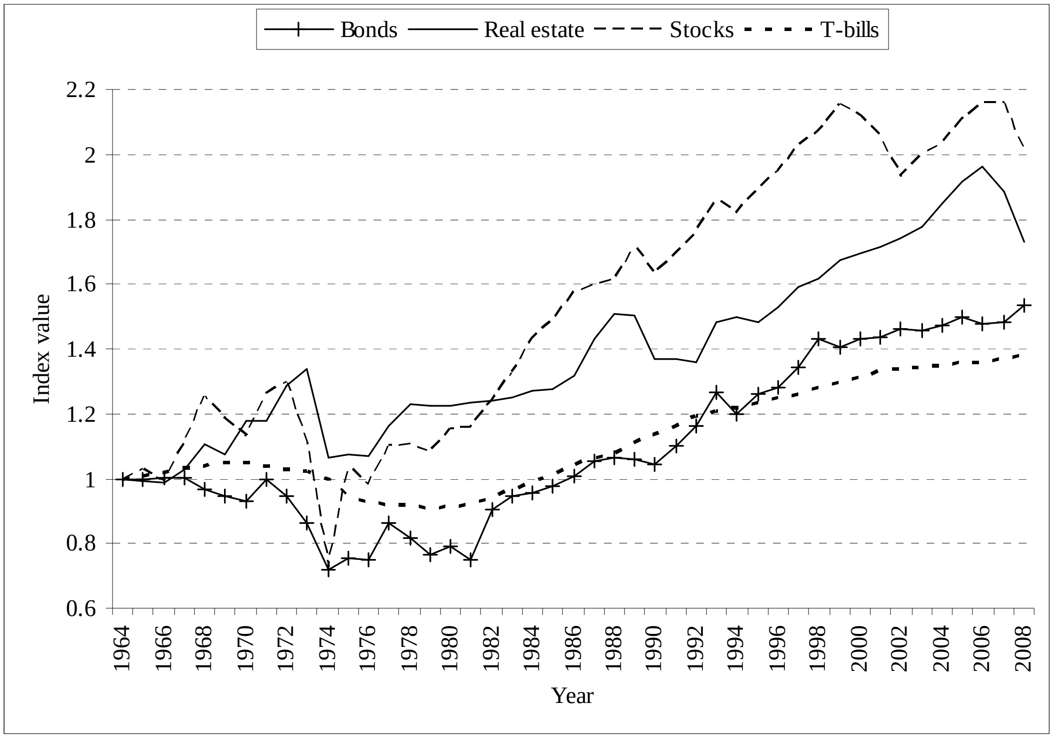


Figure 3.1 Total real return indexes

The figure shows the logarithm of the total real return index values (end of 1964 = 1) of the four asset classes considered over the time period 1964 to 2008.

3.3.3 VAR estimates

The results of the VAR(1), estimated by OLS, are given in Table 3.2.[24] Panel A contains the coefficients. In square brackets are *t*-values. Panel B contains the standard deviations (diagonal) and correlations (off-diagonals) of the VAR residuals.

[24] The Schwarz criterion and the Hannan-Quinn criterion favor a one-lag specification over a two-lag specification of the VAR model.

Table 3.2 VAR results

The results are based on annual data from 1965 to 2008. Panel A shows the VAR coefficients. The t-statistics are in square brackets; values corresponding to p-values of 10% or below are highlighted. The rightmost column contains the R^2 values and the p-value of the F-test of joint significance in parentheses. Panel B shows results regarding the covariance matrix of residuals, where standard deviations are on the diagonal and correlations are on the off-diagonals.

Panel A: VAR coefficients

		Coefficients on lagged variables								
Variable	Constant	1	2	3	4	5	6	7	8	R^2 (p)
1 Log real cash return	0.100	0.586	-0.005	0.059	-0.001	0.007	0.023	0.008	-0.749	80.31%
	[1.646]	**[5.432]**	[-0.161]	**[2.811]**	[-0.027]	[0.390]	[1.418]	[0.719]	**[-3.386]**	(0.00%)
2 Log real estate excess return	0.526	0.324	0.002	-0.191	0.204	0.242	0.195	-0.005	3.750	39.13%
	[1.110]	[0.385]	[0.008]	[-1.171]	[0.778]	[1.688]	[1.552]	[-0.057]	**[2.175]**	(1.93%)
3 Log stock excess return	1.862	0.394	-0.286	-0.259	0.156	0.290	0.318	0.294	1.878	41.61%
	[2.680]	[0.319]	[-0.775]	[-1.082]	[0.407]	[1.380]	**[1.732]**	**[2.415]**	[0.743]	(1.11%)
4 Log bond excess return	0.762	-0.083	0.093	0.110	-0.194	-0.174	0.217	0.045	1.353	37.72%
	[2.251]	[-0.138]	[0.519]	[0.944]	[-1.038]	**[-1.692]**	**[2.419]**	[0.752]	[1.098]	(2.59%)
5 Log property shares excess return	1.842	1.746	0.253	-0.275	0.103	0.151	0.392	0.242	5.169	28.70%
	[1.934]	[1.032]	[0.500]	[-0.838]	[0.195]	[0.525]	[1.557]	[1.448]	[1.492]	(13.17%)
6 Log of cap rate	-0.884	-0.700	0.048	0.236	-0.169	-0.387	0.685	-0.015	-4.727	61.43%
	[-1.521]	[-0.679]	[0.156]	[1.178]	[-0.527]	**[-2.200]**	**[4.456]**	[-0.142]	**[-2.236]**	(0.00%)
7 Log of dividend yield	-1.944	-0.198	0.324	0.260	-0.185	-0.283	-0.402	0.750	-0.630	65.37%
	[-2.732]	[-0.157]	[0.859]	[1.059]	[-0.471]	[-1.315]	**[-2.134]**	**[6.008]**	[-0.244]	(0.00%)
8 Log yield spread	0.022	-0.123	0.019	-0.008	0.023	-0.033	0.006	-0.001	0.365	44.06%
	[0.449]	[-1.428]	[0.741]	[-0.456]	[0.853]	**[-2.220]**	[0.433]	[-0.066]	**[2.066]**	(0.62%)

Table 3.2 VAR results (continued)

Panel B: Standard deviations and correlations of VAR residuals

	1	2	3	4	5	6	7	8
1 Log real cash return	1.85%	-14.75%	1.38%	44.26%	-27.63%	15.21%	-2.37%	-15.16%
2 Log real estate excess return	-14.75%	14.41%	55.82%	25.73%	74.37%	-98.50%	-54.07%	-26.74%
3 Log stock excess return	1.38%	55.82%	21.11%	49.31%	72.81%	-59.37%	-95.95%	-30.83%
4 Log bond excess return	44.26%	25.73%	49.31%	10.30%	28.97%	-27.65%	-51.48%	-10.46%
5 Log property shares excess return	-27.63%	74.37%	72.81%	28.97%	28.95%	-73.17%	-66.33%	-12.94%
6 Log of cap rate	15.21%	-98.50%	-59.37%	-27.65%	-73.17%	17.67%	58.76%	26.55%
7 Log of dividend yield	-2.37%	-54.07%	-95.95%	-51.48%	-66.33%	58.76%	21.63%	30.96%
8 Log yield spread	-15.16%	-26.74%	-30.83%	-10.46%	-12.94%	26.55%	30.96%	1.48%

The *p*-values of the *F*-test of joint significance indicate that the real return on cash and the excess returns on the other assets are indeed predictable. With an R^2 statistic of 39%, real estate has a degree of predictability that is in between that of stocks and bonds. The lagged yield spread has a significant positive influence on excess real estate returns. This makes sense, because the yield spread tracks the business cycle (Fama and French 1989) and real estate returns are closely related to changes in GDP (Case et al. 1999, Quan and Titman 1999). As expected, lagged property share returns also predict real estate returns positively (the *p*-value is slightly above 10%). The cap rate is a positive, but not significant, predictor of real estate returns. All asset returns depend positively on the lagged cap rate, indicating that low real estate prices (relative to income) are followed by high asset returns. The results with regard to the other assets and state variables are broadly similar to the US results provided by Campbell and Viceira (2005). Real cash returns are persistent. The most significant predictor of stock returns is the dividend yield. The lagged yield spread is positively related to bond returns, albeit not significantly. Somewhat surprisingly, the cap rate and the excess return on property shares are significant predictors of excess bond returns. All state variables, with the exception of the excess return on property shares, show persistent behavior. Turning to the correlations of the residuals, we see that unexpected real estate and property share returns have a high positive correlation. Excess stock and real estate return residuals are almost perfectly negatively correlated with the respective market yield (dividend yield and cap rate respectively).

3.4 Horizon effects in risk and return of ex post returns

3.4.1 The term structure of risk

In this section, the impact of return predictability on horizon effects in conditional standard deviations and correlations of (ex post) returns is analyzed. The impact of marketing period risk on the term structure of real estate's return volatility, i.e., the adjustment from ex post to ex ante risk, is explored later on. The conditional multi-period covariance matrix of the vector $\mathbf{z}_{t+1}$, scaled by the investment horizon k, is:

$$\frac{1}{k}Var_t(\mathbf{z}_{t+1}+\ldots+\mathbf{z}_{t+k})=\frac{1}{k}[\mathbf{\Sigma}_v+(\mathbf{I}+\mathbf{\Phi}_1)\mathbf{\Sigma}_v(\mathbf{I}+\mathbf{\Phi}_1)' \\ +(\mathbf{I}+\mathbf{\Phi}_1+\mathbf{\Phi}_1^2)\mathbf{\Sigma}_v(\mathbf{I}+\mathbf{\Phi}_1+\mathbf{\Phi}_1^2)'+\ldots \\ +(\mathbf{I}+\mathbf{\Phi}_1+\ldots+\mathbf{\Phi}_1^{k-1})\mathbf{\Sigma}_v(\mathbf{I}+\mathbf{\Phi}_1+\ldots+\mathbf{\Phi}_1^{k-1})'], \tag{3.4}$$

where **I** is the identity matrix. Conditional variances and covariances of real returns can be extracted from the conditional multi-period covariance matrix of $\mathbf{z}_{t+1}$, using an appropriate selector matrix. Real return statistics can be calculated, because the vector $\mathbf{z}_{t+1}$ includes the real cash return and excess returns such that the real return statistics of stocks, bonds and real estate can be calculated by adding the real cash return and the excess return of the asset (for technical details, see Campbell and Viceira 2004).

Figure 3.2 shows the results for the term structure of the annualized (divided by the square root of the horizon) standard deviation of real returns, as implied by the VAR. Real estate returns show slight mean aversion over the short run. This can be attributed to the positive dependence of real estate returns on lagged property share returns, since the correlation of the residuals is also positive (0.74). Thus, when there is a negative shock to the property share return, the unexpected return of direct real estate tends to be low as well, and a low property share return tends to be followed by a low real estate return, and vice versa. For investment horizons longer than two years, real estate returns exhibit strong mean reversion. This is due to the high negative correlation between real estate return and cap rate residuals, and the positive influence of the lagged cap rate on the return of real estate. If property prices are decreasing, this is bad news for an investor. On the other hand, the good news is that a low realized return on real estate is usually accompanied by a positive shock to the cap rate, and a high cap rate predicts high real estate returns for the future. Because the cap rate is persistent, this effect is very important for the long-term risk. The annualized volatility decreases from 14.3% at the one-year horizon to 8.0% at the twenty-year horizon. The parameter on the lagged cap rate is not significant at the ten percent level, though, but it is interesting to note that, in a smaller VAR, the regression of the log real estate excess return on a constant, the lagged log real estate excess return, and the lagged log cap rate yields a *t*-statistic of 2.71 (*p*-value of 1.0%) with regard to the regression parameter on the lagged cap rate. Excluding the cap rate from the eight variable VAR model, the conditional annualized twenty-year volatility of real estate returns is even slightly higher than the one-year volatility. Thus, it is clearly the cap rate that is driving the mean reversion effect in real estate returns.

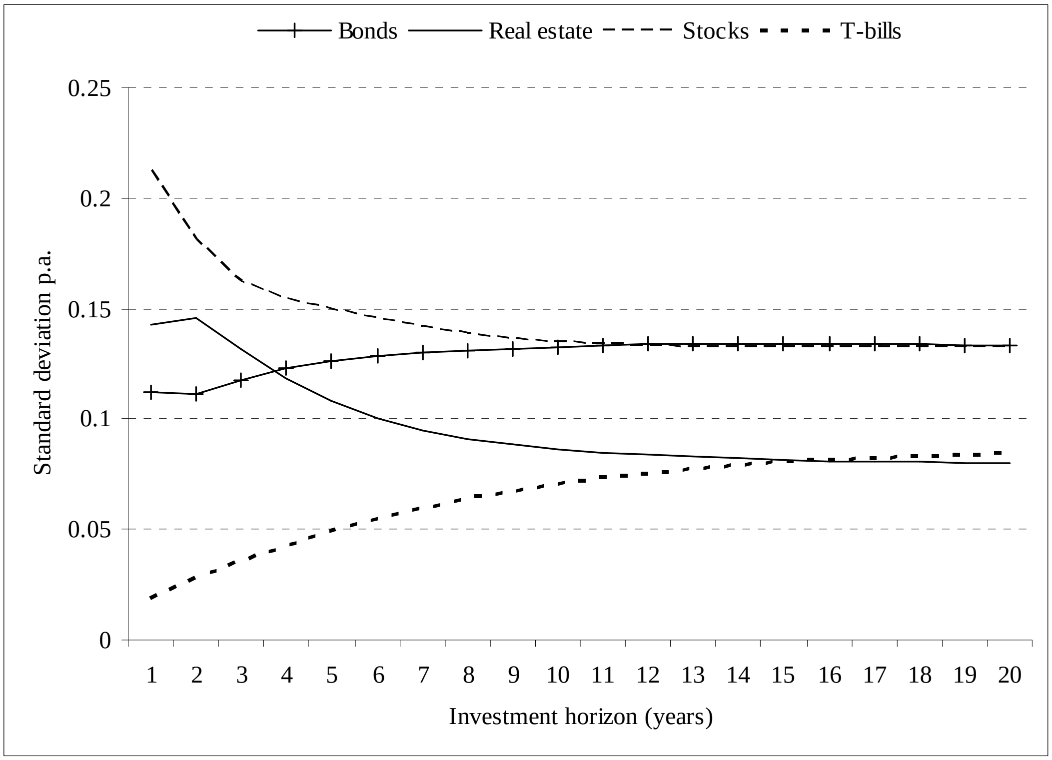


Figure 3.2 The term structure of return volatilities

The figure shows conditional annualized standard deviations of real (ex post) returns depending on the investment horizon.

The periodic long-term risk of stocks is much lower than the short-term risk. This is because the dividend yield predicts stock returns positively, and dividend yield and stock return residuals are highly negatively correlated. The annualized twenty-year standard deviation of both stock returns and real estate returns amounts to about 60% of the one-year risk. In comparison, Campbell and Viceira's (2005) estimate of the periodic long-term standard deviation of US real stock returns amounts to approximately 50% of the short-term standard deviation. Cash returns are clearly mean averting. The reason is that investments in short-term T-bills have to be rolled over at future uncertain real interest rates, and real interest rates are persistent. At long investment horizons the annualized standard deviation of cash returns is as high as that of real estate. The standard deviation of real cash returns over the whole range of investment horizons is substantially higher than in the 1952 to 2002 dataset used in

Campbell and Viceira (2005), but lower than in the 1890 to 1998 dataset used in Campbell and Viceria (2002). The line of the annualized standard deviation of long-term, constant maturity, bond returns reflects slight mean aversion so that the estimated volatility of stock and bond returns is virtually identical for investment horizons of ten years or longer. For comparison, returns of a constant maturity bond are slightly mean reverting in the Campbell and Viceria (2005) post-war dataset, but strongly mean averting in the Campbell and Viceira (2002) longer-term dataset.

Correlations implied by the VAR estimates also show interesting horizon effects (see Figure 3.3). The correlation between stock and bond returns at medium investment horizons is higher, but the long-term correlation is lower than the short-term correlation. This is similar to the Campbell and Viceira (2005) estimates. The correlation between stock and real estate returns is slightly lower in the long run than in the short run. The most remarkable difference between the short and the long run concerns the correlation between real estate and cash returns, which increases by more than 60 percentage points. A driver of this result is the cap rate, which predicts both returns positively. Bond and stock returns are highly correlated with cash returns in the long-term, too. In general, the long-term correlations are less dispersed than the short-term correlations. On average, the twenty-year asset return correlations are higher than the one-year correlations, which is intuitively appealing.

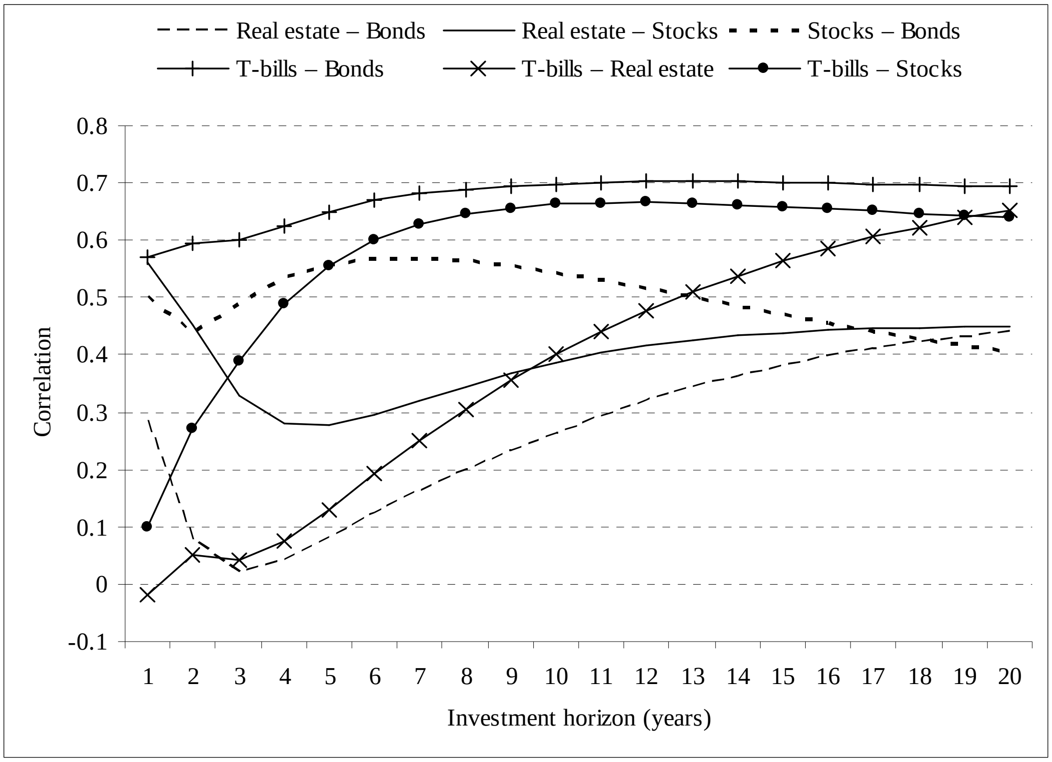


Figure 3.3 The term structure of return correlations

The figure shows conditional return correlations depending on the investment horizon.

3.4.2 The term structure of expected returns

Since the VAR system includes log returns, Campbell and Viceira (2004, 2005) use the approximation for the *k*-period log portfolio return $r_{p,t+k}^{(k)}$ introduced by Campbell and Viceira (2002). Note that the upper (*k*) indicates that this is a cumulative return. Transaction costs regarding real estate and stock and bond investments, stacked in the (3x1) vector $\boldsymbol{c}$, are deducted, so that:

$$r_{p,t+k}^{(k)} = r_{0,t+k}^{(k)} + \boldsymbol{\alpha}'(k)(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}) + \tfrac{1}{2}\boldsymbol{\alpha}'(k)[\boldsymbol{\sigma}_x^2(k) - \boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k)], \tag{3.5}$$

where $\boldsymbol{\alpha}(k)$ is the (3x1) vector containing the asset weights, except for the weight on cash, with regard to a *k*-period investment. $\boldsymbol{\Sigma}_{\mathrm{xx}}(k) = Var_t(\boldsymbol{x}_{t+k}^{(k)})$ is the conditional covariance-matrix of *k*-period excess returns, and $\boldsymbol{\sigma}_x^2(k) = diag[\boldsymbol{\Sigma}_{xx}(k)]$ is the diagonal vector of this matrix.

From (3.5) one can calculate the *k*-period log expected portfolio return as:

$$E(r_{p,t+k}^{(k)}) + \tfrac{1}{2}Var_t(r_{p,t+k}^{(k)}) = E(r_{0,t+k}^{(k)}) + \tfrac{1}{2}\sigma_0^2(k) + \boldsymbol{\alpha}'(k)[E(\mathbf{x}_{t+k}^{(k)} - \mathbf{c}) + \tfrac{1}{2}\boldsymbol{\sigma}_x^2(k) + \boldsymbol{\sigma}_{0x}(k)], \quad (3.6)$$

where $\sigma_0^2(k)$ is the *k*-period conditional variance of real cash returns, and $\boldsymbol{\sigma}_{0x}(k)$ is the vector of conditional covariances between the real cash return and the excess return on stocks, bonds and real estate, at horizon *k*. Equation (3.6) shows how to calculate the (approximation of the) cumulative log expected portfolio return or, assuming a 100% investment in the respective asset, the log expected return of any single asset class. Note that the expected log return has to be adjusted by one half the return variance to obtain the log expected return relevant for portfolio optimization (a Jensen's inequality adjustment), where the conditional *k*-period variance of the portfolio return is:

$$Var_t(r_{p,t+k}^{(k)}) = \boldsymbol{\alpha}'(k)\boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k) + \sigma_0^2(k) + 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{0x}(k). \quad (3.7)$$

This adjustment is horizon-dependent. There are no horizon effects in expected log returns because I assume that they take the values of their sample counterparts. Thus, for the k-period expected log cash return it holds that $E(r_{0,t+k}^{(k)}) = k\bar{r}_0$, where $\bar{r}_0$ denotes the sample average of log cash returns. Similarly, I assume for the vector of log excess returns: $E(\mathbf{x}_{t+k}^{(k)}) = k\bar{\mathbf{x}}$. Even if there were no horizon effects in expected log returns there would be horizon effects in log expected returns, because conditional variances and covariances will not increase in proportion to the investment horizon unless returns are unpredictable. In the remainder of this chapter, the log expected return is termed “expected return” for short.

Additional horizon effects in expected returns are due to the consideration of proportional transaction costs. With regard to stocks and bonds, transaction costs encompass brokerage commissions and bid-ask spreads. Round-trip transaction costs for stocks are assumed to be 1.0%, as in Balduzzi and Lynch (1999) and Collet et al. (2003). Bid-ask spreads of government bonds are typically tiny (Fleming 2003, Gwilym et al. 2002); total round-trip transaction costs for bonds, including brokerage commissions, are assumed to be 0.1%. The bid-ask spread is the cost of immediate buying and selling (Demsetz 1968). Immediate execution is not assumed for real estate.

Direct real estate markets are not dealer markets, i.e., markets where dealers buy and sell for their own accounts. The usual practice in the direct real estate market, represented in the assumptions of this chapter, is to instruct an agent to initiate the acquisition and disposal of properties (for the account of the principal). To avoid paying (systematically) too much and receiving too little, relative to market values, this takes time. Of course, fees accrue for the agents' activities. Overall, transaction costs for buying and selling real estate encompass professional fees and the transfer tax. According to Collet et al. (2003), round-trip transaction costs for UK real estate are 7 to 8%. Marcato and Key (2005) assume round-trip transaction costs of 7.5%. These costs cover the transfer tax ("stamp duty") of 4.0% (to be paid when buying), 1.5% for legal, agents' and other advisory fees for both purchases and sales, plus 0.5% internal investor's costs. I exclude the internal costs and hence assume total costs of 7.0%, which appears to be reasonable as Marcato and Key suggest that 7.5% may be a bit on the high side. The costs are divided into 5.5% buying costs and 1.5% selling costs. Round-trip transaction costs for stocks and bonds are divided by one half to obtain separately the costs for buying and selling. The assumed round-trip transaction costs enter the vector $\boldsymbol{c}$ in continuously compounded form, and they are obtained by adding the continuously compounded buying and selling costs, so that $\boldsymbol{c}' = [6.84\% \quad 1.00\% \quad 0.10\%]$. For example, the round-trip costs for real estate are $\ln(1.055) + \ln(1.015) \approx 6.84\%$.

Figure 3.4 plots the term structure of annualized expected real returns after transaction costs for stocks, bonds, real estate and cash. Due to transaction costs, there are major changes in the annualized expected real estate return, which increases over the whole range of investment horizons. It takes an investment horizon of fourteen years for real estate to have the same expected return as bonds. Driven by the fall in the annualized return variance, the long-term expected return of stocks is lower than the short-term statistic. This effect would be more dramatic without transaction costs, which decrease annualized expected returns particularly at short horizons. Due to the increasing annualized return variances, periodic expected cash and bond returns slightly increase with the investment horizon.

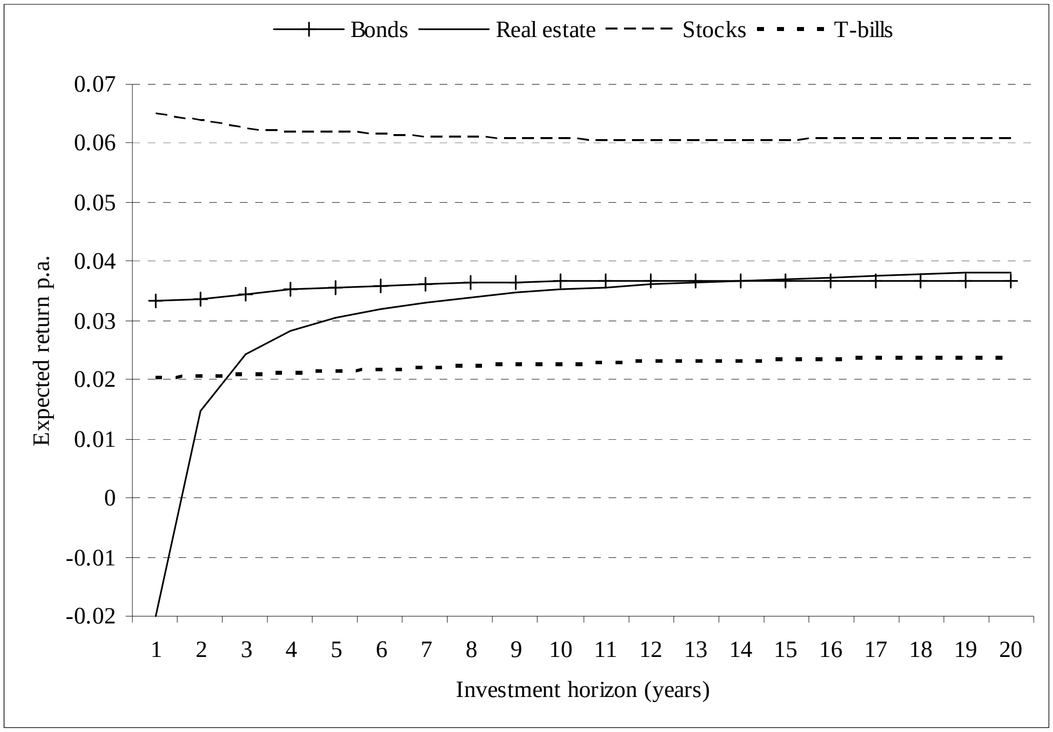


Figure 3.4 The term structure of expected returns

The figure shows annualized expected real returns depending on the investment horizon. These follow from (3.6), assuming a 100% investment in the respective asset. Round-trip transaction costs are assumed to be 0.1% for bonds, 1.0% for stocks and 6.84% for real estate.

3.5 The term structure of real estate's ex ante return volatility

As implicitly assumed for the determination of the transaction costs for real estate, I consider an investor who is not under time pressure. Therefore, the concept of marketing period risk, an aspect of illiquidity risk the "typical seller has to face" (Lin and Vandell 2007, p. 312), is used to adjust the conditional volatility of real estate returns to reflect both price risk and marketing period risk. The investment horizon k is partitioned into k^*, the period after which the marketing activities begin, and $E(m)$, the expectation of the uncertain marketing period m: $k = k^* + E(m)$. Using the variance decomposition formula for any two stochastic variables (here r_{RE} and m), the conditional variance of periodic ex ante returns, with actual investment period $k^* + m$, is:

$$Var_t^{ex\ ante}(r_{RE,t+k^*+m}) = E[Var_t(r_{RE,t+k^*+m}|m)] + Var[E(r_{RE,t+k^*+m}|m)]. \quad (3.8)$$

Note that, to be consistent with the Campbell and Viceira (2005) approach, I apply the variance decomposition formula to the conditional variance of real returns, per period.

First, I analyze the first term on the right hand side of (3.8). The mean reversion pattern in ex post real estate returns for horizons of k = 3, …, 20 (years), with $m = E(m)$, can be characterized by the following function for the conditional periodic return variance:

$$Var_t(r_{RE,t+k}) = \frac{Var_t(r_{RE,t+1})}{\sqrt{k}}. \tag{3.9}$$

This function is convex. The square root of this function, with $Var_t(r_{RE,t+1}) = 16.0\%^2$, is shown in Figure 3.5. For comparison, the estimated term structure of the volatility of ex post real estate returns is also shown (the same as in Figure 3.1). The mean reversion pattern is quite well captured by the assumed function for horizons of three years and longer. We can see directly that accounting for an uncertain marketing period increases the return variance. With an uncertain marketing period, the expectation of the conditional periodic return variance is higher than the periodic return variance corresponding to the expectation of the marketing period. Due to the convexity of the function, it is unfavorable for an investor that a property has, say, a marketing period of either four or eight months, each with probability of 50%, compared to a marketing period of six months, which is ex ante known for sure. For the same reason, a higher variability of the marketing period increases the marketing period risk premium. Based on a second-order Taylor series approximation for the function $f(m) = (k^* + m)^{-1/2}$ around $E(m)$ we have (see Appendix B):

$$E[Var_t(r_{RE,t+k^*+m} | m)] \approx Var_t(r_{RE,t+1})(k^{-1/2} + \tfrac{3}{8} Var(m) k^{-5/2}). \tag{3.10a}$$

The approximation (3.10a) is used for horizons of three to twenty years. Over investment horizons of one and two years, ex post real estate returns exhibit neither pronounced mean aversion nor mean reversion. Therefore, the expectation of the periodic return variance (accounting for an uncertain marketing) is close to the periodic return variance corresponding to the expectation of the marketing period; I assume that these are equal so that there is no bias due to the first term of the right hand side of (3.8) for k = 1, 2 (years):

$$E[Var_t(r_{RE,t+k^*+m}|m)] = Var_t(r_{RE,t+k}) = Var_t(r_{RE,t+1}). \tag{3.10b}$$

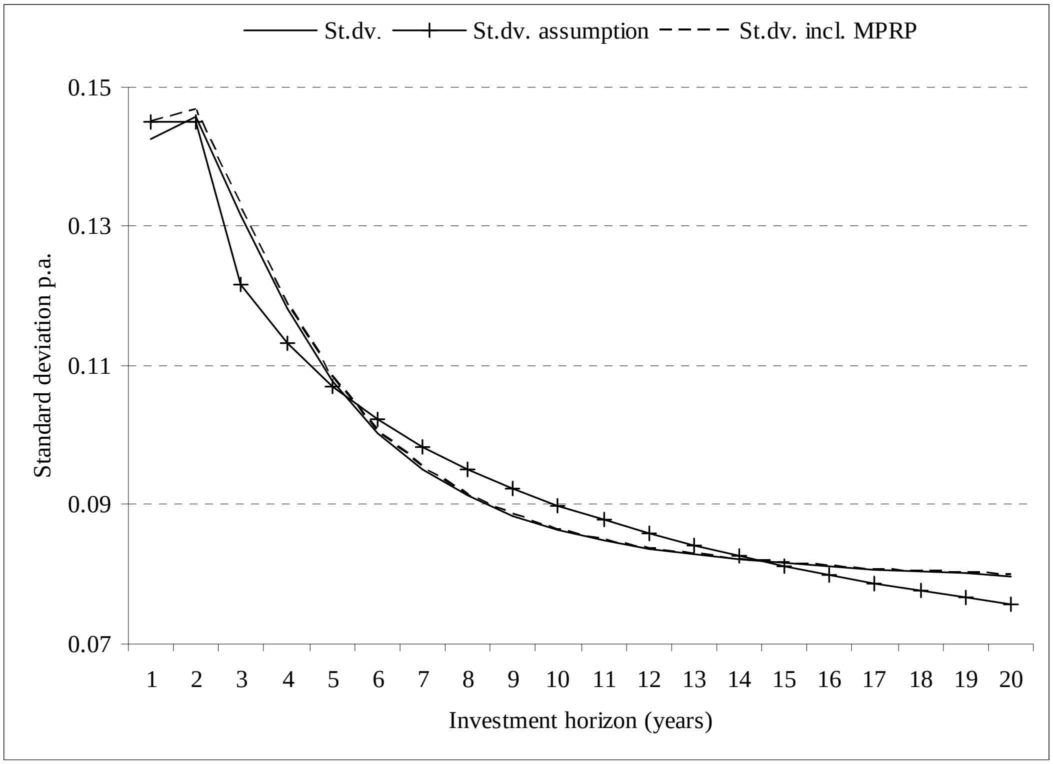


Figure 3.5 The term structure of real estate's return volatility

The figure shows real estate's conditional annualized standard deviation of real returns with and without an adjustment for the marketing period risk, depending on the investment horizon. Also shown is the assumed term structure of real estate's return volatility used for the calculation of the marketing period risk premium (MPRP). St.dv.: Standard deviation.

The second term on the right hand side of (3.8) concerns the variance of expected returns. Recall that there are substantial horizon effects in the periodic expected return on real estate. Therefore, given an investment horizon k, expected returns, per period, vary when the marketing period is uncertain. To quantify this effect, I assume that the expected return, per period, around investment horizon k is:

$$E(r_{RE,t+k^*+m}|m) = E(r_{RE,t+k}) + s_{t+k}[m - E(m)], \tag{3.11}$$

where s_{t+k} is the slope of the term structure of the periodic expected real return on real estate around k. This slope is calculated as the average of the slope of the line between the periodic expected returns for investments with a $k-1$-period and a k-period horizon, and the slope of the line between the periodic expected returns for investments with a k-period and a $k+1$-period horizon.[25] The variance of (3.11) is:

$$Var[E(r_{RE,t+k^*+m}|m)] = s_{t+k}^2 Var(m) . \tag{3.12}$$

Adding (3.10a) and (3.10b), respectively, and (3.12) yields the ex ante variance of real estate returns. Dividing the ex-ante variance by the ex post return variance given by (3.9) and (3.10b), respectively, yields:

$$\frac{Var_t^{ex\ ante}(r_{RE,t+k})}{Var_t(r_{RE,t+k})} =$$

$$\begin{cases} 1+\dfrac{s_{t+k}^2 Var(m)}{Var_t^a(r_{RE,t+1})} & \text{for } k = 1, 2 \text{ (years)} \quad (3.13a) \\ 1+\dfrac{\frac{3}{8}Var_t^b(r_{RE,t+1})Var(m)k^{-5/2}+s_{t+k}^2 Var(m)}{Var_t^b(r_{RE,t+1})k^{-1/2}} & \text{for } k = 3, ..., 20 \text{ (years)} \quad (3.13b). \end{cases}$$

Formula (3.13) provides the adjustment from ex post to ex ante variance of real estate returns in dependence on the investment horizon k. To reflect the assumption of no horizon effects in the annualized conditional return volatility over horizons of one and two years, and the finding of mean reversion over longer horizons, different values for the one-year return variance are chosen, indicated by the upper a and b respectively. Specifically, the assumed values are $Var_t^a(r_{RE,t+1}) = 14.5\%^2$ for k = 1, 2 (years), and $Var_t^b(r_{RE,t+1}) = 16.0\%^2$ for k = 3, …, 20 (years). Bond et al. (2007) find for the UK market that the negative exponential distribution best fits the data for actual marketing periods. Assuming this, $Var(m)$ equals $E(m)^2$. Based on evidence provided by Bond et al. (2007), I assume an expected marketing period of eight months [$E(m) = 8/12$ (years)].

[25] The return for a zero-year investment is -6.84%, the assumed transaction costs. For k = 20 (years) the slope between k = 19 and k = 20 is used.

In Figure 3.5 the term structure of the volatility of ex ante returns on real estate (including the horizon-dependent marketing period risk premium) is shown. Marketing period risk appears to be negligible. The term structures of ex post and ex ante returns are virtually identical. Small premiums are visible at short horizons. The maximal return variance adjustment is at the one-year horizon with 3.7%. The results in the remainder of the chapter are based on the conditional variance of real returns including the marketing period risk premium. Note that this has also a (small) effect on the term structure of the expected return on real estate due to the Jensen's inequality adjustment.

3.6 Horizon-dependent portfolio optimizations

3.6.1 Mean-variance optimization

The mean-variance problem can be stated as:

$$\min\,[\text{w.r.t. } \boldsymbol{\alpha}(k)]\ \frac{1}{2}\frac{Var_t(r_{p,t+k}^{(k)})}{k}, \tag{3.14}$$

subject to

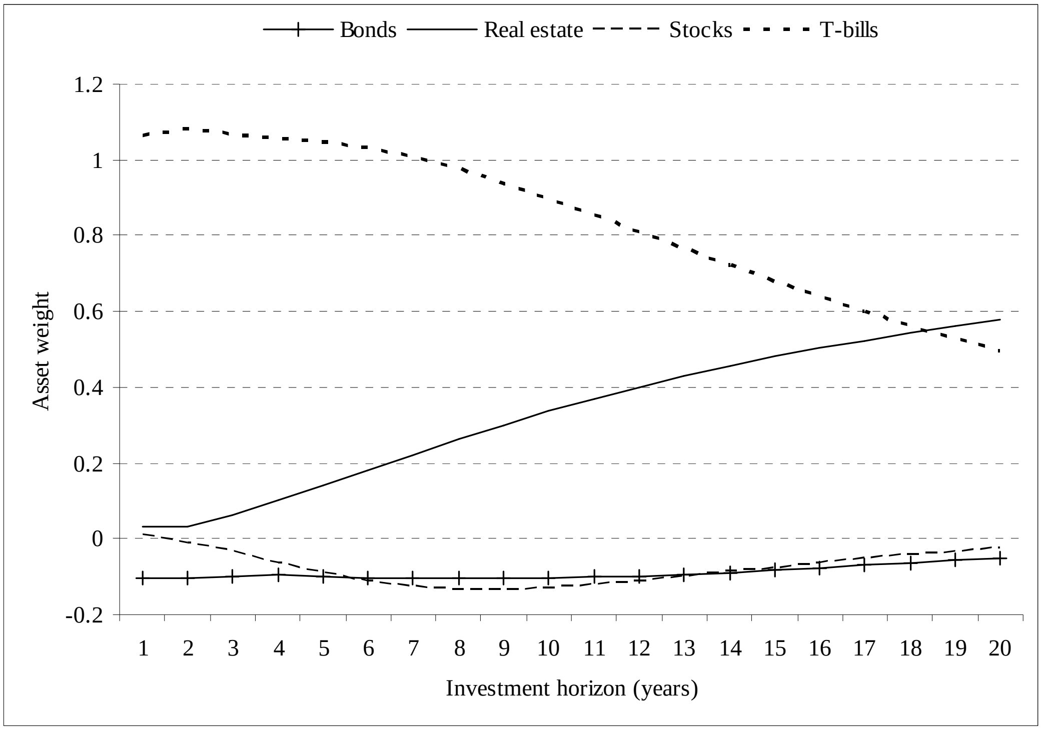
$$\frac{E(r_{p,t+k}^{(k)})+\frac{1}{2}Var_t(r_{p,t+k}^{(k)})}{k}=\mu_p, \tag{3.15}$$

where μ_P is the expected portfolio return, per period. Short-selling of real estate is not allowed, but such a restriction is not imposed on the other assets.

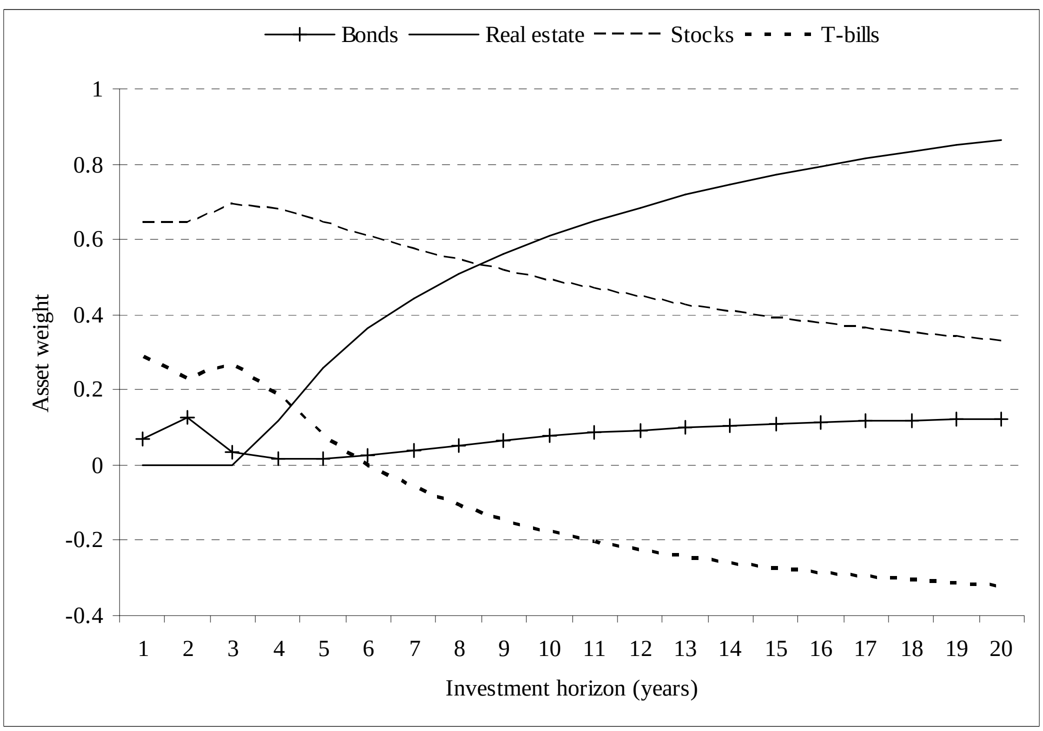
3.6.2 Mixed asset allocation results

Figure 3.6 contains two panels with optimal portfolio compositions for investment horizons of one to twenty years. Panel A shows the allocations of the four assets for the global minimum variance portfolio. As expected, the allocation to cash is about 100% at short and medium horizons, but the weight decreases with the investment horizon to 50% at the twenty-year horizon. In turn, real estate becomes more important the longer the investment horizon. At short horizons, the allocation to real estate is small due to the high volatility and a high correlation with stocks. At the twenty-year horizon, the allocation to real estate is 58%, higher than the allocation to cash. Recall that real estate's volatility at the twenty-year horizon is slightly lower than the volatility of cash returns. Stocks and bonds have weights of about 0 to -15% over all investment horizons in the minimum variance portfolio.

Panel B shows the allocations for a portfolio that has an annual expected return of 5%. This is somewhere between the expected return of stocks and the expected returns of the other assets for every investment horizon (see Figure 3.4). This portfolio therefore represents moderate risk aversion for the investor. Over short investment horizons, stocks are the asset with the highest allocation. The horizon effect with regard to the allocation to real estate is even more substantial than for the global minimum variance portfolio. The reason is that, in addition to the attractive long-term risk statistics, real estate's expected return per period is increasing with the investment horizon. The low expected return (due to the high transaction costs) makes real estate very unattractive at short investment horizons; due to the short-selling restriction, the allocation is zero. Real estate is the asset with the largest allocation for investment horizons of nine years or longer. At the twenty-year horizon the allocation is 87%. The allocation to cash is notable at short horizons, but as real estate becomes more important, the allocation to cash decreases rapidly, and it is negative at long horizons. The allocation to bonds is somewhere between 1 and 13% for all investment horizons. The reason why bonds are relatively unattractive in both portfolios (Panels A and B) is that the Sharpe ratio is relatively low, and this does not change when the investment horizon is extended.



Panel A: Global minimum variance portfolio



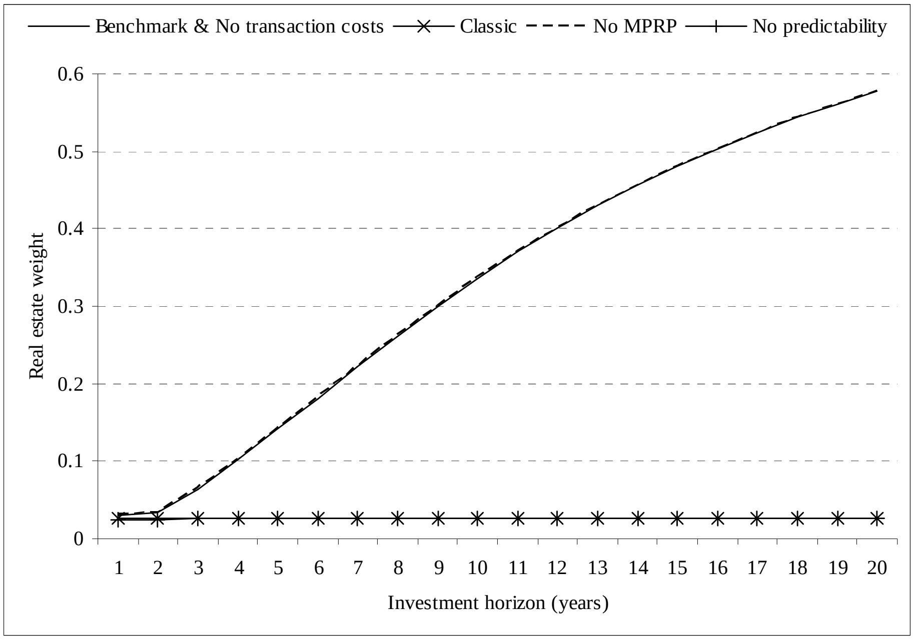
Panel B: Portfolio with expected return of 5% p.a.

Figure 3.6 Optimal portfolio compositions

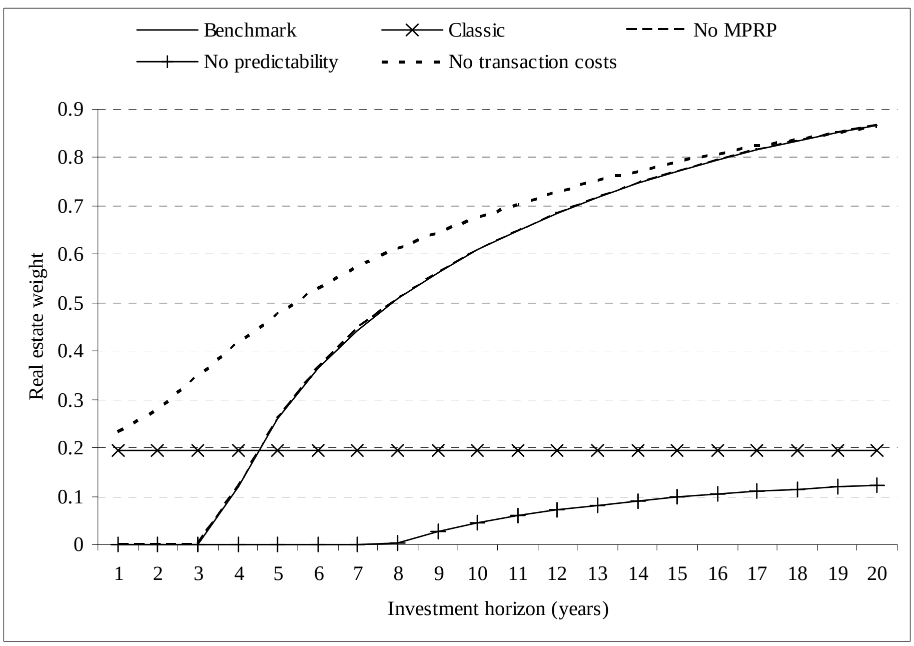
The figure shows optimized portfolio compositions for two portfolios depending on the investment horizon.

3.6.3 The allocation to real estate under different asset allocation approaches

What is the relative importance of accounting for transaction costs, marketing period risk and return predictability for the allocation to real estate? To answer this question I compare different asset allocation approaches. The benchmark case is that of incorporating transaction costs, marketing period risk and return predictability, as it has been done so far. For comparison (see Figure 3.7), I calculate the allocation to real estate that obtains, when either transaction costs, the marketing period risk premium, or return predictability is ignored. The approach of ignoring return predictability is nested in the Campbell and Viceira (2005) approach, because it is obtained by regressing returns and additional state variables on a constant only, i.e., restricting all coefficients in $\mathbf{\Phi}_1$ in the VAR model (3.1) to zero. When returns are unpredictable, the term structure of the annualized volatility of ex post real estate returns is constant. The only source for the marketing period risk premium is therefore the horizon effects in the periodic expected return due to transaction costs. Hence, the marketing period risk premium in the case of no return predictability is based on (3.13a) for all horizons with $Var_t^a(r_{RE,t+1})$ equal to the obtained variance under the IID assumption. The results from the classic approach, i.e., ignoring transaction costs, return predictability and marketing period risk altogether, are also presented. Again, Panel A reports the results for the global minimum variance portfolio and Panel B shows the allocation to real estate for the portfolio which has an expected annual return of 5%.



Panel A: Global minimum variance portfolio



Panel B: Portfolio with expected return of 5% p.a.

Figure 3.7 Real estate allocation under different asset allocation approaches

The figure shows the allocation to real estate for two portfolios under different asset allocation approaches, depending on the investment horizon. The result of the benchmark approach of incorporating return predictability, the marketing period risk premium and transaction costs ("Benchmark") is compared to the results that are obtained if either returns are assumed to be unpredictable ("No predictability"), the marketing period risk premium is set to zero ("No MPRP"), or transaction costs are set to zero ("No transaction costs"). The result of the approach of ignoring return predictability and marketing period risk premium and transaction costs altogether ("Classic") is also presented.

Marketing period risk is of least importance for the asset allocation results. For both portfolios and at all investment horizons, the differences to the benchmark approach are very small. In the global minimum variance portfolio the benchmark approach and the approach of ignoring transaction costs are identical, because expected returns remain unconsidered. For the portfolio in Panel B, ignoring transaction costs would lead to a large over-allocation to real estate at short horizons, up to 35 percentage points (pp) at the three-year horizon. At long investment horizons, the consideration of transaction costs is negligible. Ignoring return predictability reduces the allocation to real estate substantially at medium and long horizons. In the global minimum variance portfolio it decreases the allocation by 31pp at the ten-year and 55pp at the twenty-year horizon. The respective numbers are -56pp and -74pp for the portfolio with an annual expected return of 5%. The weight allocated to real estate under this asset allocation approach of ignoring return predictability is about 2.5% for the global minimum variance portfolio and up to 12.3% for the riskier portfolio. The classic approach of ignoring return predictability, transaction costs and marketing period risk leads to asset weights that are independent of the investment horizon. Interestingly, the allocation to real estate for the portfolio in Panel B is 19.3%, which is within the range of 15 to 20% that Hoesli and MacGregor (2000, Chapter 10) regard as typical results from the classic approach. The weight allocated to real estate under the classic approach is similar to the allocation under the benchmark approach at the one- and two-year horizon in Panel A, and at the four- to five-year horizon in Panel B. In general, however, the classic approach is obviously not a good approximation to the approach that accounts for return predictability, marketing period risk and transaction costs.

The low actual allocations to real estate in portfolios of institutional investors of 5 to 10% are obtained either under the benchmark approach for short investment horizons of about three or four years or under the approach of ignoring return predictability (but accounting for transaction cost, and, of less importance, marketing period risk) for longer horizons. But if institutional investors actually have a long investment horizon, this analysis suggests that they should substantially increase the allocation to real estate, because return predictability induces favorable horizon effects in risk.

3.7 Robustness checks

I conduct two robustness checks for the main results for investment horizons of one, five, ten and twenty years. First, the sensitivity of the results with regard to the parameter used to unsmooth the appraisal-based real estate returns is analyzed. I explore the importance of the choice of the smoothing parameter by recalculating the main results of this chapter for two alternative parameter values that Barkham and Geltner (1994) consider as reasonable lower and upper bounds: $a = 0.50$ and $a = 0.75$. Second, the results are recalculated for a quarterly dataset. To quantify the marketing period risk premium with (3.13), the term structures of the standard deviation of ex post returns on real estate are approximated with reasonable choices for the one-year return variance.[26]

3.7.1 Smoothing parameter

The results obtained from using the two alternative smoothing parameters are presented in Table 3.3. Risk and return statistics for cash, bonds and stocks are almost unaffected by the choice of the smoothing parameter; the results presented therefore focus on real estate. For comparison, the results obtained from the assumption made so far ($a = 0.625$) are also reported. I ignore (small) changes in the mean return on real estate that result from unsmoothing returns with different parameters.

[26] Specifically, the assumed values for the one-year return variance plugged into (3.13a) are $17.5\%^2$ (a = 0.5), $12.0\%^2$ (a = 0.75) and $12.5\%^2$ (quarterly dataset), and for (3.13b) the values are $18.5\%^2$ (a = 0.5), $15.0\%^2$ (a = 0.75) and $12.5\%^2$ (quarterly dataset).

Table 3.3 Results obtained from the use of alternative smoothing parameters

This table shows results for three parameters a used to unsmooth real estate returns, and four investment horizons. Results are obtained from re-estimated VARs where the real estate excess return and cap rate series are based on the alternative assumptions. MPRP: marketing period risk premium.

Investment horizon (years)	1			5			10			20		
Smoothing parameter a	0.5	0.625	0.75	0.5	0.625	0.75	0.5	0.625	0.75	0.5	0.625	0.75
Conditional standard deviation of real returns p.a.												
Real estate without MPRP	17.81%	14.25%	11.88%	12.21%	10.78%	9.98%	9.55%	8.64%	8.15%	8.43%	7.98%	7.75%
Real estate with MPRP	18.05%	14.51%	12.17%	12.25%	10.81%	10.01%	9.56%	8.65%	8.16%	8.44%	7.99%	7.75%
Conditional correlations of real returns												
Bonds – Real estate	29.00%	28.77%	28.54%	13.45%	8.21%	3.84%	28.96%	26.34%	23.99%	44.96%	44.21%	43.60%
Real estate – T-bills	-2.10%	-1.94%	-1.80%	12.47%	12.99%	13.04%	37.71%	39.99%	40.88%	62.12%	65.27%	66.69%
Stocks – Real estate	55.69%	56.15%	56.39%	32.28%	27.86%	23.51%	41.27%	38.71%	35.72%	46.34%	45.05%	43.48%
Expected real return p.a.												
Real estate	-1.38%	-1.95%	-2.26%	3.22%	3.05%	2.97%	3.61%	3.52%	3.48%	3.85%	3.81%	3.79%
Real estate weight at global minimum variance portfolio												
Benchmark / No transaction costs	1.91%	2.97%	3.86%	12.46%	14.13%	15.26%	28.87%	33.63%	36.75%	50.39%	57.80%	62.59%
Classic	2.04%	2.56%	3.39%	2.04%	2.56%	3.39%	2.04%	2.56%	3.39%	2.04%	2.56%	3.39%
No MPRP	1.92%	3.14%	3.61%	12.54%	14.22%	15.36%	28.93%	33.69%	36.81%	50.41%	57.83%	62.62%
No predictability	1.99%	2.41%	3.18%	2.04%	2.56%	3.39%	2.04%	2.56%	3.39%	2.04%	2.56%	3.39%
Real estate weight at portfolio with expected return of 5% p.a.												
Benchmark	0.00%	0.00%	0.00%	18.69%	25.96%	32.58%	49.38%	60.88%	68.38%	76.83%	86.59%	91.83%
Classic	12.86%	19.31%	29.13%	12.86%	19.31%	29.13%	12.86%	19.31%	29.13%	12.86%	19.31%	29.13%
No transaction costs	16.94%	23.41%	32.98%	39.24%	47.68%	53.53%	57.92%	67.65%	73.21%	78.27%	86.33%	90.40%
No MPRP	0.00%	0.00%	0.00%	18.78%	26.10%	32.75%	49.46%	60.96%	68.46%	76.85%	86.62%	91.86%
No predictability	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.85%	4.47%	10.51%	8.06%	12.29%	20.59%

The choice of the smoothing parameter has a large impact on the conditional standard deviation of real returns on real estate at the one-year horizon. When it is assumed that the original returns suffer from a lot of smoothing ($a = 0.50$), the one-year volatility is almost 18%. In contrast, when the original returns are assumed to exhibit relatively little smoothing ($a = 0.75$), the one-year volatility is only 12%. However, the longer the investment horizon, the smaller this difference is. At the ten-year horizon, for example, the difference of the annualized volatility for $a = 0.5$ and $a = 0.75$ is already only 1.4 percentage points. In general, the marketing period risk adjustments are small. Correlations are quite similar under the different smoothing parameters. Due to the Jensen's inequality adjustment, expected returns are higher for $a = 0.5$; the longer the investment horizon, the smaller the differences are. In general, the allocation to real estate is lower when the original real estate returns are assumed to be more smoothed $(a = 0.5)$ since this yields more volatile unsmoothed returns, but the allocation is still substantial at medium and long horizons. The conclusions with regard to the relative importance of marketing period risk, return predictability and transaction costs for the allocation to real estate remain unaffected by the choice of the smoothing parameter.[27] Overall, the results appear to be fairly robust to changes in the smoothing parameter.

3.7.2 Quarterly dataset

The quarterly dataset runs from 1987Q2 to 2009Q3 (90 observations). Real estate returns are based on the IPD monthly index. Details on the data used are provided in Appendix A. I use the value 0.375 for unsmoothing quarterly appraisal-based real estate returns as favored by Barkham and Geltner (1994).[28] The VAR specification used for the annual dataset is also used for the quarterly dataset.[29] The results for the quarterly dataset are presented in Table 3.4. In general, asset returns are less volatile in this dataset. Bond returns are slightly mean averting. There is also a clear mean aversion effect in cash returns, but the volatility is much lower than in the annual dataset over all

[27] Usually, the allocation to real estate increases when either the marketing period risk premium or transaction costs are ignored. Counter-intuitively, there are (a few) exceptions to this rule. The reason is that the overall investment opportunities improve when transaction costs or the marketing period risk premium are ignored, and this may decrease the allocation to real estate.

[28] Wang (2006) estimates the parameter a in (3.3) from the relationship of real estate returns with other economic variables. His estimate for quarterly UK returns is 0.4239. Being only slightly higher than 0.375, this gives support to the suggestion by Barkham and Geltner.

[29] The choice of the one-lag specification of the VAR model is justified by the Schwarz criterion and the Hannan-Quinn criterion for the quarterly dataset, too.

investment horizons. Real estate and stock returns are strongly mean reverting. While the annualized conditional stock return volatility at the ten-year horizon is the same as at the twenty-year horizon, the periodic conditional volatility of real estate returns declines further over long horizons. Compared to the annual dataset, long-term correlations are relatively low. Hence, the horizon effects in the asset correlations in the annual dataset are intuitively more appealing. Bonds are the asset class with the highest expected return over all investment horizons, which is unlikely to be a good forward-looking estimate, so the annual dataset appears to be more reasonable in this regard, too.[30] Expected stock returns are slightly lower than expected bond returns. Again, we see a strong horizon effect in the periodic expected return on real estate due to the high transaction costs.

In the global minimum variance portfolio, the allocation to real estate is hump-shaped with relatively low allocations of between 1 and 15% (at the six-year horizon), roughly in line with the low actual allocations to real estate in the portfolios of institutional investors. The minimum-variance portfolio is dominated by cash investments, though, which is clearly not representative of the portfolios of institutional investors. In the portfolio with an expected annual return of 5%, bonds have the highest allocation at all horizons. But at the twenty-year horizon, the allocation to real estate is virtually the same as the allocation to bonds. As in the annual dataset, the weight assigned to real estate is strongly increasing with the investment horizon. However, the weight assigned to real estate is generally lower than in the annual dataset, especially at long horizons. Nevertheless, the allocation to real estate at medium and long horizons still far exceeds the typical allocation of an institutional investor. For an investor who can be characterized by medium risk aversion, it suggests that the low actual allocations to real estate in the portfolios of institutional investors can only be justified when the investment horizon is short.

[30] This is not surprising, given the longer time span of the annual dataset. Merton (1980) shows that the accuracy of the estimate of the expected return improves with the time span and is independent of the number of observations.

Table 3.4 Results obtained from quarterly dataset

This table shows results obtained from the quarterly dataset for four investment horizons. MPRP: marketing period risk premium.

Investment horizon (years)	1	5	10	20
Conditional standard deviation of real returns p.a.				
Bonds	6.83%	8.52%	8.40%	8.20%
Cash	1.38%	2.63%	2.81%	2.75%
Real estate without MPRP	12.71%	8.26%	6.71%	5.56%
Real estate with MPRP	13.07%	8.29%	6.72%	5.56%
Stocks	16.10%	10.23%	9.51%	9.51%
Conditional correlations of real returns				
Bonds – T-bills	28.08%	31.46%	27.01%	23.53%
Bonds – Real estate	-40.47%	-42.71%	-14.11%	-6.13%
Bonds – Stocks	-18.22%	-21.85%	-25.44%	-33.08%
Real estate – T-bills	10.07%	-10.06%	15.88%	39.18%
Stocks – T-bills	9.48%	10.25%	29.19%	30.39%
Stocks – Real estate	52.76%	48.58%	33.14%	25.78%
Expected real returns p.a.				
Bonds	5.23%	5.44%	5.44%	5.43%
Cash	3.39%	3.42%	3.42%	3.42%
Real estate	-1.11%	3.85%	4.42%	4.69%
Stocks	5.13%	5.15%	5.18%	5.23%
Weight at global minimum variance portfolio (benchmark)				
Bonds	-1.63%	5.38%	3.44%	4.57%
Cash	101.48%	81.88%	86.28%	87.85%
Real estate	0.56%	13.99%	11.63%	6.90%
Stocks	-0.42%	-1.25%	-1.35%	0.68%
Weight at portfolio with expected return of 5% p.a. (benchmark)				
Bonds	71.86%	53.02%	42.51%	35.84%
Cash	11.54%	1.00%	4.91%	6.01%
Real estate	0.00%	22.09%	26.79%	35.58%
Stocks	16.60%	23.90%	25.78%	22.57%
Real estate weight at GMVP				
Classic	2.09%	2.09%	2.09%	2.09%
No transaction costs	0.56%	13.99%	11.63%	6.90%
No MPRP	0.31%	14.07%	11.65%	6.90%
No predictability	1.98%	2.09%	2.09%	2.09%
Real estate weight at portfolio with expected return of 5% p.a.				
Classic	21.87%	21.87%	21.87%	21.87%
No transaction costs	19.95%	35.02%	32.94%	37.06%
No MPRP	0.00%	22.16%	26.83%	35.59%
No predictability	0.00%	13.34%	18.77%	20.58%

The qualitative results with regard to the relative importance of return predictability, marketing period risk and transaction costs are the same as for the annual dataset. Again, we see that ignoring return predictability reduces the allocation to real estate at medium and long horizons. Marketing period risk appears to be negligible. Accounting for transaction costs is very important at short and medium horizons. The classic approach is usually not a good approximation of the approach of incorporating transaction costs, return predictability and marketing period risk.

3.8 Conclusion

The long-term asset allocation approach introduced by Campbell and Viceira (2005) is used to estimate the “term structure of risk” for UK stocks, bonds, cash and direct commercial real estate. Real estate returns show slight mean aversion over short investment horizons and strong mean reversion over medium and long horizons. Due to high transaction costs, the periodic expected return on real estate strongly increases with the investment horizon. A premium for real estate’s marketing period risk also induces horizon effects, but the premiums are small. The weight assigned to real estate in a mixed asset portfolio strongly increases with the investment horizon. Unless institutional investors can be characterized as having a short investment horizon, the actual allocations to real estate in their portfolios appear to be too low to be justified by this analysis. Traditional mean-variance analysis is clearly misleading for investors. For medium- and long-term investors, it is crucial to account for return predictability, inducing horizon effects in periodic return volatilities and correlations. Transaction costs are important in the short- to medium-term. Marketing period risk appears to be of little importance for the optimal allocation to real estate.

3.9 Appendix A: Data

Table 3.A1 contains information on the data.

Table 3.A1: Data information

Panel A: Annual dataset

	Description	Source
Cash return	Change (%) of Barclays UK treasury bill index	Barclays Equity Guilt Study 2009
Cash yield	UK three-month treasury bills rate	Datastream
Bond yield	Yield of Barclays gilt index	Barclays Equity Guilt Study 2009
Stock return	Change (%) of Barclays equity index	Barclays Equity Guilt Study 2009
Bond return	Change (%) of Barclays gilt index	Barclays Equity Guilt Study 2009
Real estate return	Constructed as described in this Appendix	Scott (1996), IPD
Property share index	UK-DS real estate total return index	Datastream
Inflation	Change (%) of UK cost of living index	Barclays Equity Guilt Study 2009
Cap rate	Constructed as described in this Appendix	Scott (1996), IPD
Dividend yield	Income yield of Barclays equity index	Barclays Equity Guilt Study 2009

Panel B: Quarterly dataset

	Description	Source
Cash yield*	UK three-month treasury bills rate	Datastream
Bond yield	UK government nominal spot curve 10-year yield	Datastream
Stock index	FTSE all share DS total return index	Datastream
Bond index	FTA British government 5-15 years DS total return index	Datastream
Real estate return	Constructed from IPD returns as described in this Appendix	Datastream
Property share index	UK-DS real estate total return index	Datastream
Price index	Retail price index: Seasonally adjusted all items excl. mortgage interest payments and indirect taxes	Office for National Statistics
Cap rate	Constructed from IPD returns as described in this Appendix	Datastream
Dividend yield	Dividend yield of FTSE all share	Datastream

* The return on T-bills in period t is equal to the cash yield at the end of the period t - 1.

The real estate total return and cap rate series are calculated as follows: The unsmoothed log real capital returns (see section 3.3.2 for a description of the unsmoothing procedure) are converted to simple nominal capital returns (CRU_t). This series is used to construct an unsmoothed capital value index (UCV_t). The unsmoothed capital value index is calibrated such that the average of the capital values over time matches the corresponding average of the original index. A real estate income series (Inc_t) is obtained by multiplying the (original) income return (IR_t) with the (original) capital value index (CV_t): $Inc_t = IR_t \cdot CV_{t-1}$. New income returns are computed with regard to the unsmoothed capital value index: $IRU_t = Inc_t / UCV_{t-1}$. Total returns are obtained by adding the adjusted simple income and capital returns: $RER_t = CRU_t + IRU_t$. The cap rate series is calculated as $CR_t = Inc_t / UCV_t$ in the annual dataset, and as $CR_t = 4Inc_t / UCV_t$ in the quarterly dataset, respectively.

3.10 Appendix B: Approximation (3.10a)

The mean reversion pattern in ex post real estate returns for investment periods of three years and longer can be approximated by the function $Var_t(r_{RE,t+k^*+m} | m) = Var_t(r_{RE,t+1})(k^*+m)^{-1/2}$ for the conditional periodic return variance. We need the expectation $E(Var_t(r_{RE,t+1})(k^*+m)^{-1/2}) = Var_t(r_{RE,t+1})E(k^*+m)^{-1/2}$. A second-order Taylor series approximation for the function $f(m) = (k^*+m)^{-1/2}$ around $E(m)$ yields:

$$f(m) \approx [k^*+E(m)]^{-1/2} - \frac{1}{2}[m - E(m)][k^*+E(m)]^{-3/2} + \frac{3}{8}[m - E(m)]^2[k^*+E(m)]^{-5/2}. \tag{3.B1}$$

Taking expectations we have:

$$E[f(m)] \approx [k^*+E(m)]^{-1/2} + \frac{3}{8}[E(m)^2 + Var(m) - 2E(m)^2 + E(m)^2][k^*+E(m)]^{-5/2}. \tag{3.B2}$$

Multiplying this with $Var_t(r_{RE,t+1})$ yields:

$$E[Var_t(r_{RE,t+k^*+m}|m)] \approx Var_t(r_{RE,t+1})([k^*+E(m)]^{-1/2} + \tfrac{3}{8}Var(m)[k^*+E(m)]^{-5/2}). \qquad (3.B3)$$

Substituting $k^* + E(m)$ by k yields (3.10a).

4 Inflation-Hedging, Asset Allocation, and the Investment Horizon

This chapter is joint work with Benedikt Fleischmann and Steffen Sebastian.

Abstract

Focusing on the role of the investment horizon, we analyze the inflation-hedging abilities of stocks, bonds, cash and direct commercial real estate investments. Based on vector autoregressions for the UK market we find that the inflation-hedging abilities of all assets improve with the investment horizon. For long horizons, real estate seems to hedge unexpected inflation as well as cash. This has implications for the difference between the return volatility of real returns versus the return volatility of nominal returns, and ultimately for portfolio choice. Portfolio optimizations based on real returns yield higher allocations to cash and real estate than optimizations based on nominal returns. Bonds tend to be less attractive for an investor taking into account inflation. Switching from nominal to real returns, the allocation to stocks is decreasing at medium investment horizon, but increasing at long horizons.

4.1 Introduction

The monetary base has grown considerably in many economies as a reaction to the current financial crisis. As a result, the fear of inflation has regained attention. Even modest inflation rates can have a significant effect on the real value of assets when the investment horizon is long. For example, €100 invested for 20 years at a nominal interest rate of 5% p.a. yield €265.3 final wealth, compared to €180.6 assuming a real annual interest rate of 3%. Hence, an inflation rate of $1.05/1.03-1\approx 1.94\%$ p.a. reduces the real value of the investment by 32%. Despite the important role of inflation for decision making, people often think in nominal rather than real terms, a phenomenon referred to as "money illusion" (for a review see Akerlof and Shiller 2009, Chapter 4). Assets that hedge inflation are desirable for private investors concerned about the purchasing power of their investments as well as for institutional investors whose liabilities are linked to inflation (such as pension funds).

Most of the evidence on optimal portfolio choice is based on the traditional Markowitz (1952) approach with quarterly or annual returns used to estimate expected returns, standard deviations, and correlations. This common procedure contrasts with the fact that most investors have longer investment horizons. Due to return predictability, standard deviations (per period) and correlations of asset returns may change considerably with the investment horizon (Campbell and Viceira 2005). Hence, the optimal asset allocation depends on the investment horizon. The asset classes usually considered for a mixed asset allocation optimization are cash, bonds and stocks. Real estate is a further important asset class. In the US, for example, the market capitalization of private commercial real estate is estimated to be $8 trillion, compared to a value of $17 trillion for stocks, as of the early 2000s (Geltner et al. 2007, Chapter 7). Due to high transaction costs, there are substantial horizon effects in periodic expected returns on real estate (e.g., Collet et al. 2003). This is certainly a reason why direct real estate investments are typically long-term investments with an average holding period of about ten years (Collet et al. 2003, Fisher and Young 2000). Practitioners often regard direct real estate investments to be a good inflation hedge.

In this chapter, we link the inflation-hedging analysis with the mixed asset allocation analysis, focusing on the role of the investment horizon for a buy and hold investor. Using a vector autoregression (VAR) for the UK market, we estimate correlations of nominal returns with inflation, analyzing how the inflation hedging abilities of cash, bonds, stocks and direct commercial real estate change with the investment horizon.[31] The results have implications for the difference between the term structures of annualized volatilities of real versus nominal returns, and ultimately for portfolio choice. The differences in the optimal asset weights (based on real versus nominal returns) can be interpreted as the mistake that an investor subject to inflation illusion makes. On the other hand, the results for nominal rather than real returns are relevant for investors facing liabilities that are fixed in nominal terms.

We find that cash is clearly the best inflation hedge at short and medium horizons. Real estate is a very good inflation-hedge in the long-run, too. For bonds and stocks we also find that the longer the investment horizon, the better the inflation hedging abilities. The long-term volatility of real returns on real estate is notably lower than the long-term volatility of nominal returns. This is also true for cash returns. In contrast, bonds are less attractive for an investor concerned about inflation. The same is found for stocks at medium horizons, but at long horizons, the volatility of real returns is lower than the volatility of nominal returns. Portfolio optimizations based on real returns yield higher allocations to cash and real estate than optimizations based on nominal returns. Bonds tend to be less attractive for an investor taking into account inflation. Switching from nominal to real returns, the allocation to stocks is decreasing at medium investment horizon, but increasing at long horizons.

The remainder of the chapter is organized as follows: In the next section, we review the related literature. A discussion of the VAR model, the data and the VAR results follow. Then, we analyze horizon effects in risk and return for nominal and real returns. In this section, the results with regard to the inflation hedging abilities of the assets are also discussed. The asset allocation problem is examined in the next section, again distinguishing between nominal and real returns. A discussion of a robustness check follows. Finally, the main findings are summarized.

[31] Inflation-linked bonds with a maturity equal to the investment horizon are a particularly good inflation-hedge. Given the limited supply of these bonds, it is worthwhile to analyze the inflation-hedging abilities of common asset classes.

4.2 Literature review

Academics have devoted much attention to the abilities of assets to hedge inflation. Bodie (1976), Jaffe and Mandelker (1976) and Fama and Schwert (1977) find that that nominal US stock returns are negatively related to realized inflation as well as to the two components of realized inflation, i.e., expected and unexpected inflation. Gultekin (1983) shows that the negative relation of nominal stock returns with inflation also holds for many other countries. The perverse inflation-hedging characteristics of stocks run contradictory to the general belief that stocks should be a good hedge against inflation due to the fact that stocks are essentially claims to cash-flows derived from real assets. Of all the US assets examined by Fama and Schwert (1977) (government bills and bonds, residential real estate, human capital and stocks), residential real estate is the only asset that provides a complete hedge against inflation. (An asset is said to be a complete hedge against inflation when the coefficients from a regression of nominal returns on proxies for expected and unexpected inflation are both statistically indistinguishable from one.) Bonds and bills provide a hedge against expected inflation, but not against unexpected inflation. Studies examining the direct commercial real estate market suggest at least a partial inflation hedge. US commercial real estate appears to offer a hedge against expected inflation, whereas the evidence with regard to unexpected inflation is not clear-cut (e.g., Brueggeman et al. 1984, Hartzell et al. 1987, Gyourko and Linneman 1988, Rubens et al. 1989). Examining the UK market, Limmack and Ward (1987) find that commercial real estate returns are positively related to both expected and unexpected inflation. Depending on the proxy for expected inflation, however, commercial real estate does not appear to provide a hedge against both components. In contrast to the direct real estate market, real estate stocks tend to be negatively related or unrelated to expected and unexpected inflation (e.g., Liu et al. 1997, and Maurer and Sebastian 2002).

The results of the above-cited studies are based on regressions with data that have a monthly to annual frequency. The disappointing short-term inflation hedging abilities of most asset classes motivated research analyzing the long-term relation of asset returns with inflation. For both the US and the UK, Boudoukh and Richardson (1993) find positive relationships between five-year stock returns and realized as well as expected inflation, whereas annual returns show a negative or only weakly positive relationship. Based on cross-sectional regressions for 14 countries using data over a 14-

year period, Quan and Titman (1999) find evidence that real estate is a hedge against realized inflation in the long run. In contrast, time-series regressions suggest that annual returns do not hedge against realized inflation. Hoesli et al. (2007) as well as Schätz and Sebastian (2009) use error correction approaches to distinguish between short- and long-term relationships between asset markets and macroeconomic variables. Hoesli et al. analyze the inflation hedging abilities of stocks as well as direct and securitized real estate markets in the US and the UK. For all asset markets, they find a positive long-term relationship with expected inflation. The long-term link to unexpected inflation is negative for all US assets and for UK stocks. UK property shares and direct real estate are positively linked to unexpected inflation in the long-run. In both countries, asset returns adjust rather slowly towards the long-term equilibrium, though. Schätz and Sebastian find a positive long-term link between commercial real estate markets and price indexes for both the UK and Germany. Confirming the findings of Hoesli et al., they observe that property markets in both countries are sluggish to adjust towards the long-term equilibrium existing with macroeconomic variables.

Several articles use a vector autoregressive (VAR) approach to estimate horizon-dependent correlation statistics. As the predictability of the variables is taken into account, the inflation hedging abilities of the assets are analyzed in terms of the correlation of unexpected asset returns with unexpected inflation. Campbell and Viceira (2005) calculate correlations of inflation shocks with unexpected *real* US stock returns. The correlation turns from weakly negative at short horizons to substantially negative at intermediate horizons, but it is slightly positive at the 50-year horizon. Hence, with the real return being almost unaffected by inflation, stocks seem to hedge unexpected inflation in the very long run. Hoevenaars et al. (2008) calculate correlations between unexpected *nominal* US asset returns and inflation shocks for horizons of up to 25 years. They find that cash is clearly the best inflation hedge for investment horizons of one year and longer. Bonds are a perverse inflation hedge in the short run; the correlation turns positive after about 12 years to reach more than 0.5 after 25 years. The correlation of nominal stock returns and REIT returns with inflation is negative in the short and slightly positive in the long run. Amenc et al. (2009a) report similar results with regard to cash and stocks. However, the estimated correlation of nominal REIT returns with inflation is about zero and the correlation of bonds is negative for all investment horizons. While the empirical evidence is not unambiguous, the general picture that emerges is that the inflation-hedging abilities of assets improve with the investment horizon.

Of course, the different inflation hedging characteristics of the assets have portfolio implications. Intuitively, when the nominal return on an asset is highly positively correlated with inflation, this decreases the volatility of real returns on the asset. Hence, the better the inflation-hedging ability of the asset, the more attractive is it for an investor concerned about real returns. Schotman and Schweizer (2000) show that when the investor is concern about real returns, the demand for stocks in a portfolio with a nominal zero-bond (with a maturity that equals the investment horizon) depends on two terms. The first term reflects the demand due to the equity premium. The second term depends positively on the covariance of nominal stock returns with inflation and represents the inflation hedging demand. The hedging demand changes with the investment horizon; depending on the parameterization of the model, the long-term hedging demand might be negative or positive.

Several articles calculate horizon-dependent risk statistics and optimal portfolio compositions based on real returns. Campbell and Viceira (2005) show that return predictability induces major horizon effects in annualized standard deviations and correlations of real US stock, bond and cash returns. Stocks exhibit mean reversion such that the periodic long-term volatility of real returns is only about 50% of the short-term volatility. Bonds exhibit slight mean reversion, whereas cash returns are mean averting. There are huge horizon effects in optimal portfolio compositions. In addition to stocks, bonds and cash investments, Fugazza et al. (2007) consider European property shares, whereas MacKinnon and Al Zaman (2009) consider US direct real estate and REITs.[32]

Analyzing the UK market, we follow the studies using a VAR approach. Hoevenaars et al. (2008) and Amenc et al. (2009a) analyze the US market including securitized real estate as an asset class, whereas we look at the UK market and focus on direct real estate. Hoevenaars et al. emphasize that the dynamics of REIT returns are well captured by the dynamics of stock and bond returns, so that the opportunity to invest in securitized real estate does not add much value for the investor. Given the different market microstructures of the securitized and the direct real estate market and the effect of leverage on the returns of securitized real estate, among other differences, it is interesting to analyze the direct real estate market. In addition, the market

[32] Hoevenaars et al. (2008), Porras Prado and Verbeek (2008) and Amenc et al. (2009b) extend the long-term asset allocation analysis based on VAR estimates to an asset-liability context, modelling the dynamics of liabilities of institutional investors.

capitalization of direct commercial real estate still far exceeds the market capitalization of property shares in the UK (as in many other countries). As of the end of 2008, the market capitalization of the investable direct commercial real estate market is estimated to be about €250 billion, compared to a market capitalization of €64 billion for listed real estate companies.[33] Given the huge importance of transaction costs for direct real estate investments, we account for the differing transaction costs of the asset classes. In contrast to previous studies, we compare risk, return and asset allocation results based on real versus nominal returns, which makes the impact of the differing inflation-hedging abilities of the assets evident.

4.3 VAR model and data

4.3.1 VAR specification

The basic framework follows Campbell and Viceira (2005), who introduce a model for long-term buy and hold investors. Let $\boldsymbol{z}_{t+1}$ be a vector that includes log (continuously compounded) asset returns and additional state variables that predict returns. Assume that a VAR(1) model captures the dynamic relationships between asset returns and the additional state variables:

$$\boldsymbol{z}_{t+1} = \boldsymbol{\Phi}_0 + \boldsymbol{\Phi}_1 \boldsymbol{z}_t + \boldsymbol{v}_{t+1}. \tag{4.1}$$

In the specification of this study, the nominal return on cash ($n_{0,t+1}$), and the excess returns on real estate, stocks and long-term bonds (stacked in the (3x1) vector $\boldsymbol{x}_{t+1} = \boldsymbol{n}_{t+1} - n_{0,t+1}\boldsymbol{\iota}$, where $\boldsymbol{\iota}$ is a vector of ones) are elements of $\boldsymbol{z}_{t+1}$. In addition, $\boldsymbol{z}_{t+1}$ contains the realization of inflation i_{t+1}, and three other state variables stacked in the (3x1) vector $\boldsymbol{s}_{t+1}$ (the cap rate, the dividend yield and the yield spread). Thus,

$$\boldsymbol{z}_{t+1} = \begin{bmatrix} n_{0,t+1} \\ \boldsymbol{x}_{t+1} \\ i_{t+1} \\ \boldsymbol{s}_{t+1} \end{bmatrix} \tag{4.2}$$

[33] Sources: The IPD Index Guide, Edition 5, and EPRA Monthly Statistical Bulletin, December 2008.

is of order (8x1). $\mathbf{\Phi}_0$ is a (8x1) vector of constants and $\mathbf{\Phi}_1$ is a (8x8) coefficient-matrix. The shocks are stacked in the (8x1) vector $\boldsymbol{v}_{t+1}$, and are assumed to be IID normal with zero means and covariance-matrix $\mathbf{\Sigma}_v$, which is of order (8x8):

$$\boldsymbol{v}_{t+1} \sim IIDN(\mathbf{0}, \mathbf{\Sigma}_v) \text{ with } \mathbf{\Sigma}_v = \begin{pmatrix} \sigma_0^2 & \boldsymbol{\sigma}_{0x}^{'} & \sigma_{0i} & \boldsymbol{\sigma}_{0s}^{'} \\ \boldsymbol{\sigma}_{0x} & \mathbf{\Sigma}_{xx} & \boldsymbol{\sigma}_{ix} & \mathbf{\Sigma}_{sx} \\ \sigma_{0i} & \boldsymbol{\sigma}_{ix}^{'} & \sigma_i^2 & \boldsymbol{\sigma}_{is}^{'} \\ \boldsymbol{\sigma}_{0s} & \mathbf{\Sigma}_{sx}^{'} & \boldsymbol{\sigma}_{is} & \mathbf{\Sigma}_{ss} \end{pmatrix}. \tag{4.3}$$

The main diagonal of $\mathbf{\Sigma}_v$ consists of the variance of nominal cash return shocks, σ_0^2, the covariance-matrix of excess return shocks, $\mathbf{\Sigma}_{xx}$, the variance of inflation shocks, σ_i^2, and the covariance-matrix of the residuals of the state variables, $\mathbf{\Sigma}_{ss}$. The off-diagonal elements are the vector of covariances between shocks to the nominal return on cash and shocks to the excess returns on real estate, stocks and bonds, $\boldsymbol{\sigma}_{0x}$, the covariance of shocks to the nominal cash return with inflation shocks, σ_{0i}, the vector of covariances between shocks to the excess returns on real estate, stocks and bonds with inflation shocks, $\boldsymbol{\sigma}_{ix}$, the vector of covariances between shocks to the nominal cash return and shocks to the state variables, $\boldsymbol{\sigma}_{0s}$, the covariance matrix of shocks to the excess returns and shocks to the state variables, $\mathbf{\Sigma}_{sx}$, and the vector of covariances between inflation shocks and shocks to the state variables, $\boldsymbol{\sigma}_{is}$.

4.3.2 Data

The results are based on an annual dataset from 1957 to 2008 (52 observations) for the UK market; the Appendix provides details on the data used. As noted above, cash (T-bills), real estate, stocks and long-term bonds are the assets available to the investor. The bond index represents a security with constant maturity of 20 years. The implicit strategy assumed here is to sell a bond at the end of each year and buy a new bond to keep the bond maturity constant, an assumption which is common for bond indexes. As in Campbell and Viceira (2005), the log of the dividend yield of the stock market and the log yield spread, i.e., the difference between the log yield of a long-term bond and the log yield of T-bills are incorporated as state variables that have been shown to predict asset returns. We also include the (log of the) cap rate as a state variable that has been shown to predict direct real estate returns (Fu and Ng 2001, Ghysels et al. 2007, Plazzi et al. 2010).

Appraisal-based capital and income real estate returns used to calculate the annual real estate total return and the cap rate series have been obtained from two sources. The returns from 1971 to 2008 are based on IPD's long-term index. Initially, the index covered a portfolio of 651 properties, increasing to 11,328 properties by 1981 (Newell and Webb 1994). Returns from 1956 to 1970 are from Scott (1996).[34] These returns are based on valuations of properties in portfolios of two large financial institutions covering more than 1,000 properties throughout this period (Scott and Judge 2000).[35] Key et al. (1999) find that the Scott return series used here as well as the IPD 1971 to 1980 return series are fairly reliable in terms of coverage.

Real estate returns are unsmoothed using the approach of Barkham and Geltner (1994). This unsmoothing approach is based on modeling optimal behavior of property appraisers as introduced by Geltner (1993). Appraisal-based log real capital returns g_t^* are unsmoothed using the formula

$$g_t = \frac{g_t^* - (1-a)g_{t-1}^*}{a}, \tag{4.4}$$

where g_t is the true log real capital return (or growth) and a is the smoothing parameter. We use the value 0.625 for unsmoothing annual returns as favored by Barkham and Geltner (1994). Total real estate returns and cap rates are constructed from the unsmoothed log real capital return and income return series; see the Appendix.

Table 4.1 provides an overview of the sample statistics of the variables used in the VAR model. Mean log returns of the assets are adjusted by one half of the variance to reflect log mean returns. Nominal cash returns are very persistent. Stocks have the highest mean return but also the highest volatility. Bonds have a mean excess return with regard to cash of only 1% p.a., but bond returns are quite volatile so that the Sharpe ratio is low. Real estate lies in between stocks and bonds with regard to

[34] Note that due to the unsmoothing procedure for real estate returns, one additional observation is needed.
[35] For comparison, the widely-used NCREIF Property Index (NPI) was based on 233 properties at the index inception; see "Frequently asked questions about NCREIF and the NCREIF Property Index (NPI)" on the NCREIF website (www.ncreif.org).

volatility, mean return and Sharpe ratio. The unsmoothed real estate returns do not show notable autocorrelation. The state variables exhibit high persistency, especially the inflation rate. The inflation rate has a high mean and a high volatility. The cap rate has a higher mean and a lower volatility than the dividend yield of the stock market.

Table 4.1 Sample statistics

This table shows statistics for the variables included in the VAR model for the annual dataset (1957 to 2008). Autocorrelation refers to the first-order autocorrelation.

	Mean	Standard deviation	Sharpe ratio	Auto-correlation
Nominal return on cash*	7.62%	3.14%	-	84.58%
Excess return on real estate*	3.21%	15.57%	0.2060	5.37%
Excess return on stocks*	6.76%	23.76%	0.2845	-13.69%
Excess return on bonds*	0.97%	11.50%	0.0845	-13.00%
Log inflation	5.96%	4.57%	-	80.80%
Log of cap rate	-2.8416	0.2230	-	64.05%
Log of dividend yield	-3.1613	0.3113	-	69.53%
Log yield spread	0.30%	1.80%	-	43.76%

*Mean log returns are adjusted by one half of the return variance to reflect log mean returns.

Figure 4.1 shows the logarithm of the (nominal) total return index values of the four asset classes and the development of the cost of living index. Real estate, bond and stock markets collapsed during the oil crisis of 1973-74. After that, the stock market was characterized by a long upswing until the turn of the century. The real estate market experienced a significant downturn in the early 1990s and again – like the stock market – in recent times. In general, bonds performed poorly. It took until the mid-1980s for bonds to have a higher index value than the consumer price index, and a decade later the bond index value exceeded that of cash investments. The cash index reflects the persistent behavior of cash returns.

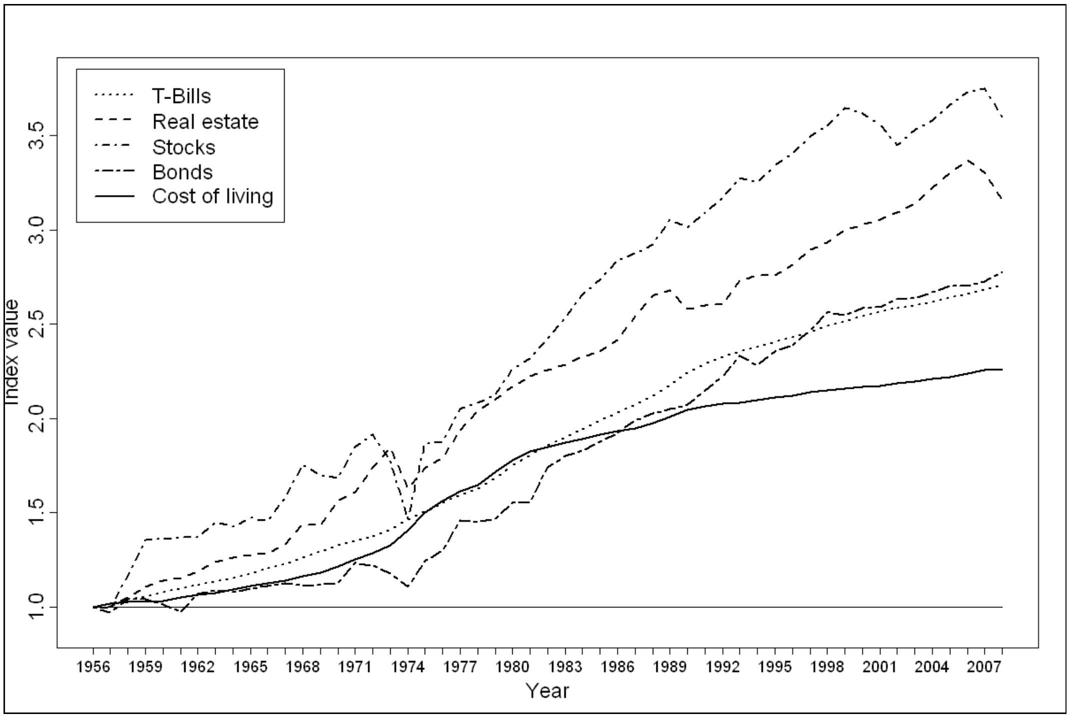


Figure 4.1 Total return and cost of living indexes

The figure shows the logarithm of the nominal total return index values and the cost of living index over the time period 1956 to 2008 (end of 1956 = 1).

4.3.3 VAR estimates

The results of the VAR(1), estimated by OLS, are given in Table 4.2. Panel A contains the coefficients. In square brackets are *p*-values. Panel B contains the standard deviations (diagonal) and correlations (off-diagonals) of the VAR residuals.

Table 4.2 VAR results

The results are based on annual data from 1957 to 2008. Panel A shows the VAR coefficients. The *p*-values are in square brackets; *p*-values of 10% or below are highlighted. The rightmost column contains the R^2 values and the *p*-value of the *F*-test of joint significance in parentheses. Panel B shows results regarding the covariance matrix of residuals, where standard deviations are on the diagonal and correlations are on the off-diagonals.

Panel A: VAR coefficients

		Coefficients on lagged variables								
Variable	Constant	1	2	3	4	5	6	7	8	R^2 (*p*)
1 Log nominal cash return	0.0135	0.7926	0.0579	0.0084	-0.0665	0.083	-0.0104	0.0105	-0.27	86.92%
	(0.751)	**(0.000)**	**(0.004)**	(0.431)	**(0.002)**	(0.225)	(0.346)	(0.201)	**(0.051)**	(0.00%)
2 Log real estate excess return	0.8872	-0.4507	0.1419	-0.0117	0.2316	-0.2394	0.2121	0.0713	3.193	31.68%
	(0.072)	(0.672)	(0.512)	(0.923)	(0.32)	(0.756)	**(0.095)**	(0.444)	**(0.043)**	(2.90%)
3 Log stock excess return	2.1727	-0.8915	-0.2858	0.0239	0.2973	-0.9771	0.2125	0.4429	1.7771	40.48%
	(0.003)	(0.557)	(0.355)	(0.890)	(0.37)	(0.375)	(0.236)	**(0.002)**	(0.420)	(0.30%)
4 Log bond excess return	0.6427	0.3368	-0.0495	-0.0372	-0.1681	0.2247	0.2203	0.0153	1.4751	33.47%
	(0.071)	(0.662)	(0.751)	(0.671)	(0.318)	(0.687)	**(0.018)**	(0.820)	(0.190)	(1.90%)
5 Log inflation rate	-0.0748	0.171	0.0511	-0.0487	-0.0635	0.6446	-0.0383	0.0088	0.4586	80.14%
	(0.332)	(0.314)	(0.141)	**(0.015)**	**(0.09)**	**(0.000)**	**(0.059)**	(0.550)	**(0.066)**	(0.00%)
6 Log of cap rate	-1.2729	0.1767	-0.24	-0.0214	-0.1471	0.5446	0.667	-0.0968	-3.7854	54.69%
	(0.029)	(0.887)	(0.343)	(0.880)	(0.587)	(0.546)	**(0.000)**	(0.374)	**(0.040)**	(0.00%)
7 Log of dividend yield	-2.1533	0.8172	0.2958	0.0467	-0.3888	0.6303	-0.3124	0.6364	-0.5733	61.81%
	(0.004)	(0.603)	(0.354)	(0.794)	(0.258)	(0.579)	**(0.095)**	**(0.000)**	(0.801)	(0.00%)
8 Log yield spread	0.0161	-0.0876	-0.0128	-0.0246	0.0224	0.0978	0.0055	-0.0015	0.3436	33.88%
	(0.744)	(0.421)	(0.561)	**(0.051)**	(0.344)	(0.217)	(0.664)	(0.878)	**(0.033)**	(1.70%)

Table 4.2 VAR results (continued)

Panel B: Standard deviations and correlations of VAR residuals

	1	2	3	4	5	6	7	8
1 Log nominal cash return	1.24%	-17.86%	-15.61%	-30.15%	60.31%	14.99%	18.88%	-43.29%
2 Log real estate excess return	-17.86%	14.15%	58.69%	19.75%	-3.06%	-96.82%	-56.47%	-25.59%
3 Log stock excess return	-15.61%	58.69%	20.16%	41.90%	-15.93%	-55.83%	-95.54%	-23.89%
4 Log bond excess return	-30.15%	19.75%	41.90%	10.23%	-55.24%	-13.85%	-45.94%	-5.59%
5 Log inflation	60.31%	-3.06%	-15.93%	-55.24%	2.25%	0.05%	19.73%	-12.23%
6 Log of cap rate	14.99%	-96.82%	-55.83%	-13.85%	0.05%	16.54%	54.47%	23.00%
7 Log of dividend yield	18.88%	-56.47%	-95.54%	-45.94%	19.73%	54.47%	20.85%	25.13%
8 Log yield spread	-43.29%	-25.59%	-23.89%	-5.59%	-12.23%	23.00%	25.13%	1.44%

The *p*-values of the *F*-test of joint significance indicate that the nominal return on cash and the excess returns on the other assets are indeed predictable. Especially nominal cash returns have a very high degree of predictability. The lagged yield spread is the most significant predictor of excess real estate returns. The yield spread tracks the business cycle (Fama and French 1989), so the relationship of real estate returns with the lagged yield spread points toward the close relationship with changes in GDP (Case et al. 1999, Quan and Titman 1999). Confirming previous studies, real estate returns can also be predicted by the cap rate.[36] The most significant predictor of stock returns is the dividend yield. The lagged yield spread is positively related to bond returns, albeit not significantly. Somewhat surprisingly, the cap rate is a significant predictor of excess bond returns. All state variables are highly significantly related to their own lag.

Turning to the correlations of the residuals, we see that excess stock and real estate return residuals are almost perfectly negatively correlated with shocks to the respective market yield (dividend yield and cap rate respectively). Unexpected nominal cash returns and unexpected inflation are positively correlated, while shocks to the excess return on bonds and inflation shocks are negatively correlated. Shocks to excess returns on real estate and stocks have a correlation of close to zero with unexpected inflation. However, even if return shocks are negatively correlated with inflations shocks, the asset may be a good long-term hedge against inflation.

4.4 Horizon effects in risk and return for nominal and real returns

4.4.1 The term structure of risk

The risk statistics are based on the covariance matrix of the VAR residuals. Hence, we calculate conditional risk statistics, i.e., taking return predictability into account. The conditional multi-period covariance matrix of the vector $\boldsymbol{z}_{t+1}$, scaled by the investment horizon k, can be calculated as follows (see, e.g., Campbell and Viceira 2004):

[36] Gyourko and Keim (1992) as well as Barkham and Geltner (1995), among others, show that returns on direct real estate are positively related to lagged returns on property shares. It should be noted that returns on real estate stocks and general stocks are highly correlated, and general stocks are included in the VAR. Nevertheless, we recalculated the results in this chapter with the excess return on property shares (UK Datastream real estate total return index) as an additional state variable for the period 1965 (the inception of the property share index) to 2008. The main results are similar to those reported in this chapter. To make use of the additional observations and to avoid proliferation of the VAR parameters, the eight-variable VAR is used.

$$\begin{aligned}\frac{1}{k}Var_t(\boldsymbol{z}_{t+1}+...+\boldsymbol{z}_{t+k}) = \frac{1}{k}[&\boldsymbol{\Sigma}_v + (\mathbf{I}+\boldsymbol{\Phi}_1)\boldsymbol{\Sigma}_v(\mathbf{I}+\boldsymbol{\Phi}_1)' \\ &+ (\mathbf{I}+\boldsymbol{\Phi}_1+\boldsymbol{\Phi}_1^2)\boldsymbol{\Sigma}_v(\mathbf{I}+\boldsymbol{\Phi}_1+\boldsymbol{\Phi}_1^2)'+... \\ &+ (\mathbf{I}+\boldsymbol{\Phi}_1+...+\boldsymbol{\Phi}_1^{k-1})\boldsymbol{\Sigma}_v(\mathbf{I}+\boldsymbol{\Phi}_1+...+\boldsymbol{\Phi}_1^{k-1})'],\end{aligned} \tag{4.5}$$

where **I** is the (8x8) identity matrix. The conditional covariance matrix of nominal returns and inflation can be calculated from the conditional multi-period covariance matrix of $\boldsymbol{z}_{t+1}$, using the selector matrix

$$\mathbf{M}_n = \begin{bmatrix} 1 & \mathbf{0}_{1x3} & 0 & \mathbf{0}_{1x3} \\ \boldsymbol{\iota}_{3x1} & \mathbf{I}_{3x3} & \mathbf{0}_{3x1} & \mathbf{0}_{3x3} \\ 0 & \mathbf{0}_{1x3} & 1 & \mathbf{0}_{1x3} \end{bmatrix}. \tag{4.6}$$

Nominal return statistics can be calculated because the vector $\boldsymbol{z}_{t+1}$ includes the nominal cash return and excess returns such that the k-period (indicated by the upper (k)) nominal return statistics of stocks, bonds and direct real estate can be calculated by adding the nominal cash return and the excess return of the respective asset:

$$\frac{1}{k}Var_t\begin{bmatrix} n_{0,t+k}^{(k)} \\ \boldsymbol{n}_{t+k}^{(k)} \\ i_{t+k}^{(k)} \end{bmatrix} = \frac{1}{k}\mathbf{M}_n Var_t(\boldsymbol{z}_{t+1}+...+\boldsymbol{z}_{t+k})\mathbf{M}_{\mathrm{n}}^{'}. \tag{4.7}$$

Similarly, real return statistics can be calculated using the selector matrix

$$\mathbf{M}_r = \begin{bmatrix} \mathbf{I}_{4x4} & -\mathbf{1}_{4x1} \\ \mathbf{0}_{1x4} & 1 \end{bmatrix}, \tag{4.8}$$

such that the k-period conditional covariance matrix of real returns and inflation, per period, is:

$$\frac{1}{k}Var_t\begin{bmatrix} r_{0,t+k}^{(k)} \\ \boldsymbol{r}_{t+k}^{(k)} \\ i_{t+k}^{(k)} \end{bmatrix} = \frac{1}{k}\mathbf{M}_r Var_t\begin{bmatrix} n_{0,t+k}^{(k)} \\ \boldsymbol{n}_{t+k}^{(k)} \\ i_{t+k}^{(k)} \end{bmatrix}\mathbf{M}_{\mathrm{r}}^{'}, \tag{4.9}$$

where $r_{0,t+1}^{(k)}$ is the *k*-period real return on cash (the benchmark asset) and $\boldsymbol{r}_{t+1}^{(k)}$ is the vector of *k*-period real returns on real estate, stocks and bonds.

The annualized standard deviations for nominal and real returns of the four asset classes, depending on the investment horizon, are shown in Figure 4.2. Due to return persistency, the periodic long-term return volatility of real cash returns is much higher than the short-term volatility. The mean aversion effect is even more pronounced for nominal returns. For long investment horizons, the volatility of nominal returns is notably higher than the volatility of real returns. Real stock returns are mean reverting. Nominal stock returns are mean reverting over short investment horizons, too, but then the term structure is increasing to such an extent that the periodic long-term volatility of nominal returns in higher than the long-term volatility of real returns. Nominal bond returns are less volatile than real returns for all investment horizons, but the 20-year volatilities are quite similar. Recall that we use a constant maturity bond index. While a 20-year (zero-) bond held to maturity is riskless in nominal terms, this is not true for a 20-year constant maturity bond index. Qualitatively, the results for real cash, stock and bond returns are similar to the US results reported in Campbell and Viceira (2005), except that they find that bond returns are slightly mean reverting. Nominal and real returns on real estate are mean reverting. For medium and long-horizons, however, the annualized volatility of nominal returns is higher than the volatility of real returns. The mean reversion effect in real stock and real estate returns can be explained by the positive relation of excess returns on the lagged market yield (dividend yield and cap rate respectively) and the high negative correlation of return shocks and market yield shocks. If (property or stock) prices are decreasing, this is bad news for an investor. On the other hand, the good news is that a low realized return on stocks (real estate) is usually accompanied by a positive shock to the dividend yield (cap rate), and a high dividend yield (cap rate) predicts high returns for the future.

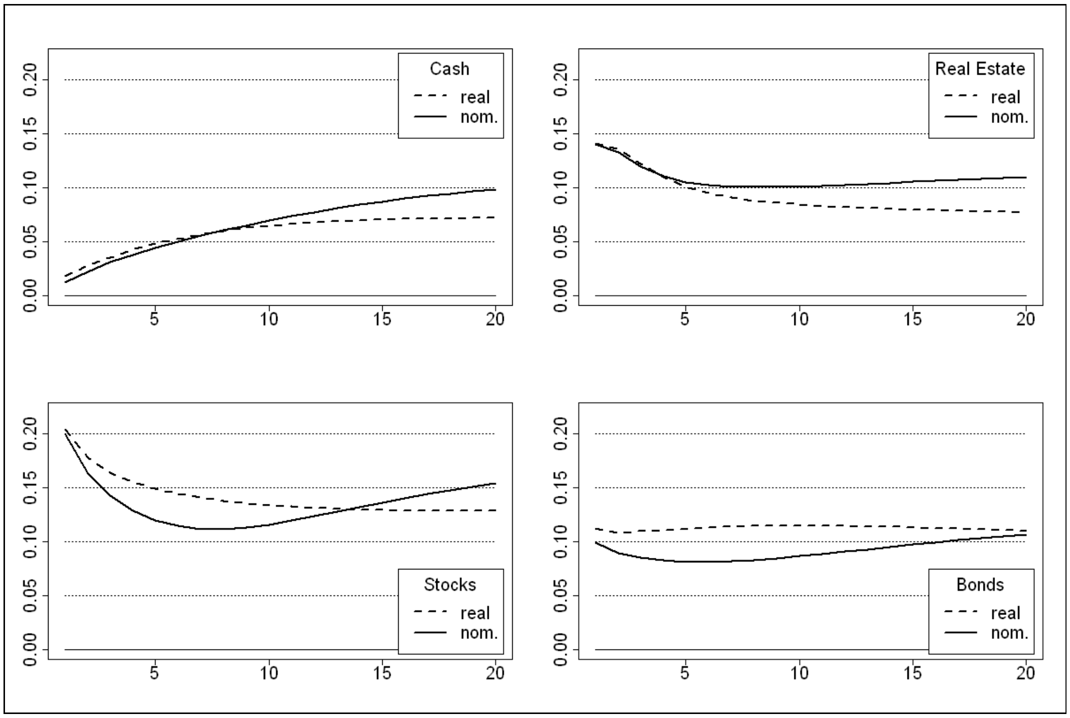


Figure 4.2 The term structure of return volatilities

The figure shows the annualized conditional standard deviations of real and nominal returns of the four assets depending on the investment horizon (years).

Figure 4.3 shows horizon-dependent asset correlations for both nominal and real returns, as implied by the VAR estimates. The correlation between real stock and bond returns at medium investment horizons is higher, but the long-term correlation is lower than the short-term correlation. This is similar to the Campbell and Viceira (2005) estimates. The correlation between real stock and real estate returns is slightly lower in the long run than in the short run. The correlation between the real returns on real estate and cash is strongly increasing with the investment horizon. Real bond and stock returns are highly correlated with cash returns in the long-term, too. In general, the long-term correlations of real asset returns are less dispersed than the short-term correlations, which is intuitively appealing. With the exception of the correlation between cash and bonds, the long-term correlations of nominal returns are higher than the long-term correlations of real returns, pointing towards inflation as a common driver of long-term nominal asset returns. In contrast, the short-term correlation of nominal cash and stock returns and in particular the short-term correlation of nominal cash and bond returns is notably lower than the respective correlation of real returns. Hence, inflation affects nominal cash and stock returns, and nominal cash and bonds returns differently in the short run.

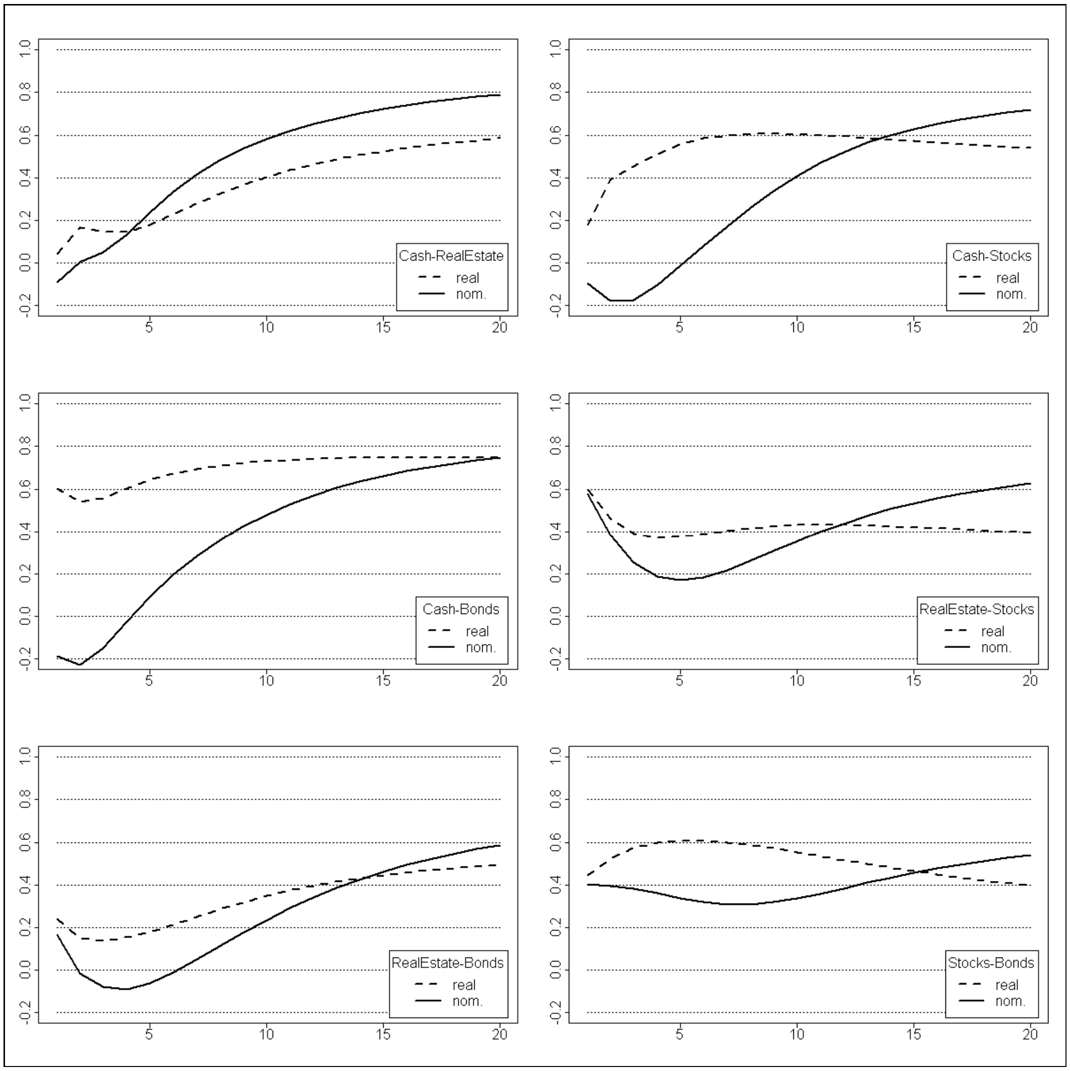


Figure 4.3 The term structure of return correlations

The figure shows conditional return correlations depending on the investment horizon (years) for both nominal and real returns.

4.4.2 Inflation hedging

To gain deeper insights into the differences between the term structures of return volatility for real and nominal returns, we derive formulas for the variance of nominal and real returns based on the approximation for the *k*-period portfolio return introduced by Campbell and Viceira (2002) and used in Campbell and Viceira (2004, 2005). Accounting for transaction costs regarding real estate and stock and bond investments, stacked in the (3x1) vector $\boldsymbol{c}$, the approximation to the nominal k-period portfolio return is:

$$n_{p,t+k}^{(k)} = n_{0,t+k}^{(k)} + \boldsymbol{\alpha}'(k)(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}) + \tfrac{1}{2}\boldsymbol{\alpha}'(k)[\boldsymbol{\sigma}_x^2(k) - \boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k)], \tag{4.10a}$$

where $\boldsymbol{\alpha}(k)$ is the (3x1) vector containing the asset weights, except for the weight on cash, with regard to a k-period investment, and $\boldsymbol{\sigma}_x^2(k) = diag[\boldsymbol{\Sigma}_{xx}(k)]$. Subtracting the k-period inflation rate $i_{t+k}^{(k)}$ yields the real portfolio return:

$$r_{p,t+k}^{(k)} = n_{0,t+k}^{(k)} + \boldsymbol{\alpha}'(k)(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}) + \tfrac{1}{2}\boldsymbol{\alpha}'(k)[\boldsymbol{\sigma}_x^2(k) - \boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k)] - i_{t+k}^{(k)}, \tag{4.10b}$$

From (4.10) one can calculate the conditional k-period variance of the portfolio return as:

$$Var_t(n_{p,t+k}^{(k)}) = \boldsymbol{\alpha}'(k)\boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k) + \sigma_0^2(k) + 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{0x}(k) \tag{4.11a}$$

$$Var_t(r_{p,t+k}^{(k)}) = \boldsymbol{\alpha}'(k)\boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k) + \sigma_0^2(k) + 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{0x}(k) + \sigma_i^2(k) - 2\sigma_{0i}(k) - 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{ix}(k). \tag{4.11b}$$

Assuming a 100% investment in the respective asset, equations (4.11a) and (4.11b) are the formulas for the variance of asset returns. The variance of the nominal return on an asset differs from the variance of the real return on the asset by the last three terms in (4.11b). The first of the three terms says that for all assets the real return volatility is higher than the nominal return volatility due to the variance of inflation shocks. The annualized k-period standard deviation of inflation shocks is shown in Figure 4.4.

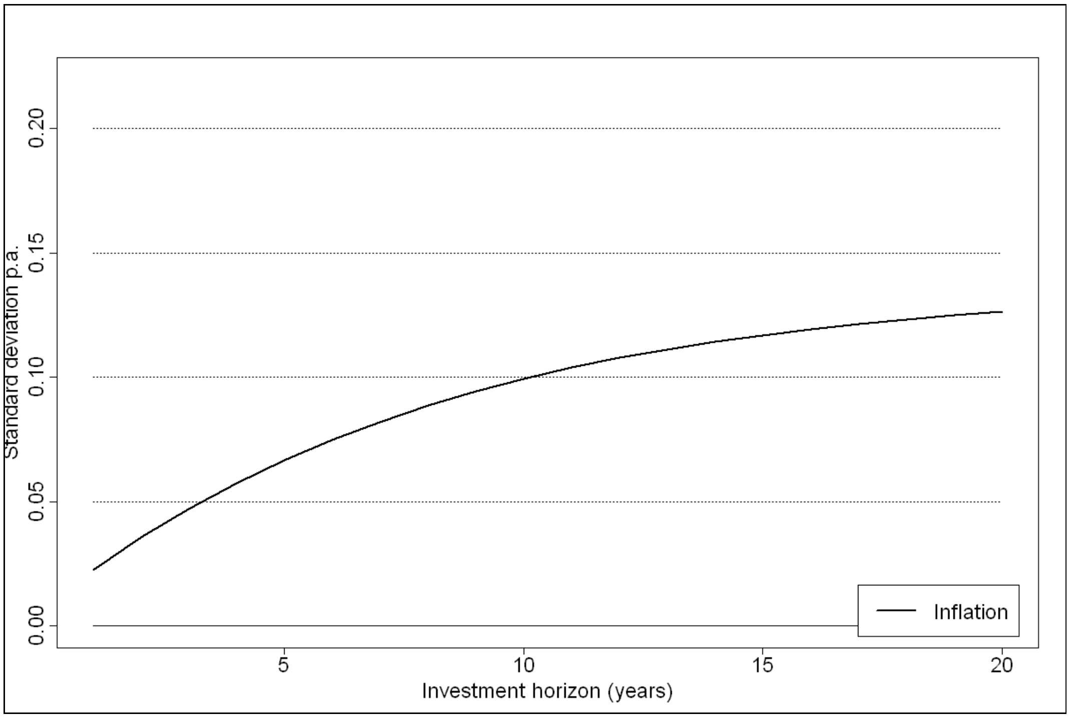


Figure 4.4: The term structure of inflation volatility

The figure shows the conditional annualized standard deviation of inflation depending on the investment horizon.

We see that due to the persistence of inflation, the periodic long-term volatility of inflation is much larger than the short-term volatility. Ceteris paribus, this significantly increases the long-term volatility of real returns. There are two additional terms with regard to the differences between the volatility of nominal and real returns, though. When the conditional covariance between nominal cash returns and inflation, σ_{0i}, is positive, this decreases the volatility of real cash returns. For the analysis of the other assets it is helpful to note that

$$-2\sigma_{0i}(k) - 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{ix}(k) = -2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{in}(k) - 2(1-\boldsymbol{\alpha}'(k)\boldsymbol{\iota})\sigma_{0i}(k), \tag{4.12}$$

where $\boldsymbol{\sigma}_{in}(k)$ is the vector of covariances between k-period inflation shocks and shocks to k-period nominal returns on real estate, stocks and bonds. The last term on the right hand side of (4.12) is zero for a 100% investment in real estate, stocks or bonds. Therefore, we see again that the conditional covariance of the nominal asset return with inflation is crucial for the difference between the variance of real versus the variance of nominal returns. Recall that the horizon-dependences of nominal return volatilities and of inflation volatility are shown in Figures 4.2 and 4.4 respectively. What we are missing to analyze the covariances are the horizon-dependent correlations of nominal asset returns with inflation, and these are shown in Figure 4.5. Cash is clearly the best inflation-hedging asset at short and medium horizons. Shocks to nominal cash returns are relatively highly correlated with inflation shocks and the correlation is increasing with the investment horizon. At the twenty-year horizon, real estate appears to hedge inflation as well as cash. Bonds are the weakest inflation-hedging asset in the short-term. In the long run, bonds and stocks have much better inflation hedging abilities than in the short run.

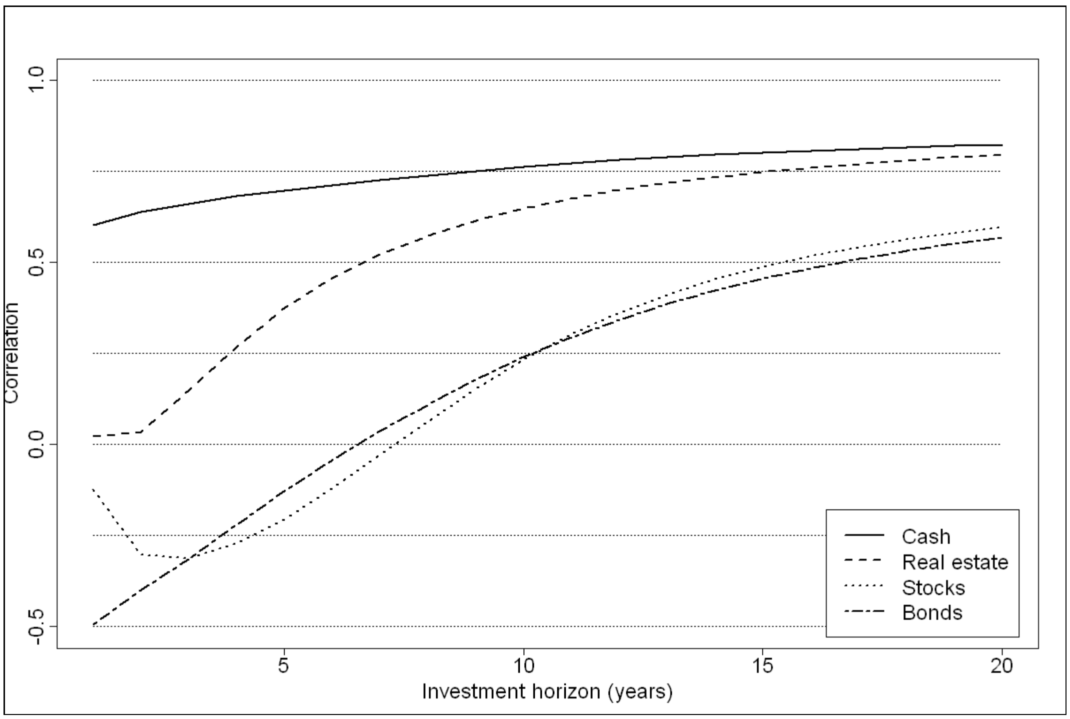


Figure 4.5: Inflation hedge properties

The figure shows conditional correlations of nominal returns and inflation depending on the investment horizon.

There are theoretical arguments supporting this empirical evidence. Fama and French (1977) point out that a strategy of rolling over short-term bills should offer a good hedge against longer-term unexpected inflation because short-term bill rates can adjust to reassessments of expected inflation. In contrast to this strategy, the cash-flows of a (default risk-free) nominal long-term bond are fixed, so the nominal long-term return does not move with inflation. Standard bond indexes, such as the one used in this chapter, are, however, representing a security with constant maturity. In terms of inflation hedging, this means that the return on these bond indexes benefits from the reassessments of expected inflation that are incorporated into the bond yield, so that the ability of constant maturity bond returns to hedge unexpected inflation improves with the investment horizon. Campbell and Vuolteenaho (2004b) suggest that the finding of stocks is a perverse inflation-hedge in the short run, but a good inflation-hedge in the long run can be explained by money illusion. They find empirical support for the Modigliani and Cohn (1979) hypothesis, who conclude that stock market investors suffer from a specific form of money illusion, disregarding the effect of changing inflation on cash-flow growth. When inflation rises unexpectedly, investors increase discount rates but ignore the impact of expected inflation on expected cash-flows, leading to an undervalued stock market, and vice versa. Because the misevaluation should eventually diminish, stocks are a good inflation-hedge in the long run. Direct real estate has both stock and bond characteristics. Bond characteristics are due to the contractual rent representing a fixed-claim against the tenant. However, rents are routinely adjusted to market level through renting vacant space or arrangements in the lease contract. For example, in the UK commercial real estate market, contractual rents are usually reviewed every five years; they are adjusted to market-rent level, when this level is above the contractual rent, otherwise the contractual rent remains unchanged. Thus, when general price and rent indexes are closely related, direct real estate should be a good long-term inflation hedge.

These inflation-hedging patterns help to reinterpret the findings shown in Figure 4.2. With regard to cash, we see that in the short-term the effect of the addition of the inflation variance dominates the covariance effect such that the volatility of real returns is slightly higher than the volatility of nominal returns. In the long-run, however, the increasing correlation of nominal cash returns with inflation makes real cash returns less volatile than nominal cash returns. For short horizons, the correlation between nominal stock returns and inflation is low, and therefore, real stock returns are more volatile than nominal stock returns. The correlation of nominal returns with inflation, however, increases with the investment horizon, so that the long-term volatility of nominal returns is higher than the volatility of real returns. For bond returns, the effect of the addition of the inflation volatility dominates the covariance effect for all horizons. But as the correlation between nominal bond returns and inflation increases with the investment horizon, the long-term standard deviations of real and nominal bond returns are quite similar. For real estate, the correlation between nominal returns and inflation is strongly increasing with the investment horizon, so that the volatility of real returns is notably smaller than the volatility of nominal returns in the long run.

4.4.3 The term structure of expected returns

From (4.10a) and (4.11a) one can calculate the k-period log expected nominal portfolio return as:

$$E(n_{p,t+k}^{(k)}) + \tfrac{1}{2} Var_t(n_{p,t+k}^{(k)}) = E(n_{0,t+k}^{(k)}) + \tfrac{1}{2}\sigma_0^2(k) + \boldsymbol{\alpha}'[E(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}) + \tfrac{1}{2}\boldsymbol{\sigma}_x^2(k) + \boldsymbol{\sigma}_{0x}(k)]. \quad (4.13a)$$

This equation shows how to calculate the (approximation of the) cumulative log expected nominal portfolio return or, assuming a 100% investment in the respective asset, the log expected nominal return of any single asset class. Note that the expected log return has to be adjusted by one half of the return variance to obtain the log expected return relevant for portfolio optimization (a Jensen's inequality adjustment); see Campbell and Viceira (2004). This adjustment is horizon-dependent. There are no horizon effects in expected log returns because we assume that they take the values of their sample counterparts. Thus, for the k-period expected log nominal cash return it holds that $E(n_{0,t+k}^{(k)}) = k\overline{n}_0$, where $\overline{n}_0$ denotes the sample average of log nominal cash returns. Similarly, we assume for the vector of log excess returns: $E(\boldsymbol{x}_{t+k}^{(k)}) = k\overline{\boldsymbol{x}}$. Even if there were no horizon effects in expected log returns, there would be horizon effects in log expected returns because conditional variances and covariances will not increase in proportion to the investment horizon unless returns are unpredictable. In the remainder of this chapter, the log expected return is termed “expected return” for short.

Additional horizon effects in expected returns are due to the consideration of proportional transaction costs. With regard to stocks and bonds, transaction costs encompass brokerage commissions and bid-ask spreads. Round-trip transaction costs for stocks are assumed to be 1.0%, as in Balduzzi and Lynch (1999) and Collet et al. (2003). Bid-ask spreads of government bonds are typically tiny (Fleming 2003, Gwilym et al. 2002); total round-trip transaction costs for bonds, including brokerage commissions, are assumed to be 0.1%. Transaction costs for buying and selling real estate encompass professional fees and the transfer tax. According to Collet et al. (2003), round-trip transaction costs for UK real estate are 7 to 8%. Marcato and Key

(2005) assume round-trip transaction costs of 7.5%. These costs cover the transfer tax ("stamp duty") of 4.0% (to be paid when buying), 1.5% for legal, agents' and other advisory fees for both purchases and sales, plus 0.5% internal investor's costs. We exclude the internal costs and hence assume total costs of 7.0%, which appears to be reasonable as Marcato and Key suggest that 7.5% may be a bit on the high side. The costs are divided into 5.5% buying costs and 1.5% selling costs. Round-trip transaction costs for stocks and bonds are divided by one half to obtain the costs for buying and selling separately. The assumed round-trip transaction costs enter the vector $\boldsymbol{c}$ in continuously compounded form, and they are obtained by adding the continuously compounded buying and selling costs, so that $\boldsymbol{c}' = [6.84\% \quad 1.00\% \quad 0.10\%]$. For example, the round-trip costs for real estate are $\ln(1.055) + \ln(1.015) \approx 6.84\%$.

The k-period expected real portfolio return can be calculated from (4.10b) and (4.11b) as:

$$\begin{aligned} E(r_{p,t+k}^{(k)}) + \tfrac{1}{2} Var_t(r_{p,t+k}^{(k)}) &= E(n_{0,t+k}^{(k)}) + \tfrac{1}{2}\sigma_0^2(k) - E(i_{t+k}^{(k)}) + \tfrac{1}{2}\sigma_i^2(k) \\ &\quad + \boldsymbol{\alpha}'[E(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}) + \tfrac{1}{2}\boldsymbol{\sigma}_x^2(k) + \boldsymbol{\sigma}_{0x}(k)] - \sigma_{0i}(k) - \boldsymbol{\alpha}'\boldsymbol{\sigma}_{ix}(k), \end{aligned} \tag{4.13b}$$

where $E(i_{t+k}^{(k)}) = k\bar{i}$, the k-period expected log inflation and $\tfrac{1}{2}\sigma_i^2(k)$, one-half of the variance of cumulative inflation shocks, are common differences for the distinction between nominal expected returns and real expected returns for every asset. In addition, the conditional covariances between asset returns and inflation ($\sigma_{0i}(k)$ and $\boldsymbol{\sigma}_{ix}(k)$ respectively) play a role. The results of the comparison between the term structures of annualized expected real and nominal returns after transaction costs for cash, real estate, stocks and bonds are shown in Figure 4.6.

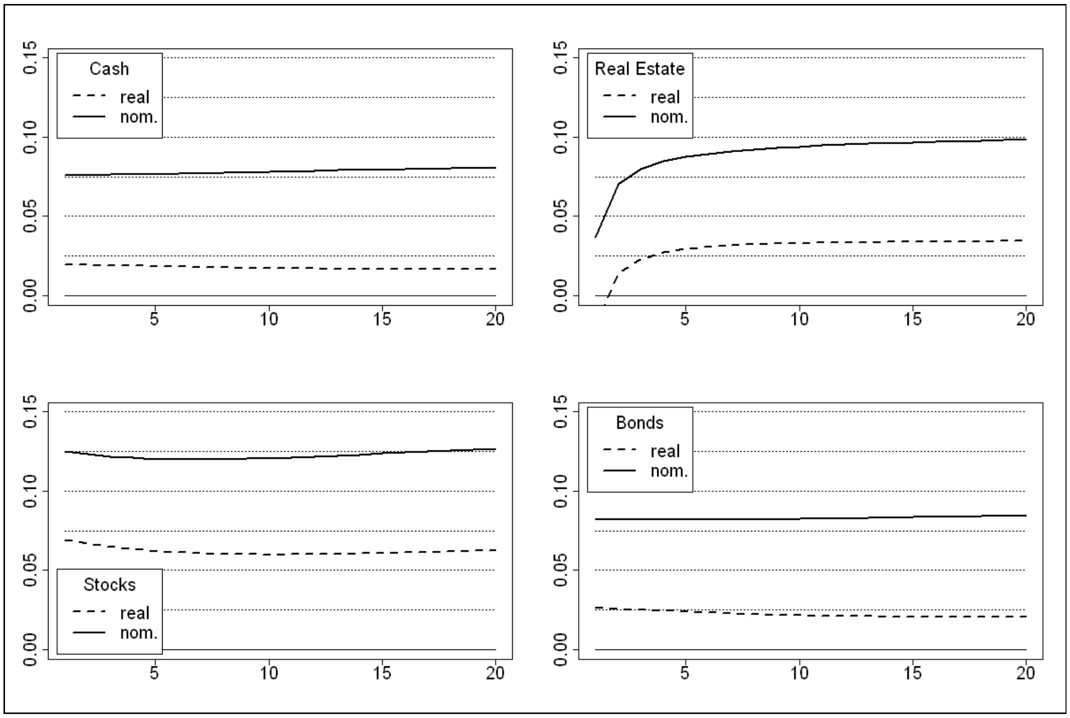


Figure 4.6 The term structure of expected returns

The figure shows annualized expected real and nominal returns depending on the investment horizon (years). These follow from (4.13a) and (4.13b), assuming a 100% investment in the respective asset. Expected log returns are assumed to equal their sample counterparts. Round-trip transaction costs are assumed to be 6.84% for real estate, 1.0% for stocks and 0.1% for bonds.

The difference between the expected real and nominal returns is a nearly parallel shift caused by the expected inflation. Due to transaction costs, there are major changes in the annualized expected real estate return, which increases strongly with the investment horizon, whereas the periodic expected returns on the other assets are roughly constant.

4.5 Horizon-dependent portfolio optimizations for nominal and real returns

4.5.1 Mean-variance optimization

Campbell and Viceira (2002, 2004) provide the formula for the solution to the mean-variance problem. Augmented by transactions, this is:

$$\boldsymbol{\alpha}(k) = \tfrac{1}{\gamma}\boldsymbol{\Sigma}_{xx}^{-1}(k)[E(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}) + \tfrac{1}{2}\boldsymbol{\sigma}_x^2(k)] + (1-\tfrac{1}{\gamma})[-\boldsymbol{\Sigma}_{xx}^{-1}(k)\boldsymbol{\sigma}_{0x}(k)], \tag{4.14}$$

where γ is the coefficient of relative risk aversion. $\boldsymbol{\alpha}(k)$ is a combination of two portfolios; the second portfolio is the global minimum variance portfolio:

$$\min\,[\text{w.r.t. } \boldsymbol{\alpha}(k)]\ \frac{1}{2}Var_t(n_{p,t+k}^{(k)}) = -\boldsymbol{\Sigma}_{xx}^{-1}(k)\boldsymbol{\sigma}_{0x}(k)\,. \tag{4.15}$$

Formula (4.14) applies directly to the mean-variance problem for nominal returns. The solution to the mean-variance problem for real returns differs from (4.14) only by the definition of the global minimum variance portfolio, which for real returns is:

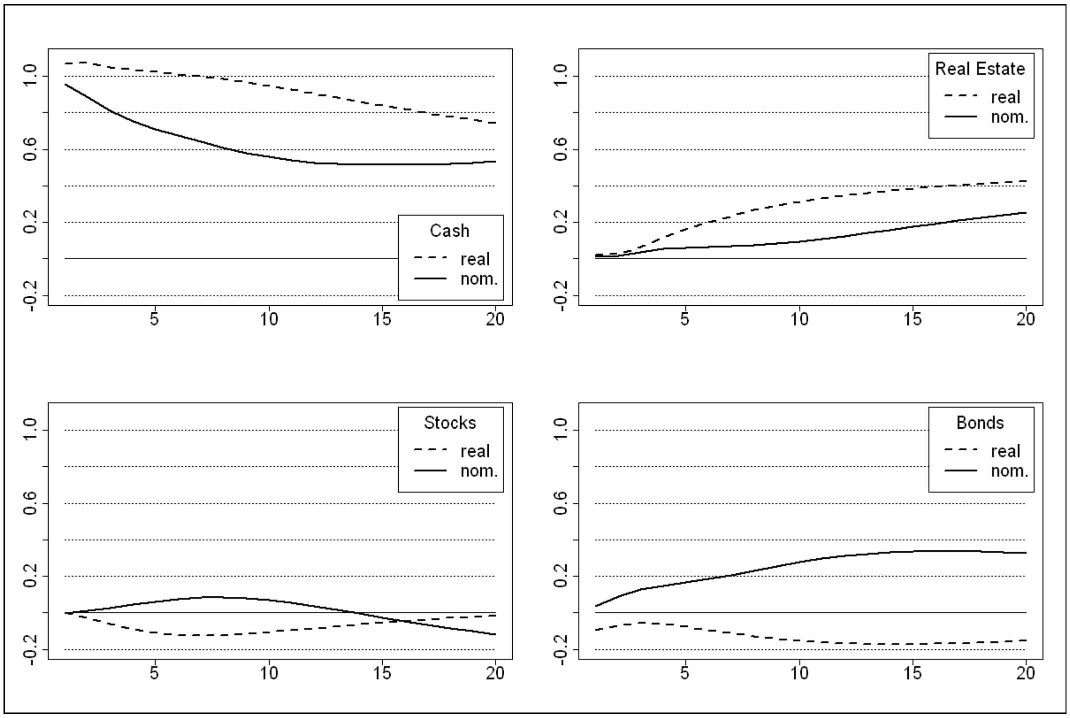
$$\min\,[\text{w.r.t. } \boldsymbol{\alpha}(k)]\ \frac{1}{2}Var_t(r_{p,t+k}^{(k)}), \tag{4.16}$$

where $Var_t(r_{p,t+k}^{(k)})$ is defined in (4.11b).

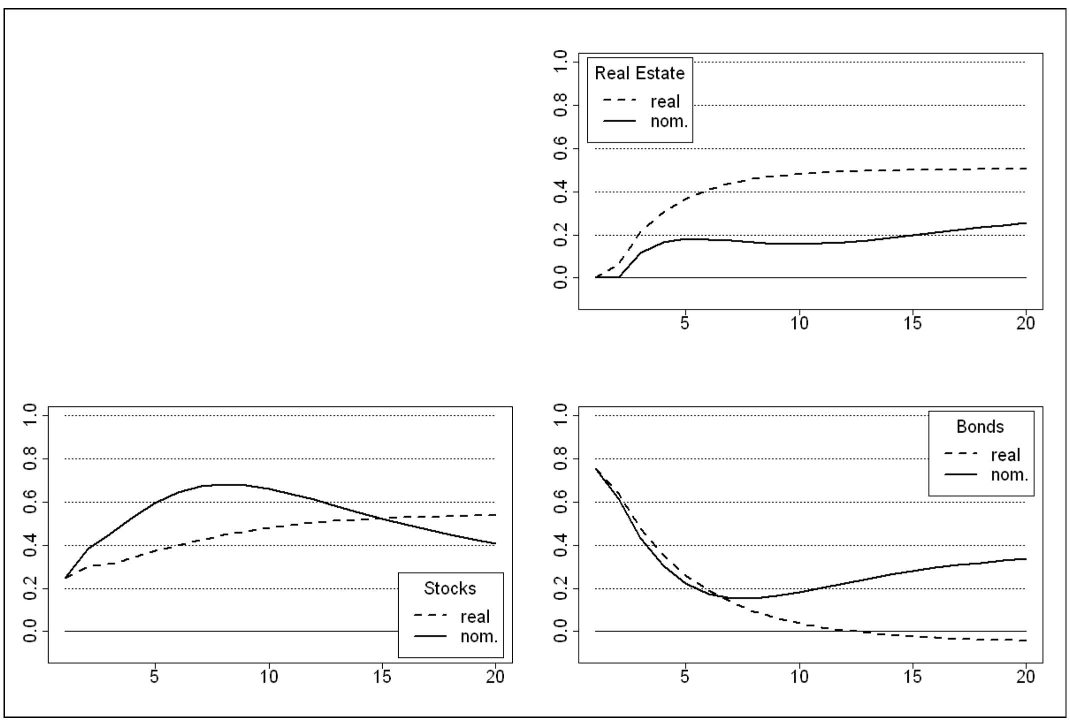
We analyze two portfolios. One portfolio is the global minimum variance portfolio. As in Campbell and Viceira (2005), we exclude cash as an available asset for the second portfolio, which represents a less risk-adverse investor than the global minimum-variance investor. Campbell and Viceira calculate a “tangency-portfolio” assuming that there would be a riskless asset. This is not suitable for our analysis because we would have to assume that both real and nominal cash returns would be riskless (at any horizon) and hence there would be no inflation risk. Therefore, we calculate optimal horizon-dependent asset weights for a portfolio consisting of bonds, stocks and real estate for a specific coefficient of relative risk aversion; we choose $\gamma = 5$. The formulas still apply to this restricted investment universe, except that not cash is the benchmark asset, but bonds, i.e., for the second portfolio $n_{0,t+1}$ is not the nominal return on cash, but on bonds, and $\boldsymbol{x}_{t+1}$ refers to the excess returns on real estate and stocks with regard to the return on bonds. The necessary statistics can be calculated by applying appropriate selection matrixes to (4.7) and (4.9). We rule out short-selling of direct real estate but do no impose short-selling restrictions for the other assets.

4.5.2 Results

Figure 4.7 shows two Panels with optimal portfolio allocations for investment horizons of up to twenty years. Panel A plots the composition of the global minimum variance (GMV) portfolio for optimizations based on real and nominal returns. At the one-year horizon, the differences between the allocations based on real returns versus the allocations based on nominal returns are small. A very risk-averse investor holds most of his money in cash because it is the least risky investment in nominal as well as in real terms over all investment horizons. However, as the annualized volatility strongly increases with the investment horizon, the weight assigned to cash decreases. Since the increase in the return volatility is stronger in nominal terms, this decrease is stronger for the optimization based on nominal returns. The weight assigned to real estate is increasing with the investment horizon. Again, the differences between the term structures of return volatility for nominal and real returns are crucial for the extent of the horizon effect. For the optimization based on nominal returns, the allocation to real estate increases to 10% at intermediate and up to 25.5% at long horizon. For real returns, the mean reversion effect is stronger and hence the weight assigned to real estate is much higher than the allocation for nominal returns at medium and long horizons. Bonds are more attractive in nominal than in real terms. Based on the optimizations for nominal returns, the weight increases from 3.6% at the one-year horizon to 32.8% at the twenty-year horizon, whereas the weight is negative for all investment horizons when real returns are considered. Because of the hump-shaped risk structure of nominal stock returns (high short- and long-term volatility – less risky in the medium term), stocks get a small positive weight at medium investment horizons and get a slightly negative weight at long investment horizons. For real returns, the allocation to stocks is negative for all investment horizons.



Panel A: Global minimum variance portfolio



Panel B: Optimal portfolio allocation with real estate, stocks and bonds for $\gamma = 5$.

Figure 4.7 Optimal portfolio compositions

The figure shows optimal portfolio compositions for real and nominal returns depending on the investment horizon (years).

Panel B reports the portfolio allocation comparison for an investor with moderate risk ($\gamma = 5$). As noted above, we only consider stocks, bonds and real estate. In addition to risk statistic, the term structures of expected returns are relevant for this portfolio. Recall that the differences with regard to nominal versus real returns are roughly parallel shifts. Hence, when comparing the results for nominal and real returns, the changing risk statistics are again crucial for the interpretation. We see once more that the differences in optimal portfolio weights are small at short horizons, since short-term return volatilities are similar for real and nominal returns. As in the GMV portfolio, real estate is much more attractive in the long run. Due to the short-selling restriction the allocation is zero at the one-year horizon. The weight increases to 50.6% for real returns and to 25.6% for nominal returns at the twenty-year horizon. For the optimization based on real returns, the allocation to stocks rises smoothly from 24.6% at the one-year to 53.8% at the twenty-year horizon due to the strong mean reversion effect of real stock returns. For the optimization based on nominal returns, the allocation to stocks is more variable and shows a hump-shaped structure with high allocations at intermediate horizons (up to 68.3%) and only 25% (40%) at short (long) horizons. Due to the low expected return on real estate and the high volatility of stock returns, bonds are the asset with the highest allocation at short horizons. The weight assigned to bonds is strongly decreasing with the investment horizon for the allocation based on real returns, since the term structure of the periodic return volatility is roughly flat, whereas stocks and real estate are getting more attractive with the investment horizon. In nominal terms, however, the weight assigned to bonds is increasing over longer investment horizons because stocks are getting very unattractive due to the increase in the periodic return volatility, which is stronger than the mean aversion of nominal bond returns over long horizons.

In summary, good inflation hedging assets classes increase their weights when the optimization is based on real rather than nominal returns. This is true for cash over all and for real estate over medium and long investment horizons. Stocks become less attractive for medium horizons, but due to the good inflation hedging abilities over long horizons, the long-term allocation to stocks is higher when the optimization is based on real instead of nominal returns. Bonds become less attractive for all investment horizons.

4.6 Robustness of the results with regard to the smoothing parameter

We recalculate main results for investment horizons of one, five, ten and twenty years for alternative parameter values used to unsmooth the appraisal-based real estate returns. Two alternative parameter values are considered, which Barkham and Geltner (1994) consider as reasonable lower and upper bounds: $a = 0.50$ and $a = 0.75$. The results are presented in Table 4.3. For comparison, the results obtained from the assumption made so far ($a = 0.625$) are also reported. We ignore (small) changes in the mean return that result from unsmoothing returns with different parameters. The results for cash, bonds and stocks are largely unaffected by the choice of the smoothing parameter; the results presented therefore focus on real estate.

The choice of the smoothing parameter has a large impact on the conditional standard deviation of the return on real estate at the one-year horizon in both nominal and real terms. When it is assumed that the original returns suffer from a lot of smoothing ($a = 0.50$), the one-year volatility is about 17.5%. In contrast, when the original returns are assumed to exhibit relatively little smoothing ($a = 0.75$), the one-year volatility is less than 12%. However, the longer the investment horizon, the smaller this difference is. At the twenty-year horizon, there is almost no difference. Due to the Jensen's inequality adjustment, expected returns are higher for $a = 0.5$; again, the longer the investment horizon, the smaller the differences are. Correlations of nominal returns on real estate with inflation are quite similar under the different smoothing parameters. In general, the allocation to real estate is lower when the original real estate returns are assumed to be more smoothed $(a = 0.5)$ since this yields more volatile unsmoothed returns, but the differences are not very large. Overall, the results appear to be fairly robust to changes in the smoothing parameter.

Table 4.3 Results obtained from the use of alternative smoothing parameters

This table shows results for three parameters a used to unsmooth real estate returns, and four investment horizons. Results are obtained from re-estimated VARs where the real estate excess return and cap rate series are based on the alternative assumptions.

Investment horizon (years)	1			5			10			20		
Smoothing parameter a	0.5	0.625	0.75	0.5	0.625	0.75	0.5	0.625	0.75	0.5	0.625	0.75
Expected return on real estate p.a.												
Real return	-1.23%	-1.91%	-2.07%	3.20%	2.93%	3.02%	3.50%	3.30%	3.42%	3.61%	3.43%	3.56%
Nominal return	4.38%	3.70%	3.55%	9.01%	8.74%	8.83%	9.58%	9.31%	9.51%	9.99%	9.82%	9.96%
Conditional standard deviation of real estate returns p.a.												
Real return	17.60%	14.11%	11.77%	11.41%	10.09%	9.33%	9.20%	8.56%	7.96%	8.11%	7.71%	7.52%
Nominal return	17.43%	13.98%	11.67%	11.54%	10.46%	9.94%	10.60%	10.08%	9.90%	11.23%	10.95%	10.94%
Conditional correlation of inflation and real estate returns												
Nominal return	-0.97%	2.27%	4.95%	30.57%	37.36%	42.65%	59.94%	64.87%	68.09%	77.43%	79.53%	80.98%
Real estate weight at global minimum variance portfolio												
Real return	1.51%	2.19%	3.02%	14.74%	16.30%	17.04%	27.56%	31.39%	33.41%	38.08%	42.48%	45.05%
Nominal return	1.12%	1.36%	1.65%	5.35%	6.26%	6.50%	6.71%	9.54%	11.41%	18.30%	25.53%	32.53%
Real estate weight at portfolio with $\gamma = 5$												
Real return	0.00%	0.00%	0.00%	31.75%	36.69%	42.92%	45.06%	48.25%	54.16%	51.17%	50.59%	55.72%
Nominal return	0.00%	0.00%	0.00%	14.94%	18.01%	23.07%	14.42%	15.72%	20.85%	25.10%	25.65%	32.35%

4.7 Conclusion

Focusing on the role of the investment horizon, we analyze the inflation-hedging abilities of stocks, bonds, cash and direct commercial real estate investments, and the implications of the inflation-hedge results for portfolio choice. Based on vector autoregressions for the UK market we find that the inflation-hedging abilities of all assets analyzed improve with the investment horizon. Cash is clearly the best inflation hedge at short and medium horizons. For long horizons, real estate hedges unexpected inflation as well as cash. This has implications for the difference between the return volatility of real returns versus the return volatility of nominal returns. The long-term volatility of real returns on real estate is notably lower than the long-term volatility of nominal returns. This is also true for cash returns. In contrast, bonds are less attractive for an investor concerned about inflation. The same is found for stocks at medium horizons, but at long horizons the volatility of real stock returns is lower than the volatility of nominal returns. Portfolio optimizations based on real returns yield higher allocations to cash and real estate than optimizations based on nominal returns. Bonds tend to be less attractive for an investor taking into account inflation. Switching from nominal to real returns, the allocation to stocks is decreasing at medium investment horizon, but increasing at long horizons. The differences between the asset allocation results can be substantial. This means that the optimal asset allocation for investors concerned about inflation (private investors and certain institutional investors) can be quite different from the optimal asset allocation for (institutional) investors with liabilities that are fixed in nominal terms.

4.8 Appendix: Data

Table 4.A1 contains information on the data.

Table 4.A1: Data information

	Description	Source
Cash return	Change (%) of Barclays UK treasury bill index	Barclays Equity Guilt Study 2009
Cash yield	UK clearing banks base rate	Datastream
Bond yield	Yield of Barclays gilt index	Barclays Equity Guilt Study 2009
Stock return	Change (%) of Barclays equity index	Barclays Equity Guilt Study 2009
Bond return	Change (%) of Barclays gilt index	Barclays Equity Guilt Study 2009
Real estate return	Constructed as described in this Appendix	Scott (1996), IPD
Inflation	Change (%) of UK cost of living index	Barclays Equity Guilt Study 2009
Cap rate	Constructed as described in this Appendix	Scott (1996), IPD
Dividend yield	Income yield of Barclays equity index	Barclays Equity Guilt Study 2009

The real estate total return and cap rate series are calculated as follows: The unsmoothed log real capital returns (see section 4.3.2 for a description of the unsmoothing procedure) are converted to simple nominal capital returns (CRU_t). This series is used to construct an unsmoothed capital value index (UCV_t). The unsmoothed capital value index is calibrated such that the average of the capital values over time matches the corresponding average of the original index. A real estate income series (Inc_t) is obtained by multiplying the (original) income return (IR_t) with the (original) capital value index (CV_t): $Inc_t = IR_t \cdot CV_{t-1}$. New income returns are computed with regard to the unsmoothed capital value index: $IRU_t = Inc_t / UCV_{t-1}$. Total returns are obtained by adding the adjusted simple income and capital returns: $RER_t = CRU_t + IRU_t$. The cap rate series is calculated as $CR_t = Inc_t / UCV_t$.

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